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Mobile-based assessment: Investigating the factors that influence behavioral intention to use

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ABSTRACT

Acceptance and intention to use mobile learning is a topic of growing interest in the field of education. Although there is a considerable amount of studies investigating mobile learning acceptance, little research exists that investigates the driving factors that influence students' intention to use mobile technologies for assessment purposes. The aim of this study is to provide empirical evidence on the acceptance of Mobile-Based Assessment (MBA), the assessment delivered through mobile devices and technologies. The proposed model, Mobile-Based Assessment Acceptance Model (MBAAM) is based on the Technology Acceptance Model (TAM). MBAAM extends TAM in the context of MBA by adding to the Perceived Ease of Use and Perceived Usefulness, the constructs of Facilitating Conditions, Social Influence, Mobile Device Anxiety, Personal Innovativeness, Mobile-Self-Efficacy, Perceived Trust, Content, Cognitive Feedback, User Interface and Perceived Ubiquity Value and investigates their impact on the Behavioral Intention to Use MBA. 145 students from a European senior-level secondary school experienced a series of mobile-based assessments for a three-week period. Structured equation modeling was used to analyze quantitative survey data. According to the results, MBAAM explains and predicts approximately 47% of the variance of Behavioral Intention to Use Mobile-Based Assessment. The study provides a better understanding towards developing mobile-based assessments that support learners, enhance learning experience and promote learning, taking advantage of the distinguished features that mobile devices may offer. Implications are discussed within the wider context of mobile learning acceptance research.

1. Introduction

The rapid growth of mobile and wireless technologies resulted in an increasing use of mobile devices in education. This trend opens new opportunities to mobile learning and assessment. Research provides evidence that mobile devices have become a learning tool with a great potential in education (Sung, Chang, & Liu, 2016).

However, effective implementation of any information system depends on user acceptance (Davis, 1989). The acceptance and adoption of mobile learning is a topic of growing interest in the field of education and it is still evolving (Briz-Ponce, Pereira, Carvalho, Juanes-Méndez, & García-Peñalvo, 2016; Cheon, Lee, Crooks, & Song, 2012; Liu, Han, & Li, 2010). Many

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scholars have investigated the acceptance of mobile learning from the students' perspective (Abu-Al-Aish & Love, 2013; Mac Callum, Jeffrey, & Kinshuk, 2014; Park, Nam, & Cha, 2012) and teachers' perspective (Uzunboylu & Ozdamli, 2011) as well. Research also exists about the acceptance of computer-based assessment (Terzis & Economides, 2011). However, to the best of our knowledge, no study exists to provide evidence regarding the driving factors contributing to the acceptance and intention to use Mobile-Based Assessment (MBA), the assessment that is delivered with the use of mobile devices and wireless technologies. MBA related research have been focusing so far only on students' perceptions and attitudes in general and not specifically on acceptance issues and intention to use. Moreover, even users' perceptions about MBA are still inconsistent (Bennett, Dawson, Bearman, Molloy, & Boud, 2017); there are several unresolved issues relating to usability (Cheon et al., 2012; Huff, 2015) and user perspectives (Wang et al., 2009). Since there is a gap in the literature regarding the acceptance of Mobile-Based Assessment, the current study is aiming at filling this gap by providing empirical about the factors that affect students' intention to use MBA. The spinning off knowledge and experience about MBA acceptance can be essential for education professionals to design, implement and deliver more engaged and effective mobile-based assessments.

The organization of the study is as follows. The next section provides a literature review. The review first draws on mobile learning and mobile-based assessment, then introduces the Technology Acceptance Model and continues by considering the more limited studies focusing on the acceptance of mobile learning and mobile-based assessment. After explaining the rationale for investigating MBA acceptance, the study presents the research model with the hypotheses to be tested. Methodology section (participants, instruments and procedure) follows with the data analysis and results section to come afterwards. Discussions and conclusions for the impact in education follow along with the limitations of the study and future work.

2. Literature review

2.1. Mobile learning

Mobile learning is an emerging trend in education. In the definition of mobile learning by Kukulska-Hulme (2005), learners are able to engage in educational activities without being tied to a tightly-delimited physical location. There is a growing body of literature about developing mobile learning systems to assist students in learning and also highlighting the positive impact of mobile learning on learners' performance (Wu et al., 2012). According to the UNESCO Policy Guidelines for Mobile Learning (West & Vosloo, 2013), mobile learning provides numerous benefits to education: it facilitates personalized learning, supports situated and context-aware learning, enhances seamless learning, bridges formal and informal learning and improves communication and collaboration among members of the learning communities. Due to the technological affordances of mobile devices (Sharples, Taylor, & Vavoula, 2007), their utilization in education opens up new windows of opportunities both in learning and assessment.

