Factors predicting University students’ behavioral intention to use eLearning platforms in the post-pandemic normal: an UTAUT2 approach with ‘Learning Value’

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Abstract
The use of eLearning platforms has made it possible to continue the learning process in universities, and other educational institutions, during the Covid pandemic. Students’ acceptance of eLearning is important because it is associated with their engagement in the online teaching–learning environment. This study used the Unified Theory of Acceptance and Use of Technology (UTAUT2: Venkatesh et al., 2012) to determine the factors predicting the behavioral intention of university students’ to use eLearning platforms in the post-pandemic era. UTAUT2 was extended to include the constructs ‘Learning Value’ and ‘Empowerment in Learning’. 314 students from different universities across Greece participated by completing an online questionnaire. Performance Expectancy, Social Influence, Hedonic Motivation, Learning Value and Habit had a significant impact on students’ intention to use eLearning platforms to learn, while Facilitating Conditions and Learning Value had a direct impact on actual use. The findings enhance the research applying the UTAUT2 model, with the Learning Value, for the investigation of students’ intention to use eLearning platforms in the post-Covid era. We suggest for Learning Value to be included in future research in an educational context.

Keywords eLearning platform · UTAUT2 · Learning Value · University education · COVID-19 pandemic

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1 Introduction

During the consecutive COVID-19 lockdowns emergency remote teaching was implemented by the majority of university education institutions (Van der Graaf et al., 2021); although some universities had some experience with distance education, it was a challenge to apply online teaching on a large scale, while many students were never taught in an online environment before the pandemic. Since educators were directed to online remote teaching, digital technology played a major role in enabling educators to teach students at a distance using various digital platforms and tools. Tools utilized for online teaching–learning included video classes, online courses, e-learning platforms (e.g., Moodle) and electronic textbooks (European Data Portal, 2020). Online platforms such as Zoom, MS Teams, Google Meet, Google classroom, and Moodle, were widely used in higher education institutions and Universities (Saikat et al., 2021). Online/eLearning platforms (e.g., learning management systems), among others, enable teaching, sharing of educational resources/materials, and real time synchronous communication between educators and students. For example, they provide both synchronous and asynchronous modes of teaching, thus enabling educators to interact with their students and deliver their lessons (Sayeh & Razkane, 2021). The use of electronic media is an essential element of e-learning, which can be accomplished via different technological devices, such as desktop computers, laptops, mobile phones, and virtual environments (Lee et al., 2009).

The purpose of this study was to determine the factors predicting university students’ behavioral intention to use eLearning platforms in the post-pandemic normal/era (e.g., learning values, habit, social influence, performance expectancy, hedonic motivation).

A significant aspect of the study is that it was conducted immediately after the consecutive lockdowns; i.e., with the return to face-to-face teaching. In this context, students’ acceptance of eLearning (platforms) is critical for the success of online learning. Researchers suggest that blended learning and online learning are becoming the new normal worldwide after the pandemic (Amitabh, 2020; Chattaraj & Vijayaraghavan, 2021), and this is more feasible for the university sector, where students are adults and more independent learners. For the purpose of this paper, some definitions of terms are presented: (i) ‘e-learning’ (or ‘online learning’) is conducted via the internet and it is distinct from distance learning, although these terms are frequently used as synonyms; distance learning is being accomplished via e-learning as a mode of learning, (ii) ‘online teaching’ and ‘emergency remote teaching’ (a new concept proposed by Hodges et al., 2020) are different concepts; but both terms refer to the spatial distance between students and teachers, and they include online technology usage to provide education (Jimoyiannis et al., 2021).

2 Theoretical framework and Research Hypotheses

The extended UTAUT2 model was the theoretical framework for this study, with the addition of the constructs “Learning Value” (LV) and “Empowerment in Learning” (EiL) (see Fig. 1). Early on, the developers of the UTAUT model (Venkatesh et al.,
validated it with Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), as the main determinants for information technology intention and acceptance-use. They also suggested for researchers, worldwide, to validate and test this model with various technologies, contexts, and participants. Several studies which examined technology adoption-use in higher education contexts, have successfully applied the UTAUT model (Kumar & Bervell, 2019). UTAUT2 emerged by extending UTAUT with three constructs (Venkatesh et al., 2012); Hedonic Motivation (HM), Price Value (PV), and Habit (HT) were the incorporated independent constructs (variables). As seen in Fig. 1, Behavioral Intention (BI) has the role of the mediating variable, and Use Behavior (USE) is the dependent variable. According to Venkatesh et al. (2016), UTAUT2 explains 74% of BI and it is recommended to be applied in the introductory phase of the relevant technology (e.g., initial use, adoption). Chang (2012) suggested UTAUT2 has been more explanatory, with implications for researchers who wish to examine behavioral intentions, and UTAUT2 is highly influential in examining adoption of e-learning technology (Lahrash et al., 2021).

