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ONLINE FIRST

**Education and Information Technologies**
The Official Journal of the IFIP Technical Committee on Education

ISSN 1360-2357

Educ Inf Technol
DOI 10.1007/s10639-020-10157-9

Springer

Education and Information Technologies
https://doi.org/10.1007/s10639-020-10157-9

# Acceptance of mobile phone by university students for their studies: an investigation applying UTAUT2 model

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Received: 18 February 2020 / Accepted: 12 March 2020/Published online: 26 March 2020


**Abstract**
Mobile phone is increasingly widespread among University students, while different factors can affect students' behavior towards the use and acceptance of mobile technology. One of the methods to measure these factors is the Unified Theory of Acceptance and Use of Technology (UTAUT). The purpose of this study was to evaluate the Behavioral Intention of University students for acceptance and use of mobile phone in their studies. The study employed the extended UTAUT2 model (Venkatesh et al. 2012) which was adapted to the Greek context. The participants were 540 students of different Universities across Greece, who completed an online questionnaire. The most important predictors for students' Behavioral Intention to use mobile phones in their studies were Habit (the strongest one), Performance Expectancy and Hedonic Motivation. The most important predictor for actual mobile phone use was Behavioral Intention. Gender, age and experience did not have any moderating effect. The findings of this study enhance the evidence on mobile phone acceptance among University students, and have implications for students' training.

**Keywords** Mobile phone acceptance and use · Mobile learning · UTAUT2 · University students · Greece

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## 1 Introduction

Mobile/Smart phones are increasingly widespread among University students, while their usage as supportive-learning tools in their studies has the potential to contribute to delivering education among students worldwide. For example, University students used their smartphones to access teaching materials or supporting information via the internet, to manage group assignments and to also interact with tutors (Anshari et al. 2017). The use of mobile devices for educational purposes (known as mobile learning) can support and enhance the learning process, anytime and anywhere, and mobile learning is an emerging educational technology aspect in different education levels (Nikolopoulou 2020). University/College students constitute the largest demographic of mobile device users, while mobile phones were reported as the most frequently used mobile device (Crompton and Burke 2018; Lavidas et al. 2019). It is expected that students' perceptions and actual use of mobile technologies in their education will influence the direction of further developments of mobile learning (Vrana 2018).

Mobile learning/technology acceptance and adoption is an active area of research (Hao et al. 2017; Kumar and Chand 2019; Cheng et al. 2020), while the Unified Theory of Acceptance and the Use of Technology (UTAUT model, Venkatesh et al. 2003) has gained credibility in the area of mobile learning/technology (García Botero et al. 2018; Venkataraman and Ramasamy 2018). However, the use of UTAUT2 model (Venkatesh et al. 2012) is still scarce when studying mobile learning/technology acceptance in higher education contexts (Arain et al. 2019). The purpose of this study was to evaluate the behavioral intention of Greek University students for acceptance and use of mobile phone in their studies (as supportive-learning tool), by applying the UTAUT2 model.

Within the Greek context, little is known about mobile technology/learning acceptance and adoption by University students, as it is still an under-developed area of research. The ITU report (2018) ranked Greece among a higher scoring European nation in the Information and Communication Technologies Development Index, while the use of mobile phones in University classrooms is not banned (neither it is encouraged by tutors/educators). Due to the above it is important to identify-explore the factors that influence University students' intention to adopt and use mobile phones in their studies as supportive-learning tools; since these constitute a criterion for mobile learning implementation. If students perceive that mobile learning has little or no value, they are less likely to embrace its use (Crompton and Burke 2018). Attitude towards the use was the main predictor of the behavioral intention (Sánchez-Prieto et al. 2019).

## 2 Theoretical framework

The UTAUT model has been successfully applied in studies investigating technology acceptance in higher education contexts (Kumar and Bervell 2019). UTAUT was validated by Venkatesh et al. (2003) with Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), as the four core determinants of intention to adopt technology; the developers confirmed the considerable improvement in explaining information technology usage behavior by the UTAUT, and encouraged other researchers to validate and test the model with different technologies, contexts, and users. UTAUT is applicable in the context of mobile learning/technology and has been reported as the optimal model for mobile learning (Venkataraman and Ramasamy 2018). Later on, UTAUT was extended with three constructs and re-introduced as UTAUT2 (Venkatesh et al. 2012); the three independent constructs/variables incorporated were Hedonic Motivation (HM), Price Value (PV), and Habit (HT). Behavioral Intention (BI) is the mediating variable, while Use Behavior (USE) plays the role of the dependent variable. In the UTAUT2 model, individual differences (age, gender, and experience) moderate the effects of these constructs on BI and technology USE. UTAUT2 was reported to explain 74% of BI, while the model can be used in the introductory phase (e.g., adoption, initial use) of the target technology (Venkatesh et al. 2016). The extended UTAUT2 was the theoretical framework for this study (see Fig. 1). The UTAUT2 main constructs that impact-predict the intention and use of mobile phones are briefly described below, while their detailed description/definition can be found in Venkatesh et al. (2003, 2012).

