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Video demonstrations can predict the intention to use digital learning technologies

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Abstract

The technology acceptance model (TAM) uses perceived usefulness and perceived ease of use to predict the intention to use a technology which is important when deciding to invest in a technology. Its extension for e-learning (the general extended technology acceptance model for e-learning; GETAMEL) adds subjective norm to predict the intention to use. Technology acceptance is typically measured after the technology has been used for at least three months. This study aims to identify whether a minimal amount of exposure to the technology using video demonstrations is sufficient to predict the intention to use it three months later. In two studies—one using TAM and one using GETAMEL—we showed students of different cohorts (94 and 111 participants, respectively) video demonstrations of four digital technologies (classroom response system, classroom chat, e-lectures, mobile virtual reality). We then measured technology acceptance immediately after the demonstration and after three months of technology use. Using partial least squares modelling, we found that perceived usefulness significantly predicted the intention to use three months later. In GETAMEL, perceived usefulness significantly predicted the intention to use for three of the four learning technologies, while subjective norm only predicted the intention to use for mobile virtual reality. We conclude that video demonstrations can provide valuable insight for decision-makers and educators on whether students will use a technology before investing in it.

KEYWORDS
digital learning technologies, e-learning, general extended technology acceptance mode for e-learning, intention to use, perceived usefulness, technology acceptance model, virtual reality

Practitioner notes

What is already known about this topic

- The technology acceptance model helps decision-makers to determine whether students and teachers will adopt a new technology.
- Technology acceptance is typically measured after users have used the technology for three to twelve months.
- Perceived usefulness is a strong predictor of intention to use the technology.
- The predictive power of perceived ease of use for the intention to use varies from insignificant to strong.

What this paper adds

- For the four digital learning technologies (classroom chat, classroom response system, e-lectures and mobile virtual reality), we measure technology acceptance after a video demonstration and again after three months of usage.
- Using structural equation modelling, we are able to predict intention to use after three months, with perceived usefulness measured after the video demonstration.
- We replicate these findings with a second study using the general extended technology acceptance model.

Implications for practice and/or policy

- Short video demonstrations can provide information for educators to predict whether students will use a technology.
- Early impressions of perceived usefulness are very important and valuable to predict whether students will use a technology.

INTRODUCTION

Even after considerable money, resources, and time have been invested, many technologies do not get used (Davis & Venkatesh, 2004). The technology acceptance model (TAM), developed by Davis (1989), is considered to be the most influential model to help solve this problem (King & He, 2006). After using a technology for several months, perceived usefulness and perceived ease of use are evaluated to predict the intention to use the technology (behavioural intention) and its usage. Many extensions and changes to the TAM have been proposed (King & He, 2006). None of these changes, however, explore the question of how much exposure to the technology is required to make predictions about the intention to use.

Our aim in this study was to determine whether a minimal amount of exposure to the technology would be enough to predict the intention to use (instead of the commonly used timeframe of three to twelve months). In the first study (Study 1), we showed students a two-minute video for four different digital learning technologies at the beginning of the semester and then measured their technology acceptance using Davis's (1989) TAM. For the following three months, the students used the four technologies, and we then repeated the measurement. Video demonstrations were chosen to convey information in this study because they are a typical and important step when researching new technologies

(HubSpot, 2022), providing direct applications for educators. One reason for the importance of videos in gathering information is that they convey visual information in a condensed way (Beheshti et al., 2018). Video demonstrations have also been shown to assist people in remembering key concepts more easily than when information is written (Willingham, 2021). Because many findings have not been replicable—known as the 'replication crisis' (Open Science Collaboration, 2012)—we repeated the study with the same procedure employing the extended version of the TAM (Study 2). The general extended technology acceptance model for e-learning (GETAMEL; Abdullah & Ward, 2016) shares the same core model as TAM; thus, we are able to test whether we can replicate Study 1's findings and extend them with the additional factors. Being able to predict technology acceptance with much lower levels of exposure could help lecturers and school administrators judge whether or not to invest in a technology. In the following literature review section, we discuss the theoretical framework of this study by reviewing the literature of the four digital learning technologies used in our study. We then elaborate on the research regarding the TAM and GETAMEL before discussing the expected results.

Digital learning technologies

A classroom response system is a technology which allows lecturers to ask students questions and rapidly collect their answers with the help of electronic devices (typically smartphones, laptops or dedicated devices called 'clickers', Wu et al., 2019). The results are presented in real time, and the lecturer can display them to the class to discuss the responses. This activates each student's attention (Solinska-Nowak et al., 2018) and also allows students to actively engage in the learning process, which has positive effects on learning outcomes (Prince, 2004). Lecturers are able to gain insight into student comprehension (Wood & Shirazi, 2020), and if necessary, the lecturers can intervene by clearing up misunderstandings or clarifying poorly understood material (Sprenger & Schwaninger, 2021). When used anonymously, classroom response systems can activate shy students (Sprenger & Schwaninger, 2021). In addition, they can improve attention, enjoyment, classroom interaction, and learning outcomes (López-Quintero et al., 2016; Ma et al., 2018; Wood & Shirazi, 2020). Classroom response systems can be used both in the classroom and for online classes (Mosquera Feijóo et al., 2021). Asking questions has been linked to higher levels of achievement in class, and causal links between asking open-ended questions in lectures and learning outcomes have been found (Kang et al., 2007). Introducing anonymity can also increase the number of questions asked and how comfortable students feel about participating (Bartsch & Murphy, 2011). Therefore, we introduced a technology—a classroom chat—to enable students to ask the lecturer questions anonymously using their electronic devices. As anonymity can encourage shy students who otherwise would not be brave enough to participate, the classroom chat offers shy and anxious students a way to ask questions without being the centre of attention (Stowell et al., 2010). This allows for better interaction with the whole class and also gives the lecturer insight into what remains unclear (Tautz et al., 2021). Lecture recordings—also known as e-lectures—are common at many educational institutions (Banerjee, 2021). While results are mixed regarding the effectiveness of e-lectures in improving learning outcomes (Demetriadis & Pombortsis, 2007; Tani et al., 2022), their popularity with students is well documented (Gormley et al., 2009). This is most likely because e-lectures allow students to review material at their own pace and to re-watch lectures they missed due to illness or other reasons (Demetriadis & Pombortsis, 2007). For these same reasons, however, there are indications that attendance may drop as students feel they are able to catch up at another time (Banerjee, 2021). E-lectures can both be used for classroom and online lectures, both of which students prefer to only having the live lecture (Yatigammana & Wijayarathna, 2021).

Another technology that has implications for education is virtual reality (VR). VR refers to a computer-generated virtual environment in which users can move and interact (Fabris et al., 2019). Apart from its use in gaming, lecturers have begun using VR in education (Fabris et al., 2019). While VR gained early approval and acceptance in the fields of engineering and the medical sciences, its use has spread to all disciplines (Vergara et al., 2021). Some findings show the positive impact of VR on student performance (Liu et al., 2020; Schott & Marshall, 2021; Tai et al., 2022) and practical skills (Chang, 2021; Morélot et al., 2021). Due to the ability to revisit training scenarios repeatedly, VR can also reduce training costs (Barteit et al., 2021). Mobile VR is a subset of VR where smartphones are inserted into a headset. In our case, the headset was a VR cardboard. Mobile VR is becoming increasingly more common in education due its low costs, high availability and similarly good learning outcomes as desktop based computer VR (Degli Innocenti et al., 2019). While all digital learning technologies discussed offer advantages, there are some notable differences. The classroom response system and classroom chat are used during lectures, while VR can be used both during and after lectures. E-lectures, however, can only be used after the lectures have been delivered. The levels of financial investment required also differ significantly. Both the classroom response system and classroom chat require very little investment, as plenty of free software solutions are available. Arguably, the classroom response system requires a higher investment in terms of preparation than the classroom chat because lecturers must prepare questions ahead of time. E-lectures do not necessarily require much investment as capturing software can be free and easy to use. However, we found that editing the lectures (adjusting volume and removing irrelevant parts, such as breaks) improved the quality significantly. Conversely, VR requires substantial investment to program the VR environment. Moreover, substantial software development resources are necessary to ensure that VR modules work with different smartphones and operating systems.