With regard to the constructs we added, “Learning Value” (LV) was used instead of Price Value (PV) because students are not required to pay something to gain advantages from eLearning technology, while they dedicate time and effort to acquire advantage/benefit from eLearning (Ain et al., 2016); the research instrument sub-section mentions the studies from which “Learning Value” and “Empowerment in Learning” were taken/adapted. The reasons we added the two constructs (LV and

![Fig. 1 The research model used](image-url)
EiL) were that they are directly related to the value of learning and recent research that used the UTAUT model in educational context, indicated them as (possible) predictors of behavioral intentions. As indicated in Fig. 1, we also tested the effect of LV and EiL on USE (students’ perceptions of positive value of learning via the platforms will possibly affect their actual use). Also, Venkatesh et al. (2012) suggested for future research to apply UTAUT2 in different countries, age groups, and technologies, as well as identify other relevant factors. A unique aspect of our study is that UTAUT2 was applied immediately after the pandemic; i.e., after a period where online teaching–learning in Universities was the only channel. Detailed description and definition of the main UTAUT2 constructs are reported by Venkatesh et al., (2003, 2012). Underneath, we describe them briefly, focusing on their meaning within the context of our study (i.e., intention and use of eLearning platforms).

**Performance expectancy (PE)** According to Venkatesh et al., (2003, 2012), PE is a main construct that regulates acceptance and consequent use of the target technology; it is also the strongest predictor of BI to use a technology. Within this study’s context it can be described as the degree to which university students believe that using eLearning platforms will make it possible to complete activities and achieve better performance in their academic studies. It is hypothesized that;

\[ H1: \text{PE influences (impacts on) students’ BI to use eLearning platforms in their academic studies.} \]

**Effort expectancy (EE)** EE represents a person’s beliefs about the ease/effort linked to technology use and it is a determinant of BI (Venkatesh et al., 2003; Wang & Wang, 2010). In our study, EE can be described as the level of expectation of students that the use of eLearning platforms will not demand much mental or physical effort (characterized as ease of use for educational purposes). It is hypothesized that;

\[ H2: \text{EE influences students’ BI to use eLearning platforms.} \]

**Social influence (SI)** SI reflects the impact of other people’s beliefs on individuals’ intention (Venkatesh et al., 2003, 2012). Wilson et al. (2021) indicated that social-cognitive factors (e.g., considering important others’ beliefs) predicted participants’ behavior. In this study, SI regards university students’ perceptions about important others’ (e.g., peers, university tutors) beliefs about them; with regard to utilization of eLearning platforms in their academic studies. It is hypothesized that;

\[ H3: \text{SI influences students’ BI.} \]

**Facilitating conditions (FC)** According to Venkatesh et al. (2003), FC regard individual’s perceptions on the existence of adequate technical and institutional
infrastructure, to support the use of technology; FC influences both intention and behavior (actual use of technology). The importance of ICT on technological infrastructure (Mugruza-Vassallo & Suárez, 2016) was reported by earlier research. For our study, FC are associated with accessibility to different technological devices (laptop, desktop computer, smartphones, etc.) and stable internet connection that students use in eLearning. It is hypothesized that;

H4a: FC has an influence on students’ BI.

H4b: FC impacts on students’ USE of eLearning platforms.

**Hedonic motivation (HM)**  HM is used synonymously to perceived enjoyment, and relevant research (El-Masri & Tarhini, 2017; Lahrash et al., 2021) found that perceived enjoyment significantly influences eLearning acceptance and use. Within this study’s context, HM regards the enjoyment/pleasure that derives when students use eLearning platforms for their studies. It is hypothesized that;

H5: HM influences students’ BI.

**Learning value (LV)**  Taken into account the ‘Price Value’ construct (Venkatesh et al., 2012), LV was defined by Ain et al. (2016) as the student’s perceptions that the time and effort put in for learning reflect a good value (since it is not required by students to pay). In this study, the value reflects the advantages derived from the intention to use eLearning; students’ perceptions of positive LV will affect their intention and actual use of eLearning platforms, for academic purposes. It is hypothesized that;

H6a: LV influences students’ BI.