2.2. Mobile – based assessment

Mobile-Based Assessment (MBA) is a relatively new mode of assessment that is delivered through wireless technologies and mobile devices. MBA, much like paper-based or computer-based assessment, gathers and reviews empirical data about student learning in order to evaluate students, the learning process itself or both, aiming at improve learning. Furthermore, mobile technologies provide new and enhanced functionalities and opportunities to assess learning. Mobile learning and assessment spans from curriculum-led classroom instruction to informal highly mobile learning on the move (Sharples, 2013). There are many successful implementations of mobile-based assessments inside the classroom boundaries replacing paper-based or web-based tests (Romero, Ventura, & De Bra, 2009). Mobile devices replace computer labs needed for computerized assessments, with the quizzes to be administered using a web browser on students' handheld devices, offering this way a cost saving solution. Mobile devices replace clicker technologies for classroom polling (Stowell, 2015; Sun, 2014). Assessments can be blended into learning management systems (Bogdanovic, Barac, Jovanic, Popovic, & Radenkovic, 2013) or Massive Online Open Courses (MOOCs) (Dahlstrom, Brooks, Grajek, & Reeves, 2015) and can easily be accessed through mobiles. Also, mobile devices can support ubiquitous and seamless learning and assessment outside the classroom boundaries. With the use of Radio Frequency Identification (Chu, Hwang, Tsai, & Tseng, 2010), geo-location features (Santos, Pérez-Sanagustín, Hernández-Leo, & Blat, 2011) or QR-coding technology (Nikou & Economides, 2015a, 2016), mobile devices facilitate student assessment in authentic contexts (Chao, Lan, Kinshuk, Chang, & Sung, 2014; Miyasawa & Ueno, 2013), providing at the same time appropriate learning guidance in situ (Hwang, & Chang, 2011). Beyond high-stakes summative testing (Arthur, Doverspike, Muñoz, Taylor, & Carr, 2014), mobile devices can support a wide range of different assessment types such as self- and peer-assessment (Chen, 2010), formative assessment (Hwang, & Chang, 2011), performance-based (Campbell & Main, 2014) and competency-based assessments (Coulby, Hennessey, Davie, & Fuller, 2010), providing immediate, adaptive and personalized feedback (Triantafillou, Georgiadou, & Economides, 2008). Mobile devices have the potential to assess competences related to real-world tasks as well as higher-level skills, the so-called 21st century skills, such as problem-solving, creativity and collaboration. The majority of the aforementioned studies about using mobile technology for assessment report positive student experiences, increased learning interest and improved learning outcomes (Nikou & Economides, 2013; Wu et al., 2012).

However, despite the fact that mobile devices offer new and enhanced opportunities to assess learning, studies about students' perceptions about MBA are still inconsistent (Bennett et al., 2017). There are studies providing evidence that web-based tests and portfolios are not amongst the students' preferences (Watering, Gijbels, Dochy, & Rijt, 2008), especially for summative assessment purposes (Deutsch, Herrmann, Frese, & Sandholzer, 2012). Also, studies reports numerous drawbacks and limitations in using mobile devices in learning and assessment: small screen size with input difficulties, high cognitive load due to the information overload from real and digital world, difficulty to concentrate (Cheon et al., 2012; Hwang & Wu, 2014; Lowenthal, 2010; Wang et al., 2009).

2.3. Technology acceptance model

A critical factor for the success of any information system or policy implementation is its acceptance by users. One valid and well-established model that addresses the issue of how users accept and use a technology is the Technology Acceptance Model (TAM) (Davis, 1989). Originally, TAM used the constructs of Perceived Usefulness (PU), Perceived Ease of Use (PEOU) and Attitudes Towards Usage (ATU) to explain and predict technology system adoption (Davis, 1989). According to Davis (1989), Perceived Usefulness (PU) is defined as the degree to which a person believes that using a particular system will enhance his/her job performance. Also, Perceived Ease of Use (PEOU) is defined as the degree to which a person believes that using the system would be free of effort. In TAM, Behavioral Intention to Use a system (BIU) is influenced by Attitude Towards Use (ATU), as well as the direct and indirect effects of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, 1989). Synthesizing recent research findings, a meta-analysis by Sumak, Hericko and Pušnik (2011) gathered proof that the perceived ease of use and the perceived usefulness are the major factors that can influence the attitudes of users toward using an e-learning technology.

Since its first invention, many external variables have been added to TAM in order to better explain and predict the acceptance and intention to use Information Technology systems. The Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh, Morris, Davis, & Davis, 2003) is a major TAM successor that considers four core determinants of intention and usage (performance expectancy, effort expectancy, social influence and facilitating conditions) with four moderators influencing the four direct determinants: gender, age, experience and voluntariness of use.