**Performance expectancy (PE)** PE is a key construct that determines adoption and eventual usage of the relevant technology and has been justified as the strongest predictor of BI to use a technology (Venkatesh et al. 2003, 2012). For the purpose of this study, it can be defined as the degree to which University students perceive that using mobile/smart phones will enable them achieve improved performance in their studies.

**Effort expectancy (EE)** Prior research has shown that constructs associated with EE will be stronger determinants of personal intention about using new technology (Venkatesh et al. 2003; Wang and Wang 2010). For this study, EE can be interpreted as the level of

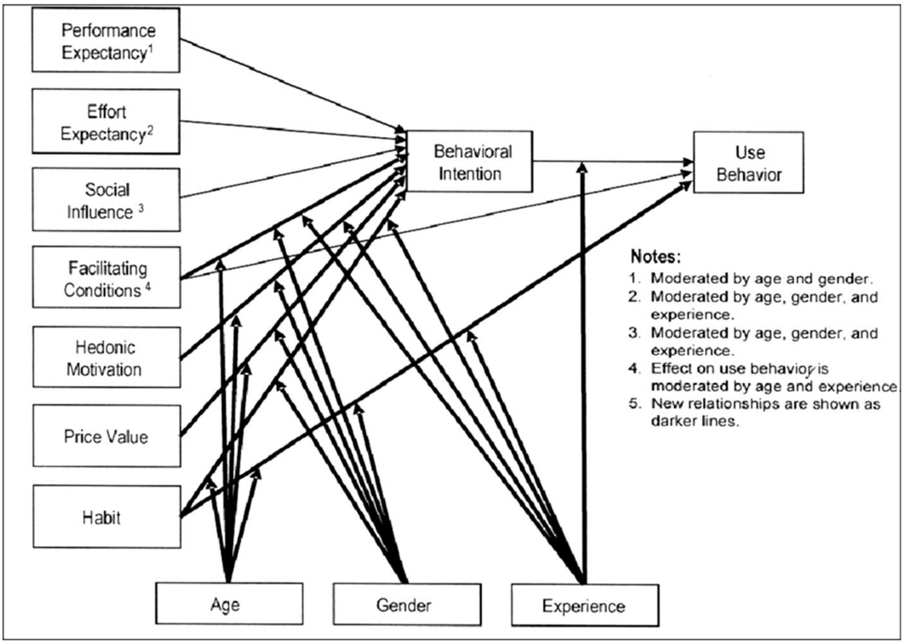


**Fig. 1** The UTAUT2 model (Venkatesh et al. 2012)

expectation of students that the use of mobile phones will not be characterized by physical and mental efforts (ease of use of phones for their studies).

**Social influence (SI)** SI regards the degree to which students perceive that important others (e.g., friends, peers, University tutors) believe they should use the mobile phone in their studies.

**Facilitating conditions (FC)** In this study, FC can be thought of as the degree to which students believe there is sufficient organizational and technical infrastructure, to support the use of mobile phones as supportive-learning tools in their studies.

**Hedonic motivation (HM)** In the context of mobile learning acceptance-usage, HM is conceptualized as perceived enjoyment. Studies reported perceived enjoyment's significant influence on mobile technology acceptance and use for learning (Wang et al. 2009; Wang and Wang 2010). In this study, HM refers to the fun/pleasure/enjoyment resulting from students' using the mobile phone in their studies.

**Price value (PV)** In this study, PV is a predictor of Behavioral Intention to use a mobile phone.

**Habit (HT)** HT is measured as the extent to which an individual believes the behavior to be automatic, because of learning and influences technology use (Venkatesh et al. 2012). In the context of mobile learning, HT reflects the results of prior experiences with mobile technology/phone usage.

**Behavioral intention (BI)** BI is a significant determinant behind the actual use of technology in different intention models (Venkatesh et al. 2003, 2012). In this study, BI is the extent to which students intend (and continue) to use mobile phones in their studies.