H6b: LV has an impact on students’ USE of eLearning platforms.

**Empowerment in learning (EiL)**  EiL was defined by Cacciamani et al. (2018) as students’ perceptions on the benefits associated with tablet use for accomplishing the learning processes. In this study, it is the degree to which students perceive that using eLearning platforms in their studies will enhance/empower their learning. EiL is a (possible) predictor of both BI and USE of eLearning platforms. It is hypothesized that;

H7a: EiL influences students’ BI.

H7b: EiL has an effect on the USE of eLearning platforms.

**Habit (HT)**  According to Venkatesh et al. (2012), HT is the extent to which a person believes his/her behaviour becomes a habit—being performed without conscious decision (automatically)—and predicts both BI and USE. In the eLearning context, HT is associated with the results of prior experiences with eLearning platforms (and their various operations such as course participation/content and discussion forums) that may encourage students to build positive intentions towards eLearning; thus influencing the use in the long run. It is hypothesized that;
H8a: HT influences students’ BI.
H8b: HT influences the actual use of eLearning platforms.

Behavioral intention (BI) and use behavior (USE) According to Venkatesh et al., (2003, 2012), BI determines the actual adoption-use of technology. In this study, BI reflects the degree to which students intend -and continue- to use eLearning platforms, while USE regards the actual use of eLearning platforms for students’ academic studies; students’ behavioral intentions lead to eLearning platforms’ adoption behavior. Therefore, it is hypothesized that;

H9: BI influences students’ actual use of eLearning platforms, for academic purposes.

According to the above, the acceptance and use of eLearning platforms, by university students for academic purposes, could be a function of the above described UTAUT2 constructs.

3 Literature review: Research related to university students’ acceptance of eLearning (using UTAUT model)

Some studies used the UTAUT model to investigate the factors that impact on university students’ acceptance of e-learning in the context of the COVID-19 pandemic (e.g., Hassan, 2021; Muangmee et al., 2021; Prasetyo et al., 2021; Raman & Thannimalai, 2021; Raza et al., 2021), and their results revealed strong links of specific UTAUT constructs to BI of e-learning, as well as between BI and students’ usage behavior of e-learning. These recent studies (published in 2020 and 2021) are initially discussed, followed by indicative studies conducted before the pandemic, while studies in the Greek context are reported at the end of this section.

In Asia, there is a number of studies that explored students’ acceptance. Raman and Thannimalai (2021), in Malaysia, applied the UTAUT2 model in order to investigate university students’ behavioral intention (BI) to use e-learning. They found that Social Influence and Habit (the strongest predictor) had an effect on participants’ BI to use e-learning. Similarly, within the context of the COVID-19 pandemic, Prasetyo et al. (2021), in the Philippines, used UTAUT2 to examine the factors predicting medical students’ adoption and use of eLearning Platforms. Their findings revealed that Performance Expectancy and Learning Value significantly influenced students’ BI, while BI influenced the platforms’ usage. Muangmee et al. (2021), in Thailand, applied the UTAUT2 in the context of the pandemic and reported that students’ BI to use e-learning tools was significantly (and positively) affected by PE, EE, SI, FC, HM, and LV (the largest positive effect), while BI effected actual usage. Raza et al. (2021), in Pakistan, used the UTAUT model to determine the factors that affect students’ acceptance and use of e-learning systems (Learning Management
Recent studies from the Arabic world and Africa are as follows. UTAUT was used to examine the factors affecting students’ intentions to adopt eLearning systems, during the pandemic, in Jordan. Fouad Altameemi et al. (2021) indicated that PE and SI had positive explanatory power of the student’s BI, while specialization/discipline played a role in exploring students’ intentions (age and gender were not significant). Abbad (2021) found that PE and EE affected BI to use eLearning, while BI and FC impacted directly on students’ use of eLearning system (Moodle). Akbar (2021) indicated that PE, EE, SI and FC, all significantly predicted university students’ eLearning adoption behavior for academic and technological learning, in the context of COVID-19, in Bahrain. Hassan (2021), in Egypt, studied the UTAUT factors that influence university students’ intentions to accept e-learning after the coronavirus pandemic. PE, EE, SI, PV, and FC, affected students’ BI to use eLearning, while BI and FC had direct impact on actual USE. In Ghana, Buabeng-Andoh and Baah (2020), applied the UTAUT to find out the predictors of students’ use of LMS; Performance Expectancy, Effort Expectancy and Institutional Support positively affected students’ actual use of the eLearning platform.