2.3.1. Mobile learning acceptance

TAM is the most-used acceptance theory in e-learning acceptance research (Sumak et al., 2011). TAM has been successfully used as a framework to study mobile learning acceptance as well (Liu, Han et al., 2010; Park et al., 2012), offering its predictive and explanatory power to a considerable large number of mobile learning acceptance related studies. The factors of perceived ease of use and perceived usefulness have been found to have a significant influence towards mobile learning acceptance.

Since its early uses of TAM in mobile learning research, many external variables have been added to it in order to explain and predict mobile learning systems acceptance. For example, the constructs of social influence and facilitating conditions, introduced with the UTAUT model (Venkatesh et al., 2003), have been extensively used in successive TAM studies since then. Wang et al. (2009) found that performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management of learning were all significant determinants of behavioral intention to use m-learning. Park et al. (2012) introduced mobile-learning self-efficacy, learning relevance, system accessibility and subjective norm. Mac Callum and Jeffrey (2013) investigated the influence of students' ICT skills on intention to use. Performance expectancy, effort expectancy, influence of lecturers, quality of service and personal innovativeness have been studied by Abu-Al-Aish and Love (2013). Joo, Lee, and Ham (2014) integrated into TAM the constructs of personal innovativeness and user interface. Mac Callum et al. (2014) addressed the impact of ICT literacy and anxiety on intention to adopt mobile learning. Arpaci (2016) found that perceived trust positively affects mobile cloud services and also Liu, Chen, and Lu (2015) highlighted that perceived trust impacts students' participation in an on-line exam. In a recent study by Briz-Ponce et al. (2016) social influence raised to be an important factor towards students' acceptance of mobile technologies for learning. Table 1 summarizes a number of selected constructs that have been found to have a significant impact on mobile learning acceptance and are used

Table 1
Constructs used in previous mobile learning acceptance studies.

Construct	Supporting mobile learning acceptance studies
Perceived Ease of Use	Wang et al., 2009; Park et al., 2012; Abu-Al-Aish & Love, 2013
Perceived Usefulness	Park et al., 2012; Abu-Al-Aish & Love, 2013; Wang et al., 2009
Facilitating Conditions	Venkatesh et al., 2003; Park et al., 2012; Abu-Al-Aish & Love, 2013
Social Influence	Briz-Ponce et al., 2016; Wang et al., 2009; Park et al., 2012; Venkatesh et al., 2003
Self-Efficacy	Mac Callum & Jeffrey, 2013; Park et al., 2012
Personal Innovativeness	Joo et al., 2014; Abu-Al-Aish & Love, 2013
Anxiety	Mac Callum et al., 2014
Perceived Mobility	Huang, Lin, & Chuang, 2007; Liu et al., 2010
Perceived Trust	Arpaci, 2016; Liu et al. (2015)
User Interface	Joo et al., 2014

in our study. Our study, based on the literature review of mobile learning acceptance, develops a casual model to explain and predict the acceptance of mobile based assessment.

2.3.2. Acceptance of mobile-based assessment

Mobile-Based Assessment (MBA), as a computerized means of assessment that is delivered through mobile devices and technologies, borrows features from both mobile learning and computer-based assessment as well. According to the above discussion, research about mobile learning acceptance is quite extensive (Liu, Han et al., 2010; Park, Nam, & Cha, 2012). Moreover, studies about Computer-Based Assessment (CBA) revealed that perceived ease of use, perceived playfulness and emotional feedback have a direct effect on behavioral intention to use a CBA system, while perceived usefulness, computer self efficacy, social influence, facilitating conditions, content and goal expectancy have only indirect effects (Terzis & Economides, 2011). However, to the best of our knowledge, no research exists that explains and predicts students' intention to use mobile-based assessment. Our study builds on the previous research on mobile learning and computer-based assessment acceptance to build a model for the acceptance of mobile-based assessment.

Although MBA fits into the wider context of mobile learning, we argue that MBA acceptance should be studied systematically and separately from other mobile learning activities. This is due to the following reasons. First, there are no mobile-based assessment related studies that focus explicitly on issues about acceptance and intention to use; existing studies mainly report students' perceptions and attitudes about MBA in general. Second, despite the affordances that MBA provides, students' reported general perceptions and attitudes about MBA are still inconsistent. Most mobile assessment related research reports positive students' attitudes about the use of mobile devices in assessment (Bogdanovic et al., 2013; Chen, 2010; Hung, Lin, & Hwang, 2010; Hwang, & Chang, 2011; Lai & Chen, 2013). However, there are some issues raised with regards to usability when comparing mobiles to desktop computers (Huff, 2015), security aspects (Thamadharan & Maarop, 2015) and technical limitations of mobile devices (Cheon et al., 2012). Even personality and psychological limitations (Wang et al., 2009) may discourage students from using mobiles for learning and assessment purposes, despite their everyday use for hedonic purposes (e.g. gaming, communicating with friends). Third, investigating the factors influencing MBA acceptance is essential for improving the educational outcome (Watering et al., 2008). Previous research provides evidence that students' perceptions and attitudes about assessment are strongly related to their approaches to learning (Dhindsa, Omar, & Waldrip, 2007). Students' attitudes on different assessment formats can have either positive or negative influences on performance (Boud, 1990). When assessment is perceived to be inappropriate, that implies a surface approach to learning (Struyven, Dochy, & Janssens, 2005). By taking into consideration students' perceptions about MBA adoption and addressing them properly, we can design and implement more student-centered and engaging assessments that cater better diverse student learning needs.