Technology acceptance model

Based on the theory of reasoned action Fishbein and Ajzen (1977), Davis (1989) developed the TAM to predict the intention to use a technology (also called behavioural intention). The TAM is considered the most widely used model for understanding technology adoption (Estriegana et al., 2019). The TAM has two predictors for the intention to use: perceived usefulness and perceived ease of use. A strong link has been shown between the intention to use and actual use (King & He, 2006). The TAM is advantageous in that it is applicable to any type of technology and has thus been applied to a large range of technologies, including for example autonomous vehicles (Yuen et al., 2021), facial recognition payment (Zhong et al., 2021) and video conferencing (Alfadda & Mahdi, 2021). While the TAM has generally provided a very good framework to predict the intention to use and usage, variations have been found in the pathway relationships among the three factors of perceived usefulness, perceived ease of use and intention to use (King & He, 2006). This is particularly true for perceived ease of use predicting the intention to use, where the predictive power of the former has ranged from non-existent to strong (Gefen & Straub, 2000; King & He, 2006). Despite the TAM's popularity, many researchers have also noted limitations to the research and the model (Al-Fraihat et al., 2020). These include the use of self-reporting (Kitsios et al., 2021), varying ways to model the relationships between factors, and the weak theoretical underpinning of the core technology acceptance factors (Alsaad & Al-Okaily, 2022). While many studies do not include specific information about how much hands-on experience participants had with a given technology (Kamal et al., 2020; Rafique et al., 2020), the TAM is typically measured after a certain amount of familiarity has been gained, usually three to twelve months (Estriegana et al., 2019). The overwhelming majority of studies have focused on multiple months of hands-on experience with a technology. In this study, we explore whether video demonstrations can predict the intention to use. This crucial question of how much exposure and experience participants should have before measuring technology acceptance has largely not been addressed. The only study we are aware of that partly addresses the temporal aspect is that of Davis and Venkatesh (2004), who simulated a change of the technology over time. They generated prototype mock-ups of an existing technology and let users gain several weeks of experience with the mock-ups, after which they measured the technology acceptance. They then let users use the actual technology for several weeks and found that the perceived usefulness measured using the prototype successfully predicted the intention to use six months later. Davis and Venkatesh (2004) provide an indication that technology acceptance can be measured without providing hands-on experience with the technology for several months. No other study has explored how much experience is required to make strong predictions for the intention to use. In our study, we push this factor to the arguable limit: we do not give any hands-on experience with the technology but instead only provide a video demonstration. Since its introduction 30 years ago, many researchers have proposed adjustments to the TAM (Kemp et al., 2022; Malanga et al., 2022). Davis also extended the TAM twice, and his co-author attempted to consolidate all its factors in a unified model called the unified theory of acceptance and use of technology (Venkatesh, 2022). King and He (2006) categorise the adjustments into four groups: prior factors influencing perceived usefulness and perceived ease of use, factors suggested by other theories affecting the intention to use, contextual factors impacting the core TAM factors, and consequent factors which follow the intention to use. The GETAMEL (Abdullah & Ward, 2016), which is aimed at e-learning technologies, falls into the first of the above-mentioned categories.

General extended technology acceptance model for e-learning (GETAMEL)

While the TAM has proven to be very influential and successful at predicting the intention to use, it does not provide any further information to help pinpoint why a technology was considered useful or easy to use in e-learning. To remedy this, Abdullah and Ward (2016) analysed 107 articles to identify which factors impact the technology acceptance of e-learning technologies. They identified five factors: self-efficacy, subjective norm, enjoyment, computer anxiety, and experience. Each of these factors predicts perceived usefulness and perceived ease use while subjective norm is the only new factor to also predict the intention to use as shown in Figure 1.

Self-efficacy is the users' judgement of being able to successfully complete a task (Abdullah & Ward, 2016). In the technical e-learning context, high levels of self-efficacy mean that students believe they can successfully solve tasks using a computer (Abdullah & Ward, 2016). Such students are more willing to use computers (Igbaria & Iivari, 1995) and e-learning (Celik & Yesilyurt, 2013) and are also more likely to show higher levels of learning performance as well as being better at selecting learning strategies (Wang & Wu, 2008). A student is influenced by their peers, lecturers, and institutional policies. This environment comprises the students' subjective norm (Fishbein & Ajzen, 1977). Perceived enjoyment is connected to intrinsic motivation (Abdullah & Ward, 2016). Its definition—in the context of e-learning—is 'the extent to which the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use' (Park et al., 2012, p. 379). Computer anxiety is a negative emotional reaction to performing a task using a computer (Abdullah & Ward, 2016) and has been linked to the avoidance of using e-learning (Park et al., 2012). Experience in this context refers to the amount of experience a student has with computers and the amount of skills that the student has acquired (Abdullah & Ward, 2016).

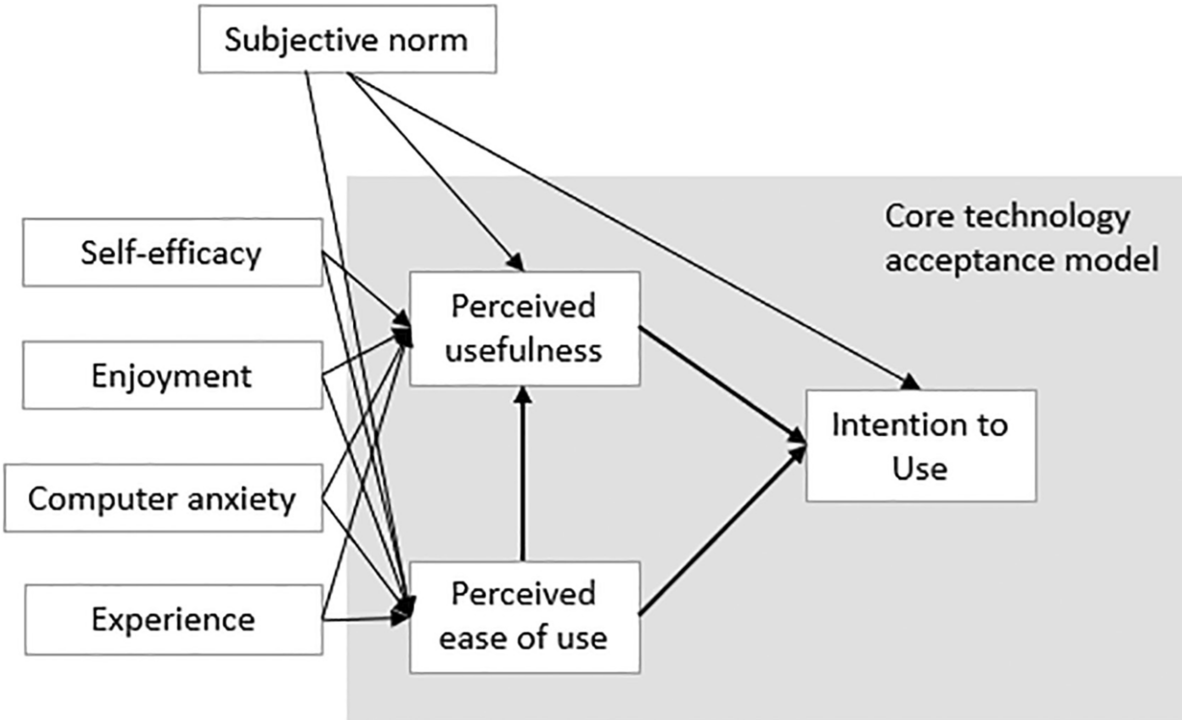

FIGURE 1 GETAMEL and its core model (the TAM).