In Greece, a small number of studies used the UTAUT2 model with university students in the mobile learning/technology context (Nikolopoulou et al., 2020; Zacharis, 2020); to our knowledge, there is no study within the eLearning context. Zacharis (2020) indicated that PE, HM, EiL, EE, SI, and FC influenced student teachers’ BI to use mobile devices for learning, while BI and EiL predicted actual use. Nikolopoulou et al. (2020) found that HT (the strongest predictor), PE and HM influenced students’ BI to use mobile phones for academic purposes, while BI affected actual usage.

Indicative studies conducted before the pandemic are as follows. UTAUT2 was applied by Tarhini et al. (2017), in England, to explore the factors that may hinder-enable the adoption of e-learning systems by university students; their results showed that PE, SI, HT, HM, EE, self-efficacy and trust influenced students’ BI. Also, El-Masri and Tarhini (2017) investigated the adoption of e-learning systems by university students in Qatar and the USA, by applying UTAUT2. Performance Expectancy, Hedonic Motivation, and Habit were significant predictors of students’ intention to use e-learning platforms, in both countries. EE and SI lead to students’ adoption of eLearning systems only in Qatar, while FC only in the USA. Ain et al. (2016), in Malaysia, extended the UTAUT2 model with the ‘Learning Value’ construct to study university students’ perceptions regarding acceptance of LMS. Their results indicated a significant effect of PE, SI and LV on students’ intention towards LMS and also of FC and BI on LMS use. Dajani and Abu Hegleh (2019) used the UTAUT2 and reported that the constructs HM, PE, LV and EE significantly affected Jordanian students’ BI of animation use during eLearning. In Italy, Cacciamani et al. (2018) used the UTAUT model with Empowerment in Learning to investigate
factors affecting Italian high school students’ acceptance of tablets; although this study was conducted in secondary education sector, it is mentioned here because we adapted the construct EiL from these researchers, and there is also scarcity of studies that incorporated this factor. Their study revealed that, among others, EiL and support conditions affected learning use.

In Greece, a small number of studies used the UTAUT2 model with university students in the mobile learning/technology context (Nikolopoulou et al., 2020; Zacharis, 2020); to our knowledge, there is no study within the eLearning context. Zacharis (2020) indicated that PE, HM, EiL, EE, SI, and FC influenced student teachers’ BI to use mobile devices for learning, while BI and EiL predicted actual use. Nikolopoulou et al. (2020) found that HT (the strongest predictor), PE and HM influenced students’ BI to use mobile phones for academic purposes, while BI affected actual usage.

4 Method

4.1 Participants and procedure

314 university students participated in the study (the characteristics of the sample are indicated in Table 1). The students were studying at different Universities across Greece, and they completed an online questionnaire in October 2021. The participation in the survey was voluntary, while the ethical standards of the institutional research committee were followed. In accordance with the new General Data Protection Regulation (GDPR), students were initially asked to consent for participation in the survey. The participants were also informed about anonymity issues; explaining that the data will be utilized only for research aims (confidentiality-privacy issues were applied). As Table 1 indicates, the demographic characteristics show that 89.2% (n = 288) of the participants were women and 10.8% (n = 21) were men. The mean age was 22.07 years (STD = 6.44), while most of the sample-students had a maximum of two years’ experience in using eLearning platforms.

For the purpose of this study, the Greek context during the pandemic period is briefly described. The Greek Ministry of education forced all Universities to close and provided online education for about three academic semesters; during the first wave of the COVID-19 pandemic (spring 2020) Universities closed in the middle of March 2020; in autumn 2020, during the first month, there was the option to carry out some face-to-face activities/laboratories, but then the semester

| Table 1 | Demographic characteristics of participants (N = 314) |
|---------|-----------------------------------------------------|
| Gender | Age | Experience (years of use eLearning platforms) |
| Female (89.2%) | ≤ 19 (34.4%) | <1 (7.3%) |
| Male (10.8%) | 20–21 (36.3%) | 1 (28.7%) |
| | 22–24 (17.8%) | 2 (60.8%) |
| | > 24 (11.5%) | 3 (3.2%) |
took place entirely online; during the spring 2021 semester, fully online education was applied. During this 1.5-year period, lectures and students’ assessment were carried out online, and eLearning platforms played a critical role. University students, across different faculties/departments in Greece, used different eLearning platforms such as Zoom, Webex, and Google Meet. We believe that after three semesters of receiving predominantly online education, most students have matured so as to frankly express their intentions about using eLearning (platforms) in the post-pandemic era. At the time of the questionnaire’s administration students were not ‘under force’, and the autumn semester 2021 began (and was completed) entirely face-to-face.