The aim of the current study is to investigate the factors that influence MBA adoption in order to further develop and improve this relatively new delivery mode of assessment adding new evidence to the existing body of knowledge.

3. The research model

The current study is based on the original Technology Acceptance Model (TAM) (Davis, 1989) as well as other subsequent studies - including UTAUT - that extended TAM model with external variables. It also considers variables related to the distinguished features of Mobile-Based Assessment (MBA). TAM is a valid and robust model (King & Jun He, 2006). Moreover, since TAM and successive studies examine technology adoption in institutional or organizational contexts (Davis, 1989; Venkatesh et al., 2003) and the use of mobile devices for assessment belongs in the context of an educational organization, TAM is an appropriate theoretical background for our study. We have developed the following hypotheses in order to test the effect of the variables of Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Facilitating Conditions (FC), Social Influence (SI), Mobile Device Anxiety (MDA), Personal Innovativeness (PI), Mobile Self-Efficacy (MSE), Perceived Trust (PT), Cognitive Feedback (CF), Content (C), Perceived Ubiquity Value (PUV), User Interface (UI) on Behavioral Intention to Use (BIU) Mobile-Based Assessment.

3.1. Perceived Ease of Use (PEOU) and Perceived Usefulness (PU)

In the technology acceptance literature (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989), Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) significantly affect intention to use technology. Previous research has shown that users perceiving a new technology as useful or as easy to use it, they are more likely to adopt it; also a positive effect of Perceived Ease of Use on the Perceived Usefulness of a new technology was found (Chin & Todd, 1995). The same relationships among these variables exist for mobile learning (Abu-Al-Aish & Love, 2013; Briz-Ponce et al., 2016; Mac Callum, Jeffrey, & Kinshuk, 2014; Park et al., 2012) and computer-based assessment acceptance as well (Terzis & Economides, 2011). In-line with previous research, our model about mobile-based assessment proposes the following hypotheses:

H1a. Perceived Ease of Use (PEOU) has a positive effect on Perceived Usefulness (PU).

H1b. Perceived Ease of Use (PEOU) has a positive effect on Behavioral Intention to Use (BIU).

H2. Perceived Usefulness (PU) has a positive effect on Behavioral Intention to Use (BIU).

3.2. Social influence

Social Influence (SI) has been introduced through the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003). Venkatesh et al. (2003) defined social influence as the "degree to which an individual perceives that important others believe he or she should use the new system". Previous studies have shown that social influence positively affects users' perceptions about the system's usefulness and has a significant impact on an individual's intention to adopt a new technology, especially during the initial stages of technology adoption (Venkatesh et al., 2003). In the context of computer-based assessment, social influence has a positive effect on Perceived Usefulness (Terzis & Economides, 2011). The same holds for mobile learning as well (Wang et al., 2009). Students may have never used mobile devices for assessment in the past. Therefore, they may need to value the opinion of their teachers, parents or other people that influence their behavior about the usefulness of the system. In the context of mobile-based assessment acceptance, we make the following hypothesis:

H3. Social Influence (SI) has a positive effect on Perceived Usefulness (PU).

3.3. Facilitating conditions

Facilitating Conditions (FC) have been also introduced through the UTAUT model and have been defined as the "degree to which users believe that the necessary infrastructures exist to support the use of a technological system" (Venkatesh et al., 2003). Facilitating Conditions can be anything that acts supportively towards the implementation of the assessment procedure such as administrative, organizational or technical support, knowledge and other resources. Research has shown that Facilitating Conditions have a significant influence on behavioral intention to use (Venkatesh et al., 2003). The same holds for mobile learning acceptance as well (Chen & Huang, 2012; Wang et al., 2009). In the context of our study, we describe Facilitating Conditions mainly as the proper technical infrastructure (e.g. internet connectivity) and the availability of a technical expert ready to support students to overcome technical problems that may arise while using the mobile devices. In computer-based assessment, facilitating conditions have a positive impact on Perceived Ease of Use (Terzis & Economides, 2011). In the context of mobile-based assessment we also hypothesize that:

H4. Facilitating Conditions (FC) have a positive effect on Perceived Ease of Use (PEOU).