**USE behavior (USE)** In this study, USE is the extent to which University students use their mobile phones in their studies (as learning tools).

Therefore, the acceptance and use of mobile phones by University students for their studies could be a function of the above described UTAUT2 constructs. Before presenting the hypotheses of this study, earlier research regarding mobile technology/phone acceptance by University students, by employing UTAUT and UTAUT2 models, is discussed.

## 3 Research Related To Mobile Technology/Phone Acceptance By University Students (Using Utaut1 And Utaut2 Models)

Many scholars have used the UTAUT model to provide empirical insights into the acceptance of different technologies by different participants in a variety of contexts (Venkatesh et al. 2016). Regarding mobile learning acceptance and adoption in University education, several studies (e.g., Ameri et al. 2020; Al-Shihi et al. 2018; Baydas and Yilmaz 2018; Al-Adwan et al. 2018a, 2018b; Kumar and Bervell 2019) used constructs from the UTAUT model. UTAUT2 has also been widely accepted and tested in many different types of educational contexts, humanities, technical education, engineering, management and health sciences. Jakkaew and Hemrungrote (2017) claimed that UTAUT2 has been used in acceptance studies on application of smart mobile devices in learning. However, the use of the extended UTAUT2 model in the context of mobile phone acceptance-adoption has been limited (Ahmed et al. 2017; Ahmed and Kabir 2018; Arain et al. 2019; Arain et al. 2018; Ameri et al. 2020; Jung and Lee 2020). An investigation of the variables affecting University students' acceptance of mobile phones as supportive-learning tools in their studies/learning is important to determine their contribution to mobile learning.

Al-Adwan et al. (2018a) proposed a framework based on the UTAUT model, to explore the potential factors that may impact University students' intention and readiness to adopt mobile learning in Jordan. The results revealed that EE, PE, and SI were significant determinants of m-learning adoption, and explained 64.8% of the variance in the students' intentions to adopt m-learning. Another factor that influenced students' intentions was perceived enjoyment (Al-Adwan et al. 2018b). Vrana (2018) applied the UTAUT theory to investigate students' acceptance of mobile technologies and mobile learning, in Croatia. He indicated that the acceptance and active participation in mobile learning requires additional effort on the side of the students to use it more frequently and on the side of academic institutions to promote mobile learning. Onaolapo and Oyewole (2018), by using the UTAUT, explored the influence of PE, EE and FC on the use of smart phones for mobile learning by postgraduate students in Nigeria. Findings revealed a significant positive relationship between each of the variables PE, EE and FC and the USE of smartphones; PE was the strongest predictor of smart phone use for mobile learning. García Botero et al. (2018) used the UTAUT model with higher education students and showed that PE, SI, and FC influenced students' attitudes towards using mobile assisted language learning (MALL), while behavioral intention had an effect on MALL use.

Research that employed the UTAUT2 model derives from around the world, but it is still limited. Huang and Kao (2015), in Taiwan, explored via the UTAUT2 model students' intentions to use Phablets. They demonstrated the direct influence of the HT on other constructs/dimensions, while HM and PE were the most important dimensions. Ahmed et al. (2017) used the UTAUT2 model to analyze the acceptance of smartphones as learning tools between engineering and education students in N. Zealand. Seven factors were extracted, those of the UTAUT2 model, and more than 60% of the variance was explained. Then, Ahmed and Kabir (2018) applied the UTAUT2 model to analyze the acceptance of smartphones as learning tools among business studies students in Bangladesh; All the constructs were significant predictors of acceptance. Arain et al. (2019) employed the UTAUT2 model with engineering students in Pakistan. PE, HM, HT had a significant impact on the BI to use smart phones as learning tools. Ameen and Willis (2018), in Dubai, used the UTAUT2 model to study the moderating effect of age on smartphone adoption and use. Age moderated the relationship between BI and the independent factors EE and PV; Differences were found between users aged 18–22 and 23–29 (age also moderated the effect of HT on USE).

Kumar and Bervell (2019) adopted UTAUT2 as a theoretical foundation to investigate University students' initial perceptions of Google Classroom as a mobile learning platform. Students' positive intentions to accept Google Classroom were anchored on HT, HM and PE. HT was the most important factor in determining actual usage. Ameri et al.