Present study and hypotheses (H)

Our goal was to determine whether a minimal amount of exposure to the four digital learning technologies is sufficient to predict the intention to use them three months later in a typical tertiary education system setting, as is used in many countries (in our case: lectures to 100+ psychology students). To this end, we conducted two studies: Study 1 using the TAM and Study 2 using its extension, the GETAMEL. We showed different student cohorts video demonstrations of the four digital technologies and then measured technology acceptance immediately after the demonstration (T1) and after three months of use (T2). We believe that perceived usefulness measured at T1 will have a significantly positive path loading to the intention to use measured at T2, both in Study 1 (H1) and Study 2 (H2), for several reasons. When Davis and Venkatesh (2004) provided study participants with mock-ups to judge technology acceptance, this led to lower, though significant, path loadings (Davis & Venkatesh, 2004). We expect the same pattern here; that is, less exposure to the technologies will reduce the ability of perceived usefulness to predict the intention to use. However, as the key functionalities can still be understood when watching a demonstration video, we expect that the strength of the path loadings will only be minimally reduced. Previous research has also shown that the relationship between perceived usefulness and intention to use is very strong (King & He, 2006). As the digital learning technologies are conceptually very easy to understand, we believe their usefulness will be evident to the students from watching the demonstration videos alone. This would indicate that the ability of perceived usefulness to predict the intention to use might be robust enough to handle slight alterations to the technology and changes in time. Having said that, we presume that the path loadings predicting the intention to use at T1 will generally be higher than those from perceived usefulness at T1 to the intention to use at T2. This is because, as students get to know the technologies better, they can adjust their judgements slightly, which will, in turn, negatively impact the strength of the path loading from T1 to T2. Regarding the ability of perceived ease of use to predict the intention to use, we propose a conditional hypothesis, as the relationship between these is much less clear. The path loadings between perceived ease of use and intention to use range from not significant to very strong (Gefen & Straub, 2000; King & He, 2006). If the perceived ease of use path loadings at T2 are strong, we expect the path loadings from perceived ease of use at T1 to the intention to use at T2 to also be significant, both in Study 1 (H3) and Study 2 (H4). If, however, the path loadings at T2 are weak, we do not expect perceived ease of use at T1 to be able to significantly predict the intention to use at T2.

For the GETAMEL (Study 2), we do not expect subjective norm at T1 to predict the intention to use at T2 (H5). This is because students cannot assess the impressions of their peers just after a video demonstration, which is an important aspect of subjective norm (Fishbein & Ajzen, 1977). The students in this study had only just started their studies, most of them did not know each other, and they did not have time to discuss their impressions after watching the demonstration videos before rating the digital technologies.

Therefore, our hypotheses are as follows:

H1 *In Study 1, perceived usefulness measured at T1 will have significantly positive path loadings to the intention to use measured at T1 for all four digital learning technologies.*

H2 *In Study 2, perceived usefulness measured at T1 will have a significantly positive path loading to the intention to use measured at T1 for all four digital learning technologies.*

H3 *In Study 1, if perceived ease of use at T2 has high path loadings to the intention to use at T2, then perceived ease of use at T1 will also have significant path loadings to the intention to use at T2 for all four digital learning technologies.*

H4 *In Study 2, if perceived ease of use at T2 has high path loadings to the intention to use at T2, then perceived ease of use at T1 will also have significant path loadings to the intention to use at T2 for all four digital learning technologies.*

H5 *In Study 2, subjective norm measured at T1 will not have a significant path loading to the intention to use at T2 for all four digital learning technologies.*

In the following section, we present Study 1 and discuss its findings regarding H1 and H3. Afterwards, we present Study 2 and discuss the findings regarding H2, H4, and H5.

STUDY 1

Methods

Participants

A total of 123 students enrolled in the module "General Psychology 1" at University of Applied Sciences and Arts Northwestern Switzerland during the autumn semester. Of those students, 94 (72 female and 22 male students) also participated in the second measurement. Participation in the study was voluntary but we encouraged students by pointing out that their feedback would influence which digital learning technologies might be employed in the future in this and other courses. All participants provided informed consent.

Design

The independent variables were the four digital technologies (classroom chat, classroom response system, e-lectures, and mobile VR) as well as the time of measurement (after the video demonstration (T1) and after three months of technology usage (T2)). The dependent variables were perceived usefulness, perceived ease of use and the intention to use.

Materials

We collected demographic information in the first section of the questionnaire and measured our constructs in the second section. Perceived usefulness and perceived ease of use were measured based on the original TAM items (Davis, 1989). We made slight adjustments to the wording to account for the technologies and times of measurement. We measured the intention to use items from a study measuring the construct (Davis & Venkatesh, 2004). We employed the back-translation method (Behr et al., 2015) to translate all the items from English into German. The items were first translated by a bilingual (German/English) psychologist from English to German, and a second psychologist (native German speaker) translated the items back to English. The two translators compared the original items with the twice-translated ones, and any inconsistencies were resolved through mutual agreement. The three factors had five items each and used a 7-point Likert scale, with 1 signifying 'completely disagree' and 7 'completely agree', which is common for TAM measurements (King & He, 2006). The items are shown in Appendix A.

Procedure

At the start of the semester, we showed the students an approximately two-minute video of each digital learning technology. The videos first explained what the technology was and how it would be employed in class, then they showed a use case of how the technology works and what it looks like. After each video, the students were asked to fill out the TAM questionnaire online.

We repeated the measurements again after three months, during which time the students had been using all four digital learning technologies. A basic overview of the design and statistical modelling approach is shown in Figure 2.

Analyses

We used the partial least squares (PLS) method to calculate the influence of perceived usefulness and perceived ease of use at the beginning of the semester (T1) on the intention to use after three months (T2). To ensure that the TAM was applicable to our settings and technologies, we also modelled the TAM for each technology at both measurement times. We used the software Smart PLS version 3.3.3, which computes PLS models while minimising the residual variance of the whole model's dependent variables and does not have any parametric conditions (Hair et al., 2016).

Results

We modelled the TAM for each technology first at T1 and then at T2 to ensure that the TAM was a good fit for our technologies and settings. Then, to test our main hypothesis, we fully modelled the TAM at both T1 and T2 to test its validity. We also examined perceived usefulness and perceived ease of use measured at T1 as predictors for the intention to use measured at T2.

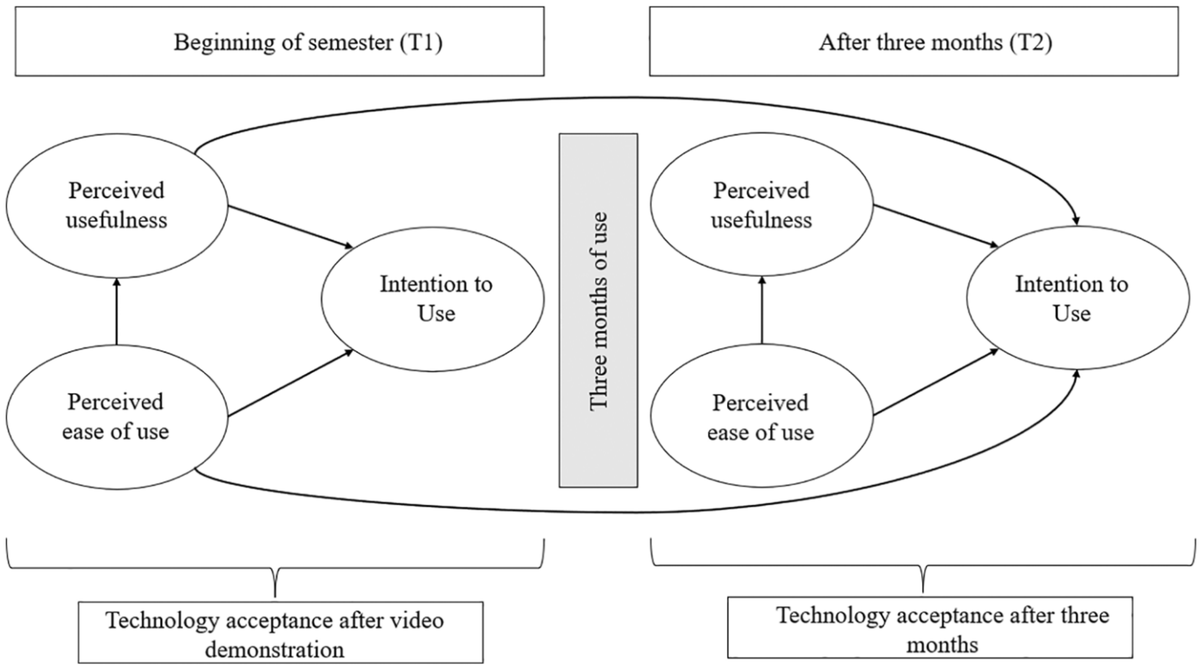

FIGURE 2 Overview of TAM measurements taken at the beginning of the semester (T1) and after three months usage (T2).