3.4. Personal innovativeness

In the Information Technology domain, Personal Innovativeness (PI) is a construct that has been developed and validated by Agarwal and Prasad (1998). It has been defined as "the willingness of an individual to try out any new information technology" (Agarwal & Prasad, 1998, p. 206). Agarwal and Prasad (1998) reported that personal innovativeness has significant effects on perceived usefulness, perceived ease of use, and ultimately, acceptance of new technology. Mobile learning acceptance research provided evidence that personal innovativeness positively relates to perceived ease of use (Liu, Li, & Carlsson, 2010; Joo et al., 2014; Nikou & Economides, 2015b). An innovative individual is more likely to perceive mobile-learning and mobile-based assessment as an ease to use activity. We hypothesize that:

H5. Personal Innovativeness (PI) has a positive effect on Perceived Ease of Use (PEOU).

3.5. Perceived Ubiquity Value (PUV)

Ubiquitous computing refers to the use of "anytime" and "anywhere" sensor enabled wireless communication objects, being able to sense the situation of the users and provide adaptive personalized services (Hwang, Tsai, & Yang, 2008). Technological advances in context-aware and ubiquitous technologies enabled the development of ubiquitous learning. Furthermore, scholars have identified that context-aware ubiquitous learning can facilitate active, authentic, cooperative and adaptive, personalized learning activities (Huang, Chiu, Liu, & Chen, 2011) inducing students to meaningful learning (Ausubel, 1963). The current study introduces the construct of Perceived Ubiquity Value (PUV) as the users' perception of the value of the ubiquity of the mobile device when using it in the mobile-based assessment. In the context of ubiquitous learning, assessment also needs to be redesigned: new strategies need to be employed in order to assess the newly introduced situated, authentic, cooperative and adaptive learning activities (Hwang et al., 2008). Based on previous research about meaningful ubiquitous learning (Huang et al., 2011), PUV has the following dimensions: active, authentic, cooperative and personalized. Users actively participate in real-world authentic learning scenarios, collaborating with peers and receiving at the same time personalized support. So far, no studies have associated Perceived Ubiquity Value with technology acceptance in the context of mobile learning. Perceived Mobility (Huang et al., 2007), a similar construct, has been found to have a positive influence on Perceived Usefulness. Perceived Ubiquity Value, compared to Perceived Mobility, encompasses not only time and location independence (like perceived mobility does) but also it incorporates context-awareness as well. Perceived Ubiquity Value can be considered as a more comprehensive construct than Perceived Mobility. The ubiquity features of mobile devices enhance their functionalities and make them more useful. Therefore, Perceived Ubiquity Value has an impact on Perceived Usefulness. We hypothesize that:

H6. Perceived Ubiquity Value (PUV) has a positive effect on Perceived Usefulness (PU).

3.6. Mobile Self-Efficacy

Self-efficacy represents judgment of general ability to perform a behavior (Agarwal & Karahanna, 2000). Compeau and Higgins (1995) defined Computer Self-Efficacy as “an individual's perceptions of his or her ability to use computers in the accomplishment of a task” (p. 191). Computer Self-Efficacy has been identified to play a significant role in the adoption of computer supported education (Celik & Yesilyurt, 2013) and computer-based testing as well (Lu, Hu, Gao, & Kinshuk., 2016). In mobile learning acceptance research, Mac Callum and Jeffrey (2013) found that ICT literacy and skills impact students' intention to adopt. Terzis and Economides (2011) found that computer self-efficacy has an important direct effect on perceived ease of use and an indirect effect on behavioral intention to use a computer-based assessment.

We define Mobile Self-Efficacy (MSE) as an individual's perceptions of his or her ability to use mobile devices in order to accomplish particular tasks (e.g. navigating through the Web). Based on the findings of the aforementioned research, we hypothesize that student efficacy in using mobile devices can directly affects his/her perceptions about the ease of use MBA. Therefore:

H7. Mobile Self-Efficacy (MSE) has a positive effect on Perceived Ease of Use (PEOU).

3.7. Mobile Device Anxiety (MDA)

Computer Anxiety is already known that plays a significant role in the adoption of computer supported education (Celik & Yesilyurt, 2013). Research has shown that perceived anxiety is negatively related to Perceived Ease of Use (Liaw & Huang, 2015; Sánchez-Prieto, Olmos-Migueláñez, & García-Peñalvo, 2016). Furthermore, previous research revealed a negative correlation between test anxiety and performance (Lu et al., 2016; Ortner & Caspers, 2011). Previous research confirmed that users with high ICT anxiety are less likely to adopt mobile learning (Mac Callum et al., 2014). In our study, we define Mobile Device Anxiety (MDA) as the degree of an individual's apprehension a user feels when he/she uses mobile technologies. A user with high anxiety levels in using mobile devices is less likely to consider mobile-based assessment as being easy to use. In accordance with previous research, we hypothesize that:

H8. Mobile Device Anxiety (MDA) has a negative effect on Perceived Ease of Use (PEOU).