(2020) applied UTAUT2 to evaluate the BI of pharmacy students for acceptance and long-term use of a mobile-based application for their studies. Their findings indicated that PE, SI and HT had positive effects on BI. BI had significant positive effects on USE, while the effect of HT on USE in men was higher than in women. Moorthy et al. (2019) applied UTAUT2 with accounting students of public Universities in Malaysia and showed that HT had the most influence on students' intention to adopt mobile learning. El-Masri and Tarhini (2017) used the UTAUT2 to investigate the factors that influence the adoption of e-learning systems by University students in Qatar and the USA. It was found that PE, HM, and HT were significant predictors of BI in both student-samples.

In Greece, only a limited number of studies investigated University students' mobile learning attitudes. Early childhood education students' attitude toward the usefulness of mobile learning in the teaching process had the strongest influence on their intention to adopt mobile learning (Kalogiannakis and Paradakis 2019). No gender or age differences were found in evaluating early childhood education students' acceptance of mobile devices (Papadakis 2018). Also, Greek University students recognize that mobile devices enhance their flexibility about learning, as these provide space and time flexibility during the learning process (Lavidas et al. 2019).

## 4 Hypotheses of the study

Accordingly to Fig. 1, for the purpose of this study, the following hypotheses were formulated and tested:

H1: PE has a positive effect/impact on students' BI to use mobile phones in their studies.

H2: EE has a positive effect on students' BI.

H3: SI has a positive effect on students' BI.

H4. FC has a positive effect on students' BI.

H5: HM has a positive effect on students' BI to use mobile phones in their studies.

H6: PV has a positive effect on BI.

H7. HT has a positive effect on students' BI.

H8: BI has a positive impact on the actual use of mobile phones in their studies.

H9: FC has a positive impact on the actual use of mobile phones in their studies.

H10: HT has a positive effect on students' actual use of mobile phones in their studies.

H11: Age, Gender and Experience moderate the effect of PE, EE, SI, FC, HM, PV and HT on BI to use mobile phones in their studies, as well as the effect of FC and HT on USE.

H12: Experience moderates the effect of BI on the actual use of mobile phones.

## 5 Method

### 5.1 Participants and procedure

The sample consisted of 540 University students (Table 1 shows the characteristics of the sample). A questionnaire was completed by Greek students studying at different Universities across the country, in October 2019. The participation in the survey was voluntary. The ethical standards of the institutional research committee were followed. We initially asked for students' consent to participate in the survey, according to the new General Data Protection Regulation (GDPR). The students were informed that the questionnaire is anonymous and the data collected will be used solely for research purposes (confidentiality and privacy issues were followed).

### 5.2 The research instruments

The data were collected using the UTAUT2 questionnaire (Venkatesh et al. 2012). All items were initially translated from English to Greek language by the authors-researchers with the help of a linguistic expert and adapted to the Greek context. The questionnaire consisted of two sections. The first section (section A) was designed to collect demographic information: gender, age, experience (years of using mobile phone with internet access) and University. Section B included the main statements/items (32 items, see Appendix Table 6). Out of 32 items, 4 items corresponded to PE, 4 items to EE, 3 items to SI, 4 items to FC, 3 items to HM, 3 items to PV, 4 items to HT, 3 items to BI, and 4 items to USE. The students were asked to rate their views on a 5-point Likert-type scale (1 = strongly disagree to 5 = strongly agree). The questionnaire was designed using the Google Forms; The items were randomly distributed so as to avoid bias in answering. To investigate the response bias to the above questions, a shortened version (11 items) of the Marlowe–Crowne Social Desirability Scale was administered to a sample of 30 students, along with the standard questionnaire. This tool has been adapted for Greek student sample and has been

**Table 1** Demographic characteristics of participants ($N = 540$)

| *Gender* | *Age* | *Experience (years of using mobile phone with internet access)* |
|---|---|---|
| Male (15.7%) | ≤19 (19.3%) | 1–2 (2.8%) |
| Female (84.3%) | 20–21 (54.1%) | 3–4 (19.1%) |
| | 22–23 (15.9%) | 5–6 (41.5%) |
| | >24 (10.7%) | >7 (36.6%) |
| | *Higher Institution* | |
| University of Patras (39.3%) | National and Kapodistrian University of Athens (21.9%) | University of Thessaly (13.0%) |
| Aristotle University of Thessaloniki (8.3%) | University of Crete (2.4%) | University of Peloponnese (2.0%) |
| Western Greece University of Applied Sciences (2.0%) | University of the Aegean (1.9%) | University of Ioannina (1.9%) |
| Democritus University of Thrace (1.9%) | University of Piraeus (1.7%) | Other (3.9%) |

confirmed for its validity and reliability (Lavidas and Gialamas 2019); No significant correlations indicating response bias were observed.