Measurement models

The outer standardised loadings of the measurement models for each tool's technology acceptance are shown in the supplementary material in Table S1 for T1 and in Table S2 for T2. We calculated the internal consistency of the measurement scales using Cronbach's alpha, all values of which were above 0.80 and considered good (Hair et al., 2016) shown in Table S3. Composite reliability values were above 0.85, which is considered good (Brunner & Suss, 2005) shown in Table S3. The average extracted variance was above 0.60, indicating acceptable levels of validity (Hair et al., 2016), see Table S3. To determine the discriminant validity, we applied the heterotrait-monotrait (HTMT) approach (Hair et al., 2016). The results are shown in Table S4. All HTMT values were below 0.90, proving the discriminant validity between the two reflective constructs, except for mobile VR between perceived usefulness and the intention to use at T2, where the value was 0.91.

Structural models

Using the bootstrap method, SmartPLS generated *t*-statistics for the significance testing of the inner and outer models (Hair et al., 2016). The bootstrap method takes a large number of subsamples (in our case, 5000 as recommended by Hair et al., 2016) with replacement to compute the standard errors, which enables SmartPLS to estimate the t-values for significance testing. Table 1 shows the inner path loadings for all four digital learning technologies at both measurement times as a validation of the TAM.

Table 2 shows the path loadings and significant testing of the ability of PU and PEOU measured at T1 to predict the intention to use the four digital learning technologies at T2.

TABLE 1 Path loadings and significance testing for the PLS modelled TAM at the beginning (T1) and after three months usage (T2) for all digital learning technologies

	Technologies			
Path loadings for	CC	CRS	E-lectures	Mobile VR
PEOU T1→PU T1	0.262*	0.448**	0.477***	0.535***
PU T1→IU T1	0.664***	0.655***	0.652***	0.790***
PEOU T1→IU T1	−0.020	0.156	−0.030	−0.046
PEOU T2→PU T2	0.426***	0.568***	0.344***	0.306***
PU T2→IU T2	0.788***	0.657***	0.830***	0.875***
PEOU T2→IU T2	0.000	0.209	−0.104	0.046

Note: Bootstrap with 5000 samples. One-tailed significance testing.

Abbreviations: CC, classroom chat; CRS, classroom response system; IU, intention to use; PEOU, perceived ease of use; PU, perceived usefulness; VR, virtual reality.

*Significant at $\alpha = 0.05$.

**Significant at $\alpha = 0.01$.

***Significant at $\alpha < 0.001$.

TABLE 2 Path loadings and significance testing for the PLS modelled TAM at T1 to predict IU at T2 for all digital learning technologies

	Technologies			
Path loadings for	CC	CRS	E-lectures	Mobile virtual reality
PU T1→IU T2	0.312**	0.653***	0.260**	0.212*
PEOU T1→IU T2	−0.097	0.156*	−0.134	−0.131

Note: Bootstrap with 5000 samples. One-tailed significance testing.

Abbreviations: CC, classroom chat; CRS, classroom response system; IU, intention to use; PEOU, perceived ease of use; PU, perceived usefulness; VR, virtual reality.

*Significant at $\alpha = 0.05$.

**Significant at $\alpha = 0.01$.

***Significant at $\alpha < 0.001$.

Discussion

Using the PLS method, we calculated the TAM's structural model for each digital learning technology at both measurement times separately. By doing so, we were able to show that the TAM was applicable to these technologies and settings at both measurement times. Our hypothesis (H1) that perceived usefulness at T1 would significantly and positively predict the intention to use at T2 was confirmed for all four digital learning technologies. At T1, the path loadings from perceived usefulness to the intention to use were all high and in a similar range. As expected, there were substantial reductions in perceived usefulness in three of the four digital learning technologies. This makes sense as the students were able to adjust and fine-tune their understanding of the technologies over the course of the three months. The students adjusted their initial opinions after gaining experience with the technologies, which in turn led to lower path loadings when predicting future outcomes. Interestingly, the path loading from perceived usefulness to the intention to use for the classroom response system was nearly the same across all three models (at T1 and T2 and from T1 to T2). One explanation might be that the video demonstration was very good at demonstrating how useful the classroom response system would be. Consequently, further experience with the actual product did not change their technology acceptance significantly. In addition, we suspect that the classroom response system had a very high course alignment. This is the case when course material—or, in our case, digital learning technology—directly helps students prepare for the course exam (FitzPatrick et al., 2015). Thus, the students would evaluate the classroom response system as being very useful and, therefore, have high intentions to use it (Sprenger & Schwaninger, 2021), leading to high path loadings between the two factors. For perceived ease of use, we presented the conditional hypothesis (H3) that if the path loading to the intention to use at T2 was significant, it would also be significant from perceived ease of use at T1 to the intention to use at T2. Perceived ease of use did not significantly predict the intention to use at T1. This is within the general range of what previous research has found, with the strength of the path loadings from perceived ease of use to the intention to use ranging from non-existent to strong (Gefen & Straub, 2000). The ratings of perceived ease of use were high for all technologies (on a scale from 1 to 7, the range of values was 5.18–6.49) as they were very straightforward to use. We suspect that the high ratings at both times of measurement could have created a ceiling effect where this factor could not contribute to predicting the intention to use. As perceived ease of use did not significantly predict the intention to use at T1, we did not expect perceived ease of use at T1 to predict the intention to use at T2. This was the case for three of the four digital learning technologies. Perceived ease of use at T1 for the classroom chat, e-lectures, and VR did not significantly predict the intention to use at T2. However, for the classroom response system, perceived ease of use at T1 significantly—albeit with a very low path loading—predicted the intention to use at T2. Considering that within each time of measurement (T1 and T2), perceived ease of use did not predict intention to use for the classroom response system is surprising. We do not have a good explanation for why the classroom response system has a significant path loading in this manner. Gefen and Straub (2000) propose that the impact of perceived ease of use on the intention to use mainly occurs when the task is intrinsically connected to the technology. This might explain why the path loadings for perceived ease of use to the intention to use are low in general (the learning technologies are merely a means to interact with the content rather than being the focus themselves). However, it does not help explain why perceived ease of use at T1 could explain the intention to use at T2.

Overall, we were able to show that after watching a two-minute demonstration video of the four digital learning technologies, perceived usefulness was able to significantly predict the intention to use three months later. In the next section, we test whether the same predictions can be made with the GETAMEL and whether those hypotheses can be confirmed.

STUDY 2

Methods

We followed the same method as in Study 1 with only minor differences. In Study 2, there were 126 students registered for the course, and 111 students completed both questionnaires (83 female and 28 male students). Moreover, we employed the GETAMEL, with the factors perceived usefulness, perceived ease of use, intention to use, computer anxiety, enjoyment, experience, self-efficacy, and subjective norm. These factors were measured using the items from Sabah (2020) Venkatesh (2000), who also measured those factors. The items of the questionnaire we used are listed in Appendix A. Based on the experience from Study 1, we made a small adjustment to how we implemented mobile VR. Instead of instructing and showing all the VR modules during class, we provided additional time before the lecture for instructions and only showed some VR modules during class. This allowed us to provide more help to students who were having technical difficulties without making other students wait.