3.8. Content (C)

The construct of Content (C) relates to the course content itself and the questions' content also. Regarding the dimensions of the Content used in our study, we examine if the questions were clear, understandable, relating with syllabus and useful for the course. Content has been identified to have a great importance in e-learning and user satisfaction value (Shee & Wang, 2008). Also, in the context of computer-based testing, previous research (Terzis & Economides, 2011) provided evidence that the construct of Content has a direct influence on Perceived Usefulness and is a significant factor towards system acceptance. We hypothesize that in order for the assessment to be considered as useful, the questions should be clear, understandable and relating with the course. When assessment questions are appropriate, the assessment itself can enhance learning progress and considered as useful by the students. Therefore, based also on previous research we hypothesize that:

H9. Content (C) has a positive effect on Perceived Usefulness (PU).

3.9. User interface (UI)

User interface (UI) in mobile learning refers to the user environment that includes the menus and various functions for controlling the mobile devices (Hiltunen, Laukka, & Luomala, 2007). Previous studies in e-learning acceptance (Liu, Chen, Sun, Wible, & Kuo, 2010) and mobile learning acceptance (Joo et al., 2014) revealed that user interface is an important factor that affects usefulness and ease of use perceived by learners. The construct of User Interface in our study has three dimensions: design (Liu, Chen et al., 2010), navigation and interactivity (Lee, Moon, Kim, & Yi, 2015). When the design of the user interface facilitates user navigation and interactivity, users can easily use the system and therefore Perceived Ease of Use is supported. Therefore we hypothesize that:

H10. User Interface (UI) has a positive effect on Perceived Ease of Use (PEOU).

3.10. Cognitive feedback (CF)

The role of feedback is vital in education. Based on the timing dimension, it is classified as *in advance, immediate* or *delayed*, while based on the different mind dimensions can be *cognitive, emotional* or *conative* (Economides, 2009). Feedback has been shown to have a strong impact on learning and achievement (Hattie & Timperley, 2007). Research shows that the following two types of feedback are more useful for learning since they promote self-efficacy and improve student performance: immediate feedback with knowledge of correct response and elaborated feedback (Wang & Wu, 2008; van der Kleij, Eggen, Timmers, & Veldkamp, 2012). In the context of technology acceptance, emotional feedback has been found to have a positive influence on perceived usefulness and behavioral intention to use computer-based testing (Terzis, Moridis, & Economides, 2012). The cognitive feedback provided by the classroom response systems, has been found to have a significant effect on students' cognitive learning outcomes (Han & Finkelstein, 2013; Hunsu, Adesope, & Bayly, 2016). However, to the best of our knowledge, no connection of cognitive feedback with the acceptance and the intention to use MBA exists. The current study introduces cognitive feedback as a new construct in the technology acceptance model. Immediate and understandable feedback, relevant to the given questions supports the learning progress and student engagement. When students receive immediate feedback with knowledge of correct response they perceive assessment to be more useful. Therefore, we hypothesize that:

H11. Cognitive Feedback (CF) has a positive effect on Perceived Usefulness (PU).

3.11. Perceived Trust (PT)

Perceived Trust (PT) in a system is defined as the students' perceptions about the reliability and trustworthiness of the system (Arpaci, 2016). The reliability, stability, creditability and security of an Information System have positive influence on users' intention to use it (Ong, Lai, & Wang, 2004). Security and privacy positively influence trust which in turns positively affects behavioral intention to use mobile cloud storage services (Arpaci, 2016). Perceived Trust is one of the most important factors of successful participation in online exams (Chang, Tseng, Chou, & Chen, 2011). Based on previous research by Liu et al. (2015), we define the construct of Perceived Trust (PT) in the MBA context, as the degree of the perceived trustworthiness of a mobile-based assessment. Perceived Trust in MBA may depend on the reliability of the notarization process of user authentication, the ability of cheating prevention, the security of the information processed and the perceived reliability of the evaluation outcome (Liu et al., 2015). Robles-Gómez et al. (2015) suggested that perceived trust in a self-evaluation assessment system influences system acceptance and improves learning. Mou, Shin, and Jason Cohen (2016) provided evidence that Perceived Trust influences Perceived Usefulness of e-services affecting user acceptance. We consider that examinees who trust the MBA system they also consider it as useful and hence they are more likely to adopt it. Therefore we hypothesize that:

H12. Perceived Trust (PT) has a positive effect on Perceived Usefulness (PU).

Based on the previous hypotheses, we have developed the model shown in Fig. 1 to explain and predict the intention to use MBA. The external TAM variables are grouped based on user profile factors (personal innovativeness, self-efficacy, anxiety, trust), mobile device features (user interface, ubiquity), environment factors (social influence, facilitating conditions) and educational content factors (content, cognitive feedback).