### 5.3 Data analysis

Variance-Based Structural Equation Modeling was applied (VB-SEM) and in particular, Partial Least Squares - SEM (PLS-SEM) analysis (Hair et al. 2017; Sanchez 2013). This analysis is flexible for normality distribution and sample size and is also considered suitable for confirmatory work (Hair et al. 2017). The PLS-SEM was conducted in R environment (R Core Team 2018) with "plspm" package (Sanchez et al. 2017). Initially, we examined the measurement model and afterwards we tested the structural model. Regarding the structural model, we tested all the path coefficients among constructs, as well as the moderating effects of Gender (GDR), Age (AGE) and Experience (EXP) of participants, as these are presented in Fig. 1. For moderating effects, we used a two-stage path modeling approach (Sanchez 2013). In the first stage, we applied a PLS-SEM analysis without the interaction term (moderator variables). In the second stage (taking the scores obtained in the first stage) we created the interaction term and afterwards we applied a second PLS-SEM analysis including the scores as indicators of the constructs (Sanchez 2013). During the above approach, in order to create the interaction terms, we transformed the variables in standardized values. These variables as mean–centered will support the interpretability of data and simultaneously will reduce multicollinearity among the interaction terms (Hair et al. 2017). We tested all possible higher-order interaction terms according to formatted hypotheses involving: (i) age, gender, experience and each one of FC, PV, HM, HT on BI, and (ii) age, gender, experience and each one of BI, FC, HT on USE. The evaluation of measurement and structural model is discussed in results.

## 6 Results

### 6.1 Measurement model

Discrepancy from normality regarding the distributions of some scale-indicators as well as the predictive character of our model advocates the use of PLS (Hair et al. 2017). The measures of skewness and kurtosis in 8 and 10 items respectively, exceed the acceptable range (−1 to +1) (Hair et al. 2017). According to the sample size an adequate size greater than 10 cases per indicator for PLS analysis was used (Hair et al. 2017). The reliability and the construct validity of the measurement model were satisfactory. Cronbach's Alpha (Cronbach 1951) and Composite Reliability (Raykov 1997) were over .7, indicating a high level of internal consistency reliability for all constructs (Table 2). The construct validity was judged by convergent and discriminant validity (Hair et al. 2017). Regarding the convergent validity, all the measurement indicators were loaded with significant values greater than .7 without cross-loadings on their theoretical reflective constructs. Moreover, Average

**Table 2** Descriptive statistics, and reliability and convergent validity indexes of measurement model

| *Constructs* | *Mean (SD)* | *Factor Loadings* | *Cronbach's Alpha* | *Composite Reliability (CR)* | *Average Variance Extracted (AVE)* |
|---|---|---|---|---|---|
| Behavioral Intention (BI) | 3.82(.72) | | .854 | .912 | .775 |
| BI1 | | .866 | | | |
| BI2 | | .861 | | | |
| BI3 | | .913 | | | |
| Use Behavior (USE) | 3.69(.69) | | .788 | .863 | .613 |
| USE1 | | .857 | | | |
| USE2 | | .707 | | | |
| USE3 | | .817 | | | |
| USE4 | | .742 | | | |
| Performance Expectancy (PE) | | | .815 | .878 | .643 |
| PE1 | 3.79(.71) | .794 | | | |
| PE2 | | .786 | | | |
| PE3 | | .826 | | | |
| PE4 | | .800 | | | |
| Effort Expectancy (EE) | 4.26(.68) | | .866 | .909 | .712 |
| EE1 | | .822 | | | |
| EE2 | | .866 | | | |
| EE3 | | .882 | | | |
| EE4 | | .804 | | | |
| Social Influence (SI) | 3.19(.76) | | .885 | .929 | .813 |
| SI1 | | .910 | | | |
| SI2 | | .930 | | | |
| SI3 | | .864 | | | |
| Facilitating Conditions (FC) | 3.93(.64) | | .760 | .848 | .581 |
| FC1 | | .768 | | | |
| FC2 | | .768 | | | |
| FC3 | | .763 | | | |
| FC4 | | .750 | | | |
| Hedonic Motivation (HM) | 3.57(.80) | | .854 | .912 | .775 |
| HM1 | | .831 | | | |
| HM2 | | .908 | | | |
| HM3 | | .901 | | | |
| Price Value (PV) | 3.63(.74) | | .759 | .862 | .674 |
| PV1 | | .785 | | | |
| PV2 | | .841 | | | |
| PV3 | | .837 | | | |
| Habit (HT) | 3.68(.74) | | .769 | .852 | .588 |
| HT1 | | .783 | | | |