Results

Measurement models

The outer standardised loadings of the measurement models for each factor in each tool are shown in the supplementary material in Table S5. Loadings lower than 0.7 (λ) are shown in italics, and we did not consider them in further analysis. For the classroom chat at T1, there were collinearity issues between enjoyment and the intention to use. Collinearity issues occur when one factor can linearly predict another (Hair et al., 2016). To remedy this, we removed IU1 and IU2 due to their high variance inflation factor loadings and replaced the three manifest items for enjoyment with their average (Hair et al., 2016). The internal consistency values (Cronbach's alpha) are shown in Table S6 and were good, with values above 0.70 (Hair et al., 2016). The Dillon-Goldstein rho (rho_A) values were above 0.79, indicating good internal consistency (Hair et al., 2016), see Table S6. Composite reliability values were very good, with values above 0.88 (Hair et al., 2016), and the average extracted variance had values above 0.59, indicating acceptable levels of validity (Hair et al., 2016). These values are shown in Table S6. Using the HTMT approach (Hair et al., 2016), we determined the discriminant validity. All HTMT values at T1 and T2 for all technologies were below 0.90, indicating good discriminant validity, except for VR, whose perceived usefulness and the intention to use had a value of 0.913. The HTMT values for the classroom chat are shown in Table S7, the classroom response system in Table S8, the e-lectures in Table S9, and the mobile VR in Table S10.

Structural models

As in Study 1, we used the bootstrap method (5000 subsamples) in SmartPLS to calculate the *t*-statistics for the significance testing of the inner and outer models (Hair et al., 2016). Table 3 shows the inner path loadings and their significance levels for all technologies in the GETAMEL for both times of measurement separately showing that the GETAMEL and its application was valid for this setting. The ranges found by Abdullah and Ward (2016) in their meta-analysis are listed as a reference.

Table 4 shows the path loadings for the prediction of the intention to use the four digital learning technologies at T2 using subjective norm, perceived usefulness, and perceived ease of use at T1.

Discussion

Using SmartPLS, we modelled the GETAMEL for all four technologies immediately after watching the video demonstration (T1), after using the technologies for three months (T2), and with the combined measurements (T1 and T2). Thus, we predicted the intention to use at T2 using perceived usefulness, perceived ease of use, and subjective norm at T1. All models met the validity criteria showing that the GETAMEL and technologies were applicable to our setting. Interestingly, depending on the digital learning technology, not all path loadings from self-efficacy, subjective norm, enjoyment, computer anxiety, and experience to perceived usefulness and perceived ease of use attained statistical significance at T2. The only path loading that was significant for all four digital learning technologies was that from enjoyment to perceived ease of use. This is in line with the findings of Abdullah and Ward (2016), who, in their meta-analysis, also found a large variance for path loadings. For multiple factors, only

TABLE 3 Path loadings and significance testing for the paths in the GETMAL PLS for all technologies at T1 and T2

Time of measurement	Path loading between factors	Normal range (Abdullah & Ward, 2016)	Classroom chat	Classroom response system	E-lectures	Mobile virtual reality
T1	SE→PU	−0.210 to 0.584	0.068	−0.049	0.001	0.019
	SE→PEOU	0.067 to 0.860	0.165*	−0.011	0.110	0.171*
	SN→PU	0.017 to 0.540	0.386***	0.172*	0.124	0.279***
	SN→PEOU	−0.002 to 0.410	0.028	0.004	0.095	0.002
	SN→IU	N/A	0.173*	0.113	0.001	0.085
	ENJ→PU	0.230 to 0.550	−0.036	0.363***	0.347***	0.556***
	ENJ→PEOU	0.067 to 0.884	−0.051	0.251*	0.075	0.183
	CA→PU	−0.193 to 0.160	−0.017	−0.020	−0.033	0.167**
	CA→PEOU	−0.530 to 0.034	−0.396***	−0.272**	−0.437***	−0.338***
	EXP→PU	−0.113 to 0.360	0.041	−0.182**	−0.057	0.049
	EXP→PEOU	−0.002 to 0.363	0.041	0.330***	0.139*	0.210*
	PU→IU	N/A	0.565***	0.550***	0.608***	0.714***
	PEOU→PU	N/A	0.221*	0.403***	0.281*	0.114
	PEOU→IU	N/A	0.102	0.207**	−0.029	0.143*
T2	SE→PU	−0.210 to 0.584	−0.069	−0.074	−0.100	−0.087
	SE→PEOU	0.067 to 0.860	0.016	0.097	0.197*	0.280**
	SN→PU	0.017 to 0.540	0.052	0.038	0.082	0.323***
	SN→PEOU	−0.002 to 0.410	0.071	0.042	0.218**	0.034
	SN→IU	N/A	0.211**	0.063	0.185*	0.215**
	ENJ→PU	0.230 to 0.550	0.809***	0.543***	0.321*	0.497***
	ENJ→PEOU	0.067 to 0.884	0.090	0.205**	0.082	0.165
	CA→PU	−0.193 to 0.160	−0.056	0.100	−0.036	0.020
	CA→PEOU	−0.530 to 0.034	−0.436***	−0.109	−0.464***	−0.348**
	EXP→PU	−0.113 to 0.360	−0.009	−0.001	0.109	−0.020
	EXP→PEOU	−0.002 to 0.363	0.107	0.235**	0.114	0.497***
	PU→IU	N/A	0.660***	0.794***	0.603***	0.715***
	PEOU→PU	N/A	0.004	0.416***	0.404**	0.173*
	PEOU→IU	N/A	0.066	0.063	−0.036	0.101*

Note: Bootstrap with 5000 samples. One-tailed significance testing.

Abbreviations: CA, computer anxiety; ENJ, enjoyment; EXP, experience; SE, self-efficacy; SN, subjective norm; IU, intention to use; N/A; not applicable; PEOU, perceived ease of use; PU, perceived usefulness.

*Significant at $\alpha = 0.05$.

**Significant at $\alpha = 0.01$.

***Significant at $\alpha < 0.001$.

50% of the studies had significant path loadings to perceived usefulness and perceived ease of use. That our findings match the range of the meta-analysis offers further support that the GETAMEL is applicable in our setting. We were able to significantly predict the intention to use at T2 with perceived usefulness at T1 for three of the four technologies (classroom response system, e-lectures, and VR), partially confirming our hypothesis (H2). However, we were not able to confirm this hypothesis for the classroom chat, where the path loading was not significant. For all technologies, there was a reduction when comparing the path loadings

TABLE 4 Path loadings and significance testing for the paths in the GETMAL PLS for all technologies for perceived usefulness, perceived ease of use, and subjective norm at T1 to predict the intention to use at T2

Path loading	Classroom chat	Classroom response system	E-lectures	Mobile virtual reality
SN T1→IUT2	0.135	0.085	0.148	0.208*
PU T1→IUT2	0.115	0.232*	279**	0.434***
PEOU T1→IUT2	0.000	0.066	0.154	0.029

Note: Bootstrap with 5000 samples. One-tailed significance testing.

Abbreviations: IU, intention to use; PEOU, perceived ease of use; PU, perceived usefulness; SN, subjective norm.

*Significant at $\alpha = 0.05$.

**Significant at $\alpha = 0.01$.

***Significant at $\alpha < 0.001$.

from perceived usefulness to the intention to use at T2 to when we predicted the intention to use at T2 using perceived usefulness at T1. As mentioned in the discussion of Study 1, this is unsurprising as the initial assessments made at T1 were adjusted, leading to lower predictive power. The path loading reduction was especially pronounced for the classroom chat. One explanation could be that the demonstration video for the classroom chat created expectations of how it would be useful, which were then not met. This creates an interesting question because the path loading from perceived usefulness at T1 to the intention to use at T2 was low; however, the same path loading measured at T2 was highly significant. It is possible that the demonstration video created expectations with the students that they would likely be using the classroom chat to ask questions instead of raising their hands. When sitting in class, however, many students would simply raise their hands to ask questions instead of using the question tool. Thus, the previous expectations were not met. The fact that the path loading from perceived usefulness to the intention to use after using the classroom chat for several months was so high suggests a change in the expectations of how the classroom chat might be useful. For instance, students might find the classroom chat useful because it allowed them to ask questions they thought of much later in the course of the lecture.