4.2 The research instruments

The UTAUT2 questionnaire (Venkatesh et al., 2012) was used for data collection. All items were initially adapted to this study’s context, and the authors (by also obtaining the help of a linguistic expert) translated them from English to Greek language. The questionnaire consisted of two sections. Its first section included the main statements/items (36 items); 4 items were associated to PE, 4 items to EE, 3 items to SI, 4 items to FC, 3 items to HM, 4 items to LV, 3 items to EiL, 4 items to HT, 3 items to BI, and 4 items to USE. The constructs LV and EiL were adapted from Ain et al. (2016) and Cacciamani et al. (2018), respectively. We asked for the students to answer/respond on a 5-point Likert-type scale (1 = strongly disagree to 5 = strongly agree). The second section was constructed to collect demographic information. We did not investigate the effects of moderating variables gender, age, and experience because of the homogeneity of the sample; it mainly consisted of female students aged 19–24 years old, with similar experience in using eLearning platforms (see Table 1). Google Forms was used for the questionnaire design, while the items were randomly distributed so as to avoid bias.

4.3 Data analysis

The research model was assessed via the investigation of internal reliability and construct validity. The measurement model was initially examined, and then the structural model was tested. Construct Validity (CV) indicates how well a construct is measured by its items and can be measured by convergent and discriminant validity (Hair et al., 2017). We examined Cronbach’s alpha, Composite Reliability (CR) and the Average Variance Extracted (AVE) for all constructs.

Regarding the structural model, all the path coefficients (as presented in Fig. 1) were tested. We conducted a regression analysis to estimate the relationship between (each one of the) eight constructs (PE, EE, FC, SI, HM, LV, EiL, HT) and BI to use eLearning platforms, as well as the relationship between four constructs (FC, LV, EiL, BI) and USE. SPSS v26 software was used for the analysis of the results. The evaluation of measurement and structural model is discussed in results.
5 Results

5.1 Measurement model

The research model presents a high level of reliability and consistency as Cronbach’s alpha exceeds the recommended value of 0.7 (0.968, Number of items = 36) (DeVellis, 2016). We also measured the validity of the instrument, and as a consequence it was included in the measurement of each of the constructs (proposed). Inner item correlations were calculated, for the ad hoc observation of their relationships with the dependent variables BI and USE.

Cronbach’s alpha coefficients for each variable ranged from 0.695 (USE) to 0.950 (HM) (Table 2), which implies a sufficient (Cronbach’s alpha > 0.6) to good (Cronbach’s alpha > 0.8) reliability and construct reliability according to Cortina (1993).

In order to evaluate the reliability and validity of the reflective constructs, indicators’ loadings, composite reliability (CR) and the average mean variance (AVE) were examined. According to the results of Table 2, CR values ranged between 0.81 (FC) and 0.97 (BI) and exceed the recommended cutoff of 0.7; according to Hair et al. (2010), such values suggest/imply a high internal reliability. The convergent validity was evaluated by the values of CR and AVE, which were higher than 0.7 and 0.5 respectively, suggesting that the instrument has an acceptable construct validity (Hair et al., 2010, 2017).

5.2 Level of acceptance of eLearning platforms

Mean value and standard deviation were performed in order to estimate the level of students’ perception-acceptance of eLearning platforms (see Table 2). The results reveal that the majority of the participants have a moderate level of acceptance for eLearning platforms; according to the mean value of the PE indicator (mean PE = 3.09). Students seem to strongly agree that eLearning platforms are easy to use and to also facilitate learning; as indicated by the high EE mean value (mean EE = 4.24). University students are rather not influenced by others who think they should use eLearning platforms (mean SI = 2.56). The findings derived from descriptive statistics indicate that students’ beliefs regarding necessary knowledge, resources and support to use eLearning platforms are at a high point (mean FC = 4.23).