**Table 2** (continued)

| *Constructs* | *Mean (SD)* | *Factor Loadings* | *Cronbach's Alpha* | *Composite Reliability (CR)* | *Average Variance Extracted (AVE)* |
|---|---|---|---|---|---|
| HT2 | | .719 | | | |
| HT3 | | .724 | | | |
| HT4 | | .834 | | | |

Variance Extracted (AVE) over 0.5 for each construct indicates a satisfactory convergent validity (Fornell and Larcker 1981).

The application of Fornell-Larcker criterion (Fornell and Larcker 1981) revealed satisfactory discriminant validity (Table 3). In particular, the square root of each construct AVE was greater than all correlations among constructs.

## 6.2 Structural model

To evaluate the structural model, paths coefficients among constructs and the amount of explained variance in the endogenous construct (R-square) by its exogenous construct were calculated (Hair et al. 2017). In Table 4, the path coefficients among constructs are shown according to the hypothesis and their estimation by robust 95% confidence intervals. In order to calculate the confidence intervals, a bootstrapping re-sampling procedure was followed. During the bootstrap procedure, 5.000 samples with replacement from the original data set, that had sample size equal to the number of cases in the original data set, were created (Sanchez 2013). As shown in Tables 4, 7 out of 10 hypotheses about the direct effect, were confirmed/supported, since direct path coefficients confidence intervals did not include zero. According to Cohen (1977) these path coefficients range from a "small" to a "medium" effect. Regarding the moderating

**Table 3** Discriminant validity matrix (Fornell-Larcker criterion)

| *Constructs* | *BI* | *USE* | *PE* | *EE* | *SI* | *FC* | *HM* | *PV* | *HT* |
|---|---|---|---|---|---|---|---|---|---|
| BI | (.880) | | | | | | | | |
| USE | .741 | (.783) | | | | | | | |
| PE | .559 | .575 | (.802) | | | | | | |
| EE | .373 | .417 | .524 | (.844) | | | | | |
| SI | .491 | .521 | .594 | .287 | (.902) | | | | |
| FC | .457 | .467 | .479 | .582 | .370 | (.762) | | | |
| HM | .552 | .607 | .488 | .422 | .432 | .554 | (.880) | | |
| PV | .348 | .348 | .276 | .281 | .263 | .353 | .417 | (.821) | |
| HT | .519 | .526 | .317 | .293 | .218 | .252 | .324 | .256 | (.767) |

*Note: Diagonals in parentheses are square roots of the AVE from items. Off-diagonal are correlations among constructs*

*Behavioral Intention (BI), Use Behavior (USE), Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), Habit (HT)* effects, Gender, Age and Experience in all possible higher-order interaction had no significant ($p > 0.05$) interactions with any of the constructs.

Finally, in Table 5, the explained variance ($R^2$) and $R^2$ adjusted is shown for each endogenous construct, ranging from moderate to high (Hair et al. 2017). Apart from the explained variance ($R^2$) of each of the endogenous constructs, its proportion (explaining each exogenous construct directly linked by endogenous constructs) is also presented. The most important predictors for BI were HT ($R^2 = 16\%$), PE ($R^2 = 15.4\%$) and HM ($R^2 = 11.9\%$). The most important predictor for USE was BI ($R^2 = 43.2\%$); Predictors for USE with $R^2 < 10\%$ were HT and FC.

## 7 Discussion

This study investigated Greek University students' behavioral intention for acceptance and use of mobile phones in their studies, by employing the UTAUT2 model; This is an under-explored area in Greece and also in other countries. Investigating University students' intentions to adopt-use mobile phones in their studies is important, since successful implementation of mobile learning significantly depends on students' acceptance/intention to adopt a new technology (Al-Adwan et al. 2018a). The results may be useful for University educators, researchers, as well as policy makers. The findings of this study provide a reference for future research employing UTAUT2 model in the area of mobile learning.

It was found that Performance Expectancy, Social Influence, Hedonic Motivation and Habit had a significant effect on students' Behavioral Intention to use of mobile phones and that Behavioral Intention, Facilitating Conditions and Habit had a direct impact on the actual use.