Our conditional hypothesis for perceived ease of use was confirmed for all technologies except for VR (H4). As with Study 1, the low and mostly not statistically significant path loadings from perceived ease of use to the intention to use do not fit the original TAM and GETAMEL propositions. However, they do fit other findings where the impact of perceived ease of use on the intention to use was not significant (Chau, 1996; Gefen & Straub, 2000; King & He, 2006; Szajna, 1996). In addition, this replicates the findings of Study 1. Though our conditional hypothesis (H4) was not confirmed for VR, the path loadings we found were unsurprising. While perceived ease of use at T2 had a significant path loading to the intention to use at T2, it was low at 0.101. As was discussed, it is to be expected that the strength of the path loading at T2 drops in comparison to the path loading of predicting perceived ease of use at T1 to the intention to use at T2. As the path loading for VR at T2 from perceived ease of use to the intention to use is only 0.101, even a small decrease in the strength of the path loading is sufficient to make it non-significant.

Our final hypothesis was that subjective norm at T1 would not significantly predict the intention to use at T2 (H5). This hypothesis was mostly confirmed by the data. Subjective norm at T1 did not significantly predict the intention to use at T2 for the classroom chat, the classroom response system, and the e-lectures, but it did so for VR. While the path loadings from subjective norm to the intention to use at T2 were significant for three of the four technologies, the path loadings were low. For all three technologies where the path loading was significant, there was a decrease in the strength of the path loading when comparing those from subjective norm to the intention to use at T2 to those from subjective norm at T1 to the intention to use at T2. One reason that the decrease over time is the smallest for VR might be that this technology is comparatively the least known and is, therefore, the most susceptible to peer opinions.

GENERAL DISCUSSION

While both studies used the same four digital learning technologies (classroom chat, classroom response system, e-lectures, and mobile VR) and study design, the two studies were conducted with different students, totalling 205 participants. In Study 1, we modelled the TAM using structural equation modelling (PLS) and showed that the models at T1, T2, and the combination were valid. Perceived usefulness at T1 was able to significantly predict the intention to use at T2 for all technologies, while perceived ease of use did not significantly predict the intention to use at T2. Study 2 replicated Study 1 but expanded on the core model using the GETAMEL. Here, too, using structural equation modelling (PLS), the models proved suitable for our setting. A comparison of the two studies is shown in Table 5.

For all technologies except the classroom chat, perceived usefulness at T1 was able to significantly predict the intention to use at T2. As in Study 1, perceived ease of use at T1 could not significantly predict the intention to use at T2. This is in line with other findings (Chau, 1996; Gefen & Straub, 2000; King & He, 2006; Szajna, 1996). Of the factors the GETAMEL adds to the TAM, only subjective norm directly predicts the intention to use. Moreover, only for VR was subjective norm at T1 able to significantly predict the intention to use at T2. In Study 1, the intention to use at T2 for VR was in the medium range, while it was high in Study 2. We attribute this increase in attitude to minor adjustments we made in the implementation of the VR modules between the two studies. In Study 1, students were unhappy about how much time it took for some to finish the VR modules. Therefore, in Study 2, we offered support on how to use VR before the lessons started for students who had technical difficulties, and we let students experience two of the four VR modules at home where they could experiment with it at their leisure.

Overall, we have shown that even minimal exposure using video demonstrations can provide enough information for users to significantly predict the intention to use several months later. These results are a testimony to how the intention to use is heavily influenced

TABLE 5 Table comparing Study 1 and Study 2

Dimension of comparison	Study 1	Study 2
Based on model	Technology acceptance model	General extended technology acceptance model for e-learning
Factors predicting intention to use	Perceived usefulness and perceived ease of use	Perceived usefulness and perceived ease of use and subjective norm
Addressing hypotheses	H1, H3	H2, H4, H5
Sample size	94	111
Educational technologies employed	Classroom chat, classroom response system, e-lectures, mobile VR	Classroom chat, classroom response system, e-lectures, mobile VR
Significant path loadings from T1 to T2 for the intention to use found for	Perceived usefulness: all technologies Perceived ease of use: classroom response system	Perceived usefulness: classroom response system, e-lectures, mobile VR Perceived ease of use: none Subjective norm: mobile VR

by the simple construct of perceived usefulness, even with limited information. The implications of this research are twofold. First, for organisations, these results demonstrate that well-designed demonstration videos can provide significant information about how likely the intended users are to use a technology months later. While technology acceptance is only one of several factors to consider when deciding on investing in new technology (others being cost, infrastructure, compliance, etc.), early warning signs—that is, very low perceived usefulness evaluations after watching demonstration videos—should be taken seriously. Second, this research provides new insight into how stable technology acceptance can be over time, both for the TAM and the GETAMEL. As with all studies, we must acknowledge that there are limitations that could be addressed by further research. While we fulfilled the requirements to model the TAM and GETAMEL using structural equation modelling—PLS—more participants would improve the validity of the models. Despite being able to adjust for multicollinearity issues for classroom chat in Study 2, conducting the study with more participants would allow us to avoid the issue entirely. However, this statement does not negate the effects we have found, as we found similar results across two studies with more than 200 participants combined. Another limitation was the length of the semester. We allowed students to use the technologies for three months, which is at the lower end of what is considered an appropriate amount of time before measuring the TAM and GETAMEL constructs. Though our goal was to employ the technologies in a tertiary education setting typical in many countries (using the common subject of psychology in lectures of more than 100 students), we cannot rule out that the same results would be found independent of cultural differences. For instance, when comparing the technology acceptance of email across the US, Switzerland, and Japan, there were differences stemming from cultural differences (Straub et al., 1997). Also, compared to more complex software, the four digital technologies we studied were comparatively simple, both regarding their implementation and usability. In the case of more complex technology, it is unclear whether a short video demonstration could convey enough information to allow potential users to make predictions for the intention to use several months later.

We would like to propose several areas worthy of further research. One line of investigation could further research how the length of exposure to the technology affects the TAM and GETAMEL. Our studies set T1 after watching a video and T2 after three months of usage. It is unclear how more exposure to the technology may or may not add to the ability of perceived usefulness to predict the intention to use. Does it correlate directly with the amount of time spent with the technology, or is there a drop-off early on when using the technology? Another interesting area of research would be to explore which factors impact the quality of prediction. For instance, would highly complex technology make a demonstration video too hard to understand and overwhelm users? If that were the case, a likely result would be that the ability to predict would be reduced. Optimising for those aspects and knowing the limitations would allow organisations to better judge how high the technology acceptance would be. The third area of interest is the low impact of perceived ease of use overall on the intention to use in our studies. While this is not new (Gefen & Straub, 2000; King & He, 2006), more research is needed to better understand why perceived ease of use sometimes has strong path loadings to the intention to use and sometimes not.

CONCLUSION

Educators often must decide whether or not to invest in digital learning technologies without knowing whether students will use them. In this study, we hypothesised that the TAM and its extension, the GETAMEL, could be used to gain insight into whether or not a given digital learning technology would be used without actually having tested it. To test this, we conducted two studies with two separate cohorts, where students saw demonstration videos of four digital learning technologies. The four digital learning technologies were classroom chat, a classroom response system, e-lectures, and VR. The students then completed a technology acceptance questionnaire in Study 1 or a GETAMEL questionnaire in Study 2. In both studies, we let the students use the four digital learning technologies for three months, after which the measurements were repeated. We found that the perceived usefulness measured right after watching the demonstration videos was a good predictor for the intention to use three months later in both studies. The perceived ease of use and subjective norm measured right after watching the demonstration videos were not able to predict the intention to use three months later. This study provides a practical approach for educators to assess technology acceptance before investing in it. It does this by introducing a new way of using the influential TAM.

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CONFLICTS OF INTEREST

There is no conflict of interest.

DATA AVAILABILITY STATEMENT

Data from this study is not included in an open-access repository in order to help preserve the anonymity of students. Data may be provided upon request to the authors and the university research ethics board.

ETHICS STATEMENT

Study participants gave informed consent, and participation was voluntary. The research was conducted in accordance with the ethics guidelines of the School of Applied Psychology, University of Applied Sciences and Arts, Northwestern Switzerland.

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REFERENCES

Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior*, *56*, 238–256.

Alfadda, H. A., & Mahdi, H. S. (2021). Measuring students' use of zoom application in language course based on the technology acceptance model (TAM). *Journal of Psycholinguistic Research*, *50*(4), 883–900.

Al-Fraihat, D., Joy, M., Masa'deh, R., & Sinclair, J. (2020). Evaluating E-learning systems success: An empirical study. *Computers in Human Behavior*, *102*, 67–86.