5.3 Structural model

For the investigation of the suitability of chosen variables for the factor analysis, the Kaiser–Meyer–Olkin (KMO) test for sampling adequacy and Bartlett’s test for sphericity were used (Bryman, 1989). The KMO test resulted in the value of 0.928; this was greater than the cutoff for adequacy (0.5). A very good sphericity was also shown by Bartlett’s test (\(\chi^2 = 2440.665, \text{df} = 45, p < 0.001\)).
| Constructs                | Mean (SD) | Factor Loadings | AVE | CR  | Cronbach’s Alpha |
|--------------------------|-----------|---------------|-----|-----|------------------|
| Performance Expectancy   |           |               |     |     |                  |
| (PE)                     | 3.09 (1.14)| 0.78          | 0.94| 0.907|                  |
| PE1                      | 0.763     |               |     |     |                  |
| PE2                      | 0.850     |               |     |     |                  |
| PE3                      | 0.753     |               |     |     |                  |
| PE4                      | 0.802     |               |     |     |                  |
| Effort Expectancy        |           |               |     |     |                  |
| (EE)                     | 4.24 (0.77)| 0.77          | 0.93| 0.901|                  |
| EE1                      | 0.748     |               |     |     |                  |
| EE2                      | 0.783     |               |     |     |                  |
| EE3                      | 0.819     |               |     |     |                  |
| EE4                      | 0.769     |               |     |     |                  |
| Social Influence         |           |               |     |     |                  |
| (SI)                     | 2.56 (1.11)| 0.90          | 0.86| 0.946|                  |
| SI1                      | 0.902     |               |     |     |                  |
| SI2                      | 0.882     |               |     |     |                  |
| SI3                      | 0.876     |               |     |     |                  |
| Facilitating Conditions  |           |               |     |     |                  |
| (FC)                     | 4.23 (0.76)| 0.52          | 0.92| 0.806|                  |
| FC1                      | 0.595     |               |     |     |                  |
| FC2                      | 0.677     |               |     |     |                  |
| FC3                      | 0.721     |               |     |     |                  |
| FC4                      | 0.534     |               |     |     |                  |
| Hedonic Motivation       |           |               |     |     |                  |
| (HM)                     | 2.72 (1.28)| 0.908         | 0.98| 0.950|                  |
| HM1                      | 0.908     |               |     |     |                  |
| HM2                      | 0.898     |               |     |     |                  |
| HM3                      | 0.880     |               |     |     |                  |
| Learning Value           |           |               |     |     |                  |
| (LV)                     | 3.37 (1.10)| 0.74          | 0.92| 0.884|                  |
| LV1                      | 0.729     |               |     |     |                  |
| LV2                      | 0.718     |               |     |     |                  |
| LV3                      | 0.755     |               |     |     |                  |
| LV4                      | 0.792     |               |     |     |                  |
| Empowerment in Learning  |           |               |     |     |                  |
| (EiL)                    | 3.16 (1.07)| 0.75          | 0.90| 0.829|                  |
| EiL1                     | 0.732     |               |     |     |                  |
| EiL2                     | 0.720     |               |     |     |                  |
| EiL3                     | 0.622     |               |     |     |                  |
| Habit                    |           |               |     |     |                  |
| (HT)                     | 3.05 (1.00)| 0.65          | 0.88| 0.819|                  |
| HT1                      | 0.547     |               |     |     |                  |
| HT2                      | 0.603     |               |     |     |                  |
| HT3                      | 0.667     |               |     |     |                  |
| HT4                      | 0.751     |               |     |     |                  |
| Behavioral Intention     |           |               |     |     |                  |
| (BI)                     | 3.04 (1.20)| 0.61          | 0.98| 0.942|                  |
| BI1                      | 0.883     |               |     |     |                  |
| BI2                      | 0.849     |               |     |     |                  |
| BI3                      | 0.904     |               |     |     |                  |
| Use Behavior             | 4.13 (0.72)|               |     |     |                  |
A multiple regression analysis was carried out in order to assess the relationship between eight main factors (PE, EE, SI, FC, HM, LV, EiL, HT) and BI to use eLearning platforms and the link between five main factors (FC, LV, EiL, HT, BI) and USE. Table 3 illustrates the graphical presentation of the β-value for each factor.

According to the results from Table 4, six of thirteen hypotheses were supported. More specific, five factors (PE, SI, HM, LV, and HT) had significant impact on students’ intention to use eLearning platforms to learn; Hypotheses 1, 3, 5, 6a, and 8a are supported. Facilitating Conditions and Learning Value significantly predict actual use; Hypotheses 4b and 6b are supported. Figure 2 illustrates the research model’s explanatory power. The model explains a 71.9% and 43.0% of the BI and USE variance, respectively; i.e., students’ intention to use eLearning platforms to learn.