4. Methodology

4.1. Participants and procedure

The participants in the study were 145 students randomly selected from a senior-level high school in Europe. There were 68 males (47%) and 77 females (53%). The average age of students was 16.5 ($SD = 1.24$). One hundred and five students (73%) were enrolled in the first year while forty students (27%) were enrolled in the second year of the three-year high school located in an urban area. Students' were informed in advance about the research procedure; their participation was voluntarily and all the data collected anonymously. Appropriate parental permissions and school ethical approval for the participation requested and approved. Semi-structured student interviews about their attitudes for assessment in general did not reveal any special favor or disfavor towards assessment with all students to acknowledge the importance of assessment in learning. All participating students had used mobile devices for personal purposes in the past (gaming, web searching, communication, etc.). One-hundred and five students (72%) had used mobile devices for their own personal study (search for educational content, download class material, etc) while students' experience with technology-based assessment (e.g. computer-based tests and classroom response systems) was very limited. Participating students used Wi-Fi enabled smartphones (79% Android, 16% iOS, 4% Windows Phone and 1% other) in order to participate in a series of mobile-based assessments.

Since, the current study is aiming not to narrow itself in a particular assessment type (e.g. mobile-based survey or quiz) and is attempting to model assessment in high school settings more generally, it implements a series of different mobile-based assessment activities, spanning in a time period of three weeks, as Table 2 shows.

During the first week, students used their mobile devices indoors, during their science class. Students used the mobile devices to participate in the following mobile-based assessment activities: i) classroom polling, ii) formative assessments with feedback (checking understanding of the subject matter taught) embedded in the science laboratory instructions (Fig. 2), iii) mobile-based portfolio to upload artifacts from their science experiments on the cloud and iv) summative assessment at

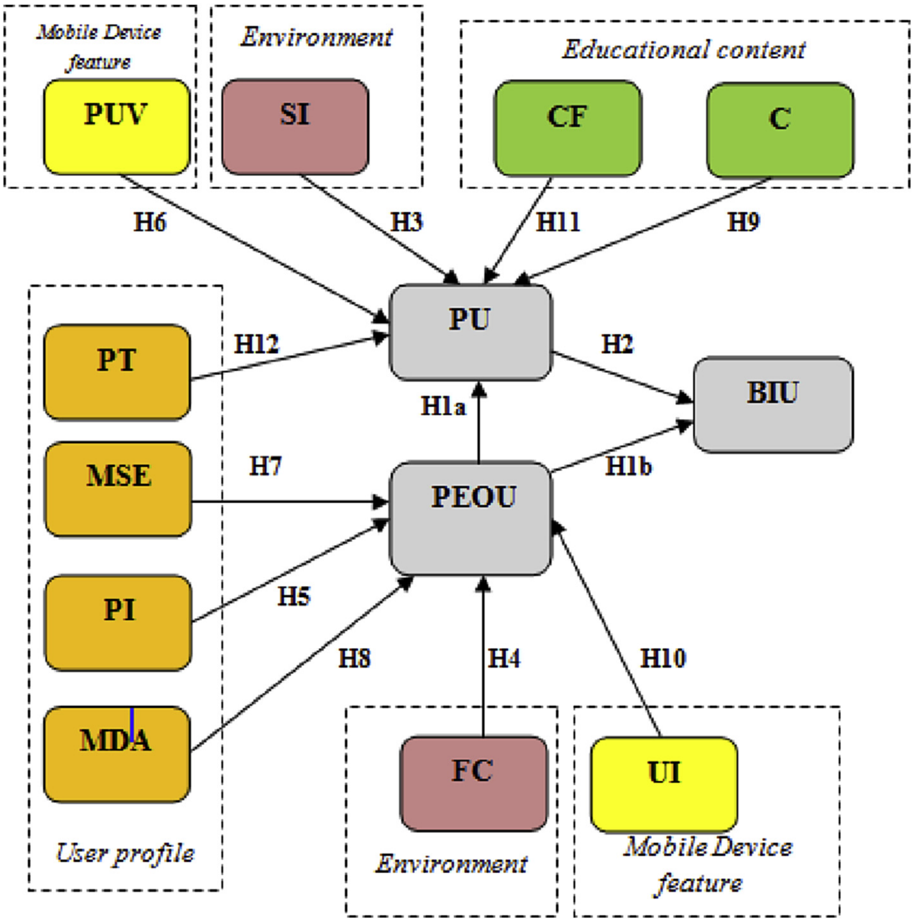

Fig. 1. Mobile-based assessment Acceptance model (MBAAM).

Table 2
Assessment activities supported with mobile devices.