Alsaad, A., & Al-Okaily, M. (2022). Acceptance of protection technology in a time of fear: The case of Covid-19 exposure detection apps. *Information Technology & People*, *35*(3), 1116–1135.

Banerjee, S. (2021). To capture the research landscape of lecture capture in university education. *Computers in Education*, *160*, 104032.

Barteit, S., Lanfermann, L., Barnighausen, T., Neuhann, F., & Beiersmann, C. (2021). Augmented, mixed, and virtual reality-based head-mounted devices for medical education: Systematic review. *JMIR Serious Games*, *9*(3), e29080.

Bartsch, R. A., & Murphy, W. (2011). Examining the effects of an electronic classroom response system on student engagement and performance. *Journal of Educational Computing Research*, *44*(1), 25–33.

Beheshti, M., Taspolat, A., Kaya, O. S., & Sapanca, H. F. (2018). Characteristics of instructional videos. *World Journal on Educational Technology: Current Issues*, *10*(1), 61–69.

Behr, D., Braun, M., & Dorer, B. (2015). Messinstrumente in internationalen Studien. https://doi.org/10.15465/gesis-sg_006
Brunner, M., & Suss, H. M. (2005). Analyzing the reliability of multidimensional measures: An example from intelligence research. *Educational and Psychological Measurement*, *65*(2), 227–240.
Celik, V., & Yesilyurt, E. (2013). Attitudes to technology, perceived computer self-efficacy and computer anxiety as predictors of computer supported education. *Computers & Education*, *60*(1), 148–158.
Chang, Y. S. (2021). Effects of virtual reality application on skill learning for optical-fibre fusion splicing. *British Journal of Educational Technology*, *52*(6), 2209–2226.
Chau, P. Y. (1996). An empirical assessment of a modified technology acceptance model. *Journal of Management Information Systems*, *13*(2), 185–204.
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.
Davis, F. D., & Venkatesh, V. (2004). Toward preprototype user acceptance testing of new information systems: Implications for software project management. *IEEE Transactions on Engineering Management*, *51*(1), 31–46.
Degli Innocenti, E., Geronazzo, M., Vescovi, D., Nordahl, R., Serafin, S., Ludovico, L. A., & Avanzini, F. (2019). Mobile virtual reality for musical genre learning in primary education. *Computers & Education*, *139*, 102–117.
Demetriadis, S., & Pombortsis, A. (2007). e-lectures for flexible learning: A study on their learning efficiency. *Educational Technology & Society*, *10*(2), 147–157 <Go to ISI>://WOS:000246947900013.
Estriegana, R., Medina-Merodio, J. A., & Barchino, R. (2019). Student acceptance of virtual laboratory and practical work: An extension of the technology acceptance model. *Computers & Education*, *135*, 1–14.
Fabris, C. P., Rathner, J. A., Fong, A. Y., & Sevigny, C. P. (2019). Virtual reality in higher education. *International Journal of Innovation in Science and Mathematics Education*, *27*(8). https://doi.org/10.30722/IJISME.27.08.006
Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research. *Philosophy and Rhetoric*, *10*(2), 130–132.
FitzPatrick, B., Hawboldt, J., Doyle, D., & Genge, T. (2015). Alignment of learning objectives and assessments in therapeutics courses to foster higher-order thinking. *American Journal of Pharmaceutical Education*, *79*(1), 10.
Gefen, D., & Straub, D. W. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. *Journal of the Association for Information System*s, 1(1), 8–30.
Gormley, G. J., Collins, K., Boohan, M., Bickle, I. C., & Stevenson, M. (2009). Is there a place for e-learning in clinical skills? A survey of undergraduate medical students' experiences and attitudes. *Medical Teacher*, *31*(1), e6–e12.
Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage.
HubSpot. (2022). *State of inbound marketing trends*. https://www.hubspot.com/state-of-marketing
Igbaria, M., & Iivari, J. (1995). The effects of self-efficacy on computer usage. *Omega*, *23*(6), 587–605.
Kamal, S. A., Shafiq, M., & Kakria, P. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technology in Society*, *60*, 101212. https://doi.org/10.1016/j.techsoc.2019.101212
Kang, S. H. K., McDermott, K. B., & Roediger, H. L. (2007). Test format and corrective feedback modify the effect of testing on long-term retention. *European Journal of Cognitive Psychology*, *19*(4–5), 528–558.
Kemp, A., Palmer, E., Strelan, P., & Thompson, H. (2022). Exploring the specification of educational compatibility of virtual reality within a technology acceptance model. *Australasian Journal of Educational Technology*, *38*(2), 15–34.
King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740–755.
Kitsios, F., Giatsidis, I., & Kamariotou, M. (2021). Digital transformation and strategy in the banking sector: Evaluating the acceptance rate of e-services. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(3), 204.
Liu, R. X., Wang, L., Lei, J., Wang, Q., & Ren, Y. Q. (2020). Effects of an immersive virtual reality-based classroom on students' learning performance in science lessons. *British Journal of Educational Technology*, *51*(6), 2034–2049. https://doi.org/10.1111/bjet.13028
López-Quintero, J. L., Varo-Martínez, M., Ana, M., & Pontes-Pedrajas, A. (2016). Opinions on "Classroom Response System" by first-year engineering students. *Procedia-Social and Behavioral Sciences*, *228*, 183–189.
Ma, S. H., Steger, D. G., Doolittle, P. E., & Stewart, A. C. (2018). Improved academic performance and student perceptions of learning through use of a cell phone-based personal response system. *Journal of Food Science Education*, *17*(1), 27–32.
Malanga, A. C. M., Bernardes, R. C., Borini, F. M., Pereira, R. M., & Rossetto, D. E. (2022). Towards integrating quality in theoretical models of acceptance: An extended proposed model applied to e-learning services. *British Journal of Educational Technology*, *53*(1), 8–22.
Morélot, S., Garrigou, A., Dedieu, J., & N'Kaoua, B. (2021). Virtual reality for fire safety training: Influence of immersion and sense of presence on conceptual and procedural acquisition. *Computers & Education*, *166*, 104145.

Mosquera Feijóo, J. C., Suárez, F., Chiyón, I., & Alberti, M. G. (2021). Some web-based experiences from flipped classroom techniques in aec modules during the covid-19 lockdown. *Education Sciences*, *11*(5), 211.

Open Science Collaboration. (2012). An open, large-scale, collaborative effort to estimate the reproducibility of psychological science. *Perspectives on Psychological Science*, *7*(6), 657–660.

Park, Y., Son, H., & Kim, C. (2012). Investigating the determinants of construction professionals' acceptance of web-based training: An extension of the technology acceptance model. *Automation in Construction*, *22*, 377–386.

Prince, M. (2004). Does active learning work? A review of the research. *Journal of Engineering Education*, *93*(3), 223–231.

Rafique, H., Almagrabi, A. O., Shamim, A., Anwar, F., & Bashir, A. K. (2020). Investigating the acceptance of mobile library applications with an extended technology acceptance model (TAM). *Computers & Education*, *145*, 103732. https://doi.org/10.1016/j.compedu.2019.103732

Sabah, N. M. (2020). Motivation factors and barriers to the continuous use of blended learning approach using Moodle: Students' perceptions and individual differences. *Behaviour & Information Technology*, *39*(8), 875–898.

Schott, C., & Marshall, S. (2021). Virtual reality for experiential education: A user experience exploration. *Australasian Journal of Educational Technology*, *37*(1), 96–110.

Solinska-Nowak, A., Magnuszewski, P., Curl, M., French, A., Keating, A., Mochizuki, J., Liu, W., Mechler, R., Kulakowska, M., & Jarzabek, L. (2018). An overview of serious games for disaster risk management—Prospects and limitations for informing actions to arrest increasing risk. *International Journal of Disaster Risk Reduction*, *31*, 1013–1029.