More precisely, PE had a significant effect on students' BI to use mobile phones. It means that students perceive that using mobile phones will enable them achieve improved performance in their studies. This finding is in line with earlier research that

**Table 4** Structural model: Path coefficients and 95% confidence intervals with bootstrapping (5000 samples)

| *Hypotheses* | | *Path Coeff.* | *95% CI* | *Results* |
|---|---|---|---|---|
| H1 | PE- > BI | .276 | (.169–.403) | Supported |
| H2 | EE- > BI | −.058 | (−.171–.066) | Not supported |
| H3 | SI- > BI | .141 | (.039–.224) | Supported |
| H4 | FC- > BI | .078 | (−.043–.201) | Not supported |
| H5 | HM- > BI | .216 | (.102–.305) | Supported |
| H6 | PV- > BI | .073 | (−.014–.175) | Not Supported |
| H7 | HT- > BI | .309 | (.211–.399) | Supported |
| H8 | BI- > USE | .583 | (.506–.650) | Supported |
| H9 | FC- > USE | .157 | (.085–.222) | Supported |
| H10 | HT- > USE | .164 | (.085–.238) | Supported |
| H11 & H12 | Moderating effect of Age, Gender and Experience | | | Not Supported |

**Table 5** Effects on endogenous variables and analysis of explained variance

| *Endogenous* | *Exogenous* | *Direct eff.* | *Indirect eff.* | *Total eff.* | *Correlation* | *Explained variance ($R^2$)* |
|---|---|---|---|---|---|---|
| *BI* ($R^2$-adj* = 58.14%) | | | | | | *62.70%* |
| | PE | .276 | – | .275 | .559 | 15.43% |
| | EE | −.058 | – | −.058 | .373 | 2.16% |
| | SI | .141 | – | .141 | .491 | 6.92% |
| | FC | .078 | – | .078 | .457 | 3.56% |
| | HM | .216 | – | .216 | .552 | 11.92% |
| | PV | .073 | – | .073 | .348 | 2.54% |
| | HT | .309 | – | .309 | .519 | 16.04% |
| | Interaction terms (n.s.) | | | | | 4.11% |
| *USE* | | | | | | *63.40%* |
| ($R^2$-adj = 58.93%) | PE | – | .161 | .161 | .575 | |
| | EE | – | −.034 | −.034 | .417 | |
| | SI | – | .082 | .082 | .521 | |
| | FC | .157 | .045 | .202 | .467 | 7.33% |
| | HM | – | .126 | .126 | .607 | |
| | PV | – | .043 | .043 | .348 | |
| | HT | .164 | .180 | .344 | .526 | 8.63% |
| | BI | .583 | – | .597 | .741 | 43.20% |
| | Interaction terms (n.s.) | | | | | 4.24% |

*Note: *$R^2$-adjusted is designated as: R_adj^2 = 1-(1-R^2) (n-1)/(n-k-1), n = sample size, k = exogenous factors*

employed UTAUT2 model (e.g., Huang and Kao 2015; Arain et al. 2019; Ahmed and Kabir 2018; Kumar and Bervell 2019; Ameri et al. 2020).

The effect of SI on BI was also shown by Ameri et al. (2020) and Moorthy et al. (2019). This result suggests that students believe the perceptions of their peers, parents and University educators can impact them in using the mobile phone; They are more inclined to use their phone in their studies when they perceive their important others support them.

HM was shown to impact on BI. It can be inferred that when the students find the mobile phone enjoyable, the probability in using it is higher. This finding is in line with the work of Huang and Kao (2015), Arain et al. (2019), Ahmed and Kabir (2018), Kumar and Bervell (2019), and Moorthy et al. (2019).

HT was the strongest determinant/predictor of students' BI to use mobile phone. Increased use of mobile phones among the digital natives results in stronger automaticity levels in employing mobile phone in their studies. This finding is supported by the work of Huang and Kao (2015), Arain et al. (2019), Kumar and Bervell (2019), Ameri et al. (2020) and Moorthy et al. (2019).

BI was the most important predictor for USE, and this was also found by Ameri et al. (2020). That is students intend (and continue) to use their mobile phones in their studies. The effects of HT on USE were also confirmed by Ameri et al. (2020), Ameen and Willis (2018), and Kumar and Bervell (2019).

The constructs EE and PV did not have a significant effect on BI. Also none of the moderators (gender, age, experience) had an impact. It may be due to the homogeneity of the sample, which was predominantly female students aged 19–24 years old.