6 Discussion

This study, applied a modified-extended UTAUT2 model so as to examine the factors predicting university students’ intention and use of eLearning platforms, in their studies. This examination is crucial since acceptance is possible to increase their engagement in the online teaching–learning environment; student

Table 2 (continued)

| Constructs | Mean (SD) Factor Loadings | AVE | CR | Cronbach’s Alpha |
|------------|---------------------------|-----|----|------------------|
| (USE)      |                           |     |    |                  |
| USE1       | 0.628                     | 0.58| 0.84| 0.695            |
| USE2       | 0.309                     |     |    |                  |
| USE3       | 0.641                     |     |    |                  |
| USE4       | 0.495                     |     |    |                  |

Table 3 Inter-item correlation matrix

|     | PE  | EE  | SI  | FC  | HM  | LV  | EiL | HT  | BI  | USE | UB  |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| PE  | 1   |     |     |     |     |     |     |     |     |     |     |
| EE  | 0.397** 1 |
| SI  | 0.728** 0.401** 1 |
| FC  | 0.397** 0.679** 0.348** 1 |
| HM  | 0.787** 0.428** 0.669** 0.420** 1 |
| LV  | 0.798** 0.484** 0.661** 0.484** 0.769** 1 |
| EiL | 0.734** 0.409** 0.669** 0.471** 0.743** 0.803** 1 |
| HT  | 0.628** 0.428** 0.624** 0.399** 0.677** 0.676** 0.690** 1 |
| BI  | 0.729** 0.364** 0.679** 0.368** 0.732** 0.732** 0.722** 0.774** 1 |
| USE | 0.569** 0.449** 0.469* 0.486** 0.602** 0.592** 0.564** 0.527** 0.547** 1 |

** Correlation is significant at the 0.01 level (2-tailed)
engagement, especially in online learning, is important since it may improve learning, performance, and persistence (Bond, 2020). This paper enhances the body of empirical evidence by applying UTAUT2 in a different country (Greece), technology (eLearning platforms), and by adding two learning related constructs (LV and EiL). The findings of this study may be useful for improving online teaching–learning in the post-pandemic normal; it is possible online learning (eLearning) adoption will continue post-pandemic, for example, in a hybrid form/mode. According to the proposed model, the constructs PE, SI, HM, LV and HT significantly affected students’ intention to use eLearning platforms to learn, while FC and LV directly affected actual use.

More specifically, PE significantly affected university students’ BI to use eLearning platforms meaning that using eLearning platforms will enable students to perform better in their studies. This finding is in agreement with many studies worldwide; Prasetyo et al. (2021) in the Philippines; Muangmee et al. (2021) in Thailand; Raza et al. (2021) in Pakistan; Fouad Altameemi and Abdula Fatah Al-Slehat (2021), Abbad (2021), Dajani and Abu Hegleh (2019), in Jordan; Hassan (2021) in Egypt; Akbar (2021) in Bahrain; Buabeng-Andoh and Baah (2020) in

| Hypotheses | Result | Conclusion |
|------------|--------|------------|
| H1 PE→BI   | (Beta = 0.153, p < 0.01) | Supported |
| H2 EE→BI   | (Beta = -0.067, p > 0.05) | Not Supported |
| H3 SI→BI   | (Beta = 0.117, p < 0.01) | Supported |
| H4a FC→BI  | (Beta = 0.002, p > 0.05) | Not Supported |
| H4b FC→USE | (Beta = 0.244, p < 0.01) | Supported |
| H5 HM→BI   | (Beta = 0.131, p < 0.01) | Supported |
| H6a LV→BI  | (Beta = 0.124, p < 0.05) | Supported |
| H6b LV→USE | (Beta = 0.198, p < 0.05) | Supported |
| H7a EiL→BI | (Beta = 0.084, p > 0.05) | Not Supported |
| H7b EiL→USE| (Beta = 0.139, p > 0.05) | Not Supported |
| H8a HT→BI  | (Beta = 0.403, p < 0.01) | Supported |
| H8b HT→USE | (Beta = 0.089, p > 0.05) | Not Supported |
| H9 BI→USE  | (Beta = 0.143, p > 0.05) | Not Supported |
Ghana; Tarhini et al. (2017), in England; El-Masri and Tarhini (2017), in Qatar and the USA; Ain et al. (2016) in Malaysia.