Sprenger, D. A., & Schwaninger, A. (2021). Technology acceptance of four digital learning technologies (classroom response system, classroom chat, e-lectures, and mobile virtual reality) after three months' usage. *International Journal of Educational Technology in Higher Education*, *18*(1), 1–17. https://doi.org/10.1186/s41239-021-00243-4

Stowell, J. R., Oldham, T., & Bennett, D. (2010). Using student response systems ("clickers") to combat conformity and shyness. *Teaching of Psychology*, *37*(2), 135–140.

Straub, D., Keil, M., & Brenner, W. (1997). Testing the technology acceptance model across cultures: A three country study. *Information & Management*, *33*(1), 1–11.

Szajna, B. (1996). Empirical evaluation of the revised technology acceptance model. *Management Science*, *42*(1), 85–92.

Tai, K. H., Hong, J. C., Tsai, C. R., Lin, C. Z., & Hung, Y. H. (2022). Virtual reality for car-detailing skill development: Learning outcomes of procedural accuracy and performance quality predicted by VR self-efficacy, VR using anxiety, VR learning interest and flow experience. *Computers & Education*, *182*, 104458. https://doi.org/10.1016/j.compedu.2022.104458

Tani, M., Manuguerra, M., & Khan, S. (2022). Can videos affect learning outcomes? Evidence from an actual learning environment. *Educational Technology Research and Development*, *70*, 1–19.

Tautz, D., Sprenger, D. A., & Schwaninger, A. (2021). Evaluation of four digital tools and their perceived impact on active learning, repetition and feedback in a large university class. *Computers & Education*, *175*, 104338. https://doi.org/10.1016/j.compedu.2021.104338

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, *11*(4), 342–365.

Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1), 641–652.

Vergara, D., Anton-Sancho, A., Extremera, J., & Fernandez-Arias, P. (2021). Assessment of virtual reality as a didactic resource in higher education. *Sustainability*, *13*(22), 12730. https://doi.org/10.3390/su132212730

Wang, S. L., & Wu, P. Y. (2008). The role of feedback and self-efficacy on web-based learning: The social cognitive perspective. *Computers & Education*, *51*(4), 1589–1598.

Willingham, D. T. (2021). *Why don't students like school?: A cognitive scientist answers questions about how the mind works and what it means for the classroom*. John Wiley & Sons.

Wood, R., & Shirazi, S. (2020). A systematic review of audience response systems for teaching and learning in higher education: The student experience. *Computers & Education*, *153*, 103896. https://doi.org/10.1016/j.compedu.2020.103896

Wu, Y. C. J., Wu, T. H., & Li, Y. B. (2019). Impact of using classroom response systems on students' entrepreneurship learning experience. *Computers in Human Behavior*, *92*, 634–645.

Yatigammana, K., & Wijayarathna, G. (2021). Students' perceptions of online lecture delivery modes: Higher education during Covid-19 pandemic and beyond. *International Journal of Emerging Technologies in Learning*, *16*(21), 58–73.

Yuen, K. F., Cai, L., Qi, G., & Wang, X. (2021). Factors influencing autonomous vehicle adoption: An application of the technology acceptance model and innovation diffusion theory. *Technology Analysis & Strategic Management*, *33*(5), 505–519.

Zhong, Y. P., Oh, S., & Moon, H. C. (2021). Service transformation under industry 4.0: Investigating acceptance of facial recognition payment through an extended technology acceptance model. *Technology in Society*, *64*, 101515. https://doi.org/10.1016/j.techsoc.2020.101515

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A

The items used for Study 1 and Study 2. [Name of technology] refers to the four digital learning technologies (classroom response system, classroom chat, e-lectures, and mobile virtual reality). The English version is in brackets. The items for the factors perceived usefulness, perceived ease of use, and the intention to use marked with "*", mark the items that were used in both Study 1 and Study 2.

Factor	Item
Perceived usefulness	Der Einsatz von [name of technology] führt zu einer Verbesserung meiner Lernleistungen. (Using [name of technology] would help me learn.)
Perceived usefulness*	Ich halte [name of technology] für nützlich. (Using [name of technology] would be useful.)
Perceived usefulness*	[Name of technology] erleichtern das Lernen und Verstehen der Modulinhalte. ([Name of technology] helps me learn and understand the course content.)
Perceived usefulness	Mit dem Einsatz von [Name of technology] würde ich die Modulinhalte schneller lernen. (Using [Name of technology] would help me learn the course contents faster.)
Perceived usefulness*	Ich finde [Name of technology] nützlich für mein Studium. (I find [name of technology] useful for my studies.)
Perceived ease of use*	Die Bedienung von [name of technology] zu erlernen ist einfach für mich. (Learning to use [name of technology] would be easy for me.)
Perceived ease of use*	[Name of technology] ist einfach zu benutzen. ([Name of technology] is easy to use.)
Perceived ease of use*	Mit [name of technology] zu interagieren braucht nicht viel mentale Anstrengung. (I would find interacting with [name of technology] easy to interact with.)
Perceived ease of use	Insgesamt denke ich, dass es einfach ist [name of technology] zu benutzen. (All in all, I think it is easy to use [name of technology].)
Perceived ease of use	Mit [name of technology] zu interagieren ist klar und verständlich. (Interacting with [name of technology] is clear and understandable.)
Intention to use*	Wenn sie verfügbar sind, plane ich [name of technology] häufig für mein Studium einzusetzen. (Assuming I had access to [name of technology], I would use it often for my studies.)

(Continues)

APPENDIX A (Continued)

Factor	Item
Intention to use*	Wenn [name of technology] verfügbar sind, beabsichtige ich sie während dem Semester häufig zu benutzen. (Assuming I had access to [name of technology], I would intend to use it often during the semester.)
Intention to use	Wenn [name of technology] verfügbar sind, werde ich sie versuchen häufig einzusetzen. (Assuming I had access to [name of technology], I would try to use it often.)
Intention to use*	Angenommen ich hätte Zugang zu [name of technology], würde ich sie benutzen. (Given I had access to [name of technology], I would intend to use it)
Intention to use	Wenn ich Zugang zu [name of technology] hätte, gehe ich davon aus, dass ich es benutzen würde. (Given that I had access to [name of technology], I predict that I would use it.)
Computer anxiety	[Name of technology] gibt mir ein unbehagliches Gefühl. ([Name of technology] makes me uncomfortable.)
Computer anxiety	Der Gedanke das [name of technology] zu nutzen macht mich nervös. (I feel anxious about using [name of technology].)
Computer anxiety	Ich finde das [name of technology] etwas einschüchternd. ([Name of technology] is somewhat intimidating.)
Enjoyment	I find using [name of technology] enjoyable. (Ich glaube das [name of technology] zu benutzen wird Spass machen.)
Enjoyment	I have fun using [name of technology]. (Ich glaube ich werde Freude am [name of technology] haben.)
Enjoyment	I will enjoy using the [name of technology]. (Ich glaube ich werde Freude am [name of technology] haben.)
Experience	I have experience using [name of technology]. (Ich habe Erfahrung mit dem [name of technology].)
Experience	The [name of technology] is similar to other technologies I know. (Das [name of technology] ist ähnlich zu anderen Technologien, die ich kenne.)
Experience	I know how to use this type of [name of technology]. (Die Art das [name of technology] zu nutzen, kenne ich.)
Self-efficacy	I could complete the job using [name of technology] if someone else had helped me getting started. (Ich könnte eine Aufgabe mit dem [name of technology] abschliessen, wenn mir jemand zu Beginn helfen würden.)
Self-efficacy	I am confident of using [name of technology] even if I have never used such [name of technology] before. (Ich bin zuversichtlich, dass ich [name of technology] nutzen könnte, auch wenn ich es noch nie benutzt habe.)
Self-efficacy	It would be not a challenge to use [name of technology]. (Es wäre für mich keine Herausforderung [name of technology] zu benutzen.)
Subjective norm	People who are important to me would think that I should use [name of technology]. (Leute, die mir wichtig sind, finden, dass ich [name of technology] nutzen sollte.)
Subjective norm	I need to experience [name of technology] for my future job. (Ich sollte [name of technology] einmal erleben für meinen zukünftigen Job.)
Subjective norm	People who influence my behavior think that I should use [name of technology]. (Leute, die mein Verhalten beeinflussen, finden, dass ich [name of technology] nutzen sollte.)