## 8 Conclusion and recommendations

This study indicated that the most important predictors for students' BI to use mobile phones in their studies were HT (the strongest one), PE and HM. The most important predictor for actual mobile phone use was BI. The findings of this study add significant value to mobile phone acceptance among University students and have implications for students' training.

The main limitations of the study were related to the homogeneity of the sample, and this does not facilitate the comparison of our findings with research involving greater demographic spread. We intend to conduct similar investigations with other populations such as in-service teachers. Qualitative research will also be included in collecting data through open questions. Future research could explore the impact of other constructs (e.g., self-efficacy) on USE. There is a need to continue studying the effect of new factors on the technology adoption process (Sánchez-Prieto et al. 2019).

Mobile learning plays an increasingly important role in the development of teaching methods in higher education (Lebzar and Jahidi 2017). When an educational institution provides support to its students, it influences elements of their behavioral intention (Hao et al. 2017). University educators could design appropriate teaching interventions that incorporate mobile phones as learning-supportive tools. University students should receive training with regard to effective mobile phone usage in their studies; Librarians could, for example, organize workshops/seminars for students, to expose them to ways of using their mobile phones to access electronic databases. In parallel, there is a requirement for efficient mobile phone applications which can be purposefully used in different University subjects. Since today's generations of students are willing to continue to use their mobile phones, investments in mobile infrastructure and design of apps are worthy. UTAUT2 is an appropriate model for identifying the impact of factors such as HT, PE and HM on BI to use mobile phones, in educational contexts.

**Funding** This research did not receive any grant.

## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.
Approval was obtained from the ethics committee of the Department of Early Childhood Education, National and Kapodistrian University of Athens. The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

**Availability of data and material** (by the 2nd and 3rd author, if needed)

**Code availability** (n.a)

## Appendix

**Table 6** Constructs and corresponding items (32 items)

| | *Performance Expectancy (PE)* |
|---|---|
| PE1. | I find mobile phone useful in my studies |
| PE2. | Using mobile phone increases my chances of achieving things that are important to me |
| PE3. | Using mobile phone helps me accomplish various activities, related to my studies, more quickly |
| PE4. | Using mobile phone increases my productivity in my studies |
| | *Effort Expectancy (EE)* |
| EE1. | Learning how to use mobile phone is easy for me |
| EE2. | My interaction with mobile phone is clear and understandable |
| EE3. | I find mobile phone easy to use |
| EE4. | It is easy for me to become skilful at using mobile phone |
| | *Social Influence (SI)* |
| SI1. | People who are important to me think that I should use mobile phone (and) in my studies |
| SI2. | People who influence my behavior think that I should use mobile phone in my studies |
| SI3. | People whose opinions I value prefer that I use mobile phone (and) in my studies |
| | *Facilitating Conditions (FC)* |
| FC1. | I have the resources necessary to use mobile phone in my studies |
| FC2. | I have the knowledge necessary to use mobile phone |
| FC3. | Mobile applications of my mobile phone are compatible with other technologies I use |
| FC4. | I can get help from others when I have difficulties using mobile phone |
| | *Hedonic Motivation (HM)* |
| HM1. | Using mobile phone in my studies is fun |
| HM2. | Using mobile phone in my studies is enjoyable |
| HM3. | Using mobile phone in my studies is very entertaining |
| | *Price Value (PV)* |
| PV1. | Mobile phone is reasonably priced |
| PV2. | The cost of the services that I have access to through my mobile phone is worth their money |
| PV3. | At the current price, mobile phone provides a good value |
| | *Habit (HT)* |
| HT1. | The use of mobile phone has become a habit for me |
| HT2. | I am addicted to using mobile phone |
| HT3. | I must use mobile phone |
| HT4. | Using mobile phone has become natural to me |
| | *Behavioral Intention (BI) to use mobile phone as a tool for learning* |
| BI1. | I intend to continue using mobile phone in the future, in my studies |
| BI2. | I will always try to use mobile phone in my studies |
| BI3. | I plan to continue to use mobile phone frequently, in my studies |
| | *Use Behavior (USE)* |
| USE1. | I regularly use my mobile phone in my studies |

**Table 6** (continued)

| | *Performance Expectancy (PE)* |
|---|---|
| USE2. | Mobile phone usage is a pleasant experience |
| USE3. | I currently use mobile phone as a supporting tool in my studies |
| USE4. | I spend a lot of time on mobile phone use in my studies |

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

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