The effect of SI on BI was also shown in different countries such as Malaysia (Ain et al., 2016; Raman & Thannimalai, 2021), Thailand (Muangmee et al., 2021), Pakistan (Raza et al., 2021), Jordan (Fouad Altameemi et al., 2021), Egypt (Hassan, 2021), Bahrain (Akbar, 2021), USA and Qatar (Tarhini et al., 2017). SI also influenced university students’ intentions towards mobile devices’ usage in Greece (Zacharis, 2020). This finding means that university students believe the perceptions of their university tutors, peers, or parents can influence them in using eLearning platforms. It is expected that students will use eLearning platforms for academic purposes when they believe important others (will) support them.

HM had an effect on BI. This means that when university students perceive eLearning platforms as enjoyable, it is more probable to use them; this finding is in accordance with other studies worldwide (Dajani & Abu Hegleh, 2019; El-Masri & Tarhini, 2017; Muangmee et al., 2021; Tarhini et al., 2017), as well as in the mobile learning context (Nikolopoulou et al., 2020; Zacharis, 2020).

LV was also shown to impact on BI. With regard to LV, a few studies reported it was a predictor of university students’ eLearning technology acceptance intentions (Ain et al., 2016; Dajani & Abu Hegleh, 2019; Muangmee et al., 2021; Prasetyo et al., 2021); it is noted that in Muangmee et al. (2021), LV was the UTAUT2 factor with the largest effect on students’ BI. LV was also shown to impact on USE and it is linked to the advantages derived from the intention to use eLearning. To the best of our knowledge, to date, no research examined the effect of LV on USE. Students’
positive perceptions about LV will affect their intention and actual use of eLearning platforms, for academic purposes.

HT also predicted university students’ BI to use eLearning platforms to learn (strongest predictor). The frequent/higher use of eLearning platforms among the students will bring stronger automaticity levels in adopting eLearning platforms for academic purposes. This finding is supported by the work of Raman and Thannimalai (2021) within the context of pandemic, as well as by earlier studies (El-Masri & Tarhini, 2017; Tarhini et al., 2017).

FC was the most important predictor on university students’ actual use of eLearning platforms, and this was also found by Abbad (2021), Hassan (2021) and Ain et al. (2016). The accessibility to use different technological devices (laptop, desktop computer, smartphones, etc.) and stable internet connection seem to increase university students’ actual use in eLearning platforms, for academic purposes.

According to the regression analysis, the research model explained 71.9% and 43.0% of the variance in students’ BI and USE respectively; suggesting that adding two learning related constructs to UTAUT2 possibly increases the model’s power to explain university students’ BI to actually adopt-use eLearning platforms for their studies.

7 Implications and future research

The results have implications for educational policy makers, university educators, and eLearning platform designers. Policy makers could, for example, improve facilitating conditions such as technological infrastructure. Earlier research indicated the importance of ICT on institutional development and technological infrastructure (Mugruza-Vassallo & Suárez, 2016), as well as for integral and quality education (Mugruza-Vassallo, 2016). Educators are suggested to be aware of students’ perceptions, so as to enhance online pedagogy (e.g., providing feedback, encouraging and motivating students). Universities and eLearning platform designers could improve the performance of eLearning platforms to enhance the utilization among students. When students perceive that an eLearning platform is useful and enjoyable, then it is more likely to adopt-use it in their studies.

Limitations of this study include the homogeneity of the sample and that the effects of moderating variables gender, age, and experience were not studied. We intend to conduct similar investigation with more diverse sample.

The extended model with LV could be applied with students of different disciplines, in different countries, in the eLearning and blended learning context. For example, Azizi et al. (2020) reported that almost all UTAUT2 constructs (PE, EE, SI, FC, HM, PV, HT) significantly affected students’ BI to use blended learning. Future research is suggested to investigate students’ intentions and use of specific digital platforms and online environments, as well as Universities’ digital infrastructure. For example, mobile technology has a good potential for online education, and mobile technology-enhanced teaching platforms were adopted during the pandemic (Tang et al., 2021). Future research could also investigate opportunities that come with online education in the post-pandemic era. Additionally,
future research is suggested to evaluate the characteristics of eLearning/online platforms used by students, and to evaluate/test UTAUT2 with additional learning related constructs.

Authors’ contributions (KN) and (GZ) both contributed to this paper. More Specifically, (KN) performed Literature review and (GZ) performed Data analysis and Results.

Data availability The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare that they have no competing interests.

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