Time	Context	Activity	Details	Duration
1st week	Indoors: Classroom and Science Lab	A1	Classroom Response System using mobiles	20 min
		A2	Formative assessments embedded in learning instructions	60 min
		A3	Performance-based assessment: on-line student portfolios uploaded on cloud through mobile devices	60 min
		A4	Summative assessment	15 min
2nd week	Homework assignments	A5	Mobile-based self- and formative-assessments	3 × 20 min
3rd week	Outdoors: Botanic Gardens	A6	Authentic assessment: QR-code supported plant observation activity	90 min
		A7	Summative assessment	30 min

the end of the learning cycle. During the second week, students used their mobiles outside class in order to participate in two self-assessments and one formative assessment delivered as homework from the teacher. Finally, during the third week, students visited the city's Botanic garden and participated in a two-hours learning and assessment activity, in the context of an environmental project (Fig. 3). Students used the mobile devices and QR-coding technology in order to navigate through the Botanic garden, collect artifacts (e.g. photos of the plants) and answer to a series of questions through a mobile-based authentic assessment.

As Fig. 4 shows, our procedure follows the approach suggested from Sharples (2013), where mobile learning activities range from fixed settings - curriculum led to more informal and mobile settings. The current study, highlighting and supporting the continuity of mobile learning across contexts (classroom, outdoor school activities, homework), is aiming at modeling mobile assessment acceptance across a wide spectrum of high-school education activities.

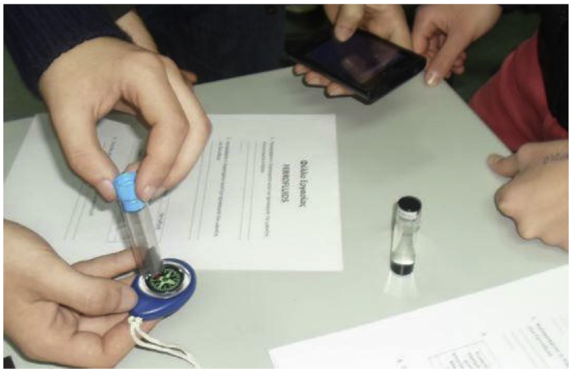

Fig. 2. MBA in science lab.

After the three week period, students were asked to fill-out a questionnaire with their perceptions about their experiences using mobile devices for their assessments and their level of acceptance of mobile-based assessment.

4.2. Instruments

In order to develop the instrument for our research about the acceptance of Mobile-Based Assessment (MBA), we have adapted some items of the constructs from previously validated instruments. For Perceived Usefulness (PU), Perceived Ease of Use (PEOU) and Behavioral Intention to Use (BIU) we adopted items form Davis (1989). For Social Influence (SI), Facilitating Conditions (FC), Mobile Device Anxiety (MDA), we have adopted items from Venkatesh et al. (2003). For Mobile Self-Efficacy (MSE) we adopted items from Compeau and Higgins (1995), properly modified for the context of mobile-based assessment. For Personal Innovativeness (PI) we adopted the items from Liu, Li et al. (2010). For Content (C) we adopted items from Terzis and Economides (2011). For Perceived Trust (PT) we adopted items from Liu et al. (2015). For the Cognitive Feedback (CF) we have developed an instrument consisting of four items referring to cognitive immediate feedback with knowledge of correct response. For the internal consistency of the instrument, Cronbach's a was 0.85. For the Perceived Ubiquity Value (PUV), and in order to collect students' perceptions about the ubiquity value of the MBA, we have developed an instrument consisting of four items referring to the following dimensions: activity, authenticity, cooperativeness and adaptivity (Huang et al., 2011). For the internal consistency of the instrument, Cronbach's a was 0.80. For User Interface (UI) we have adopted one item from Liu, Chen, Sun, Wible and Kuo (2010) referring to design and two items from Lee et al. (2015) referring to navigation and interactivity. For the internal consistency of the instrument, Cronbach's a was 0.79. To conclude, our measurement instrument consists of 47 items and our research model consists of 13 constructs. Table 3 summarizes the aforementioned instruments that contributed to the construction of the Mobile-Based Assessment Model (MBAAM).

The questionnaire was developed in English and then translated into the native language of the students. The translation was made by certified translators to ensure linguistic equivalence. All items were measured on a seven point Likert-type scale with 1 corresponding to “strongly disagree” and 7 to “strongly agree”. The questionnaire used is shown in Table 7 (Appendix).

5. Data analysis and results

Partial Least-Squares (PLS) with Smart PLS 2.0 (Ringle, Wende, & Will, 2005) was used as the analysis technique to predict factors influencing mobile-based assessment adoption. Our sample size exceeds the recommended value of 50 e.g.10 times the largest number of independent variables impacting a depended variable (Chin, 1998).

5.1. Instrument validation

Internal consistency, convergent and discriminant validity of the proposed research model are verified in order to ensure the quality of the model. All criteria for convergent validity are satisfied: all factor loadings on their relative construct exceed 0.70, composite reliability of each construct exceed 0.70 and all average variance extracted (AVE) values range from 0.607 to 0.749 (AVE > 0.50) exceeding the variance due to measurement error for that construct (Table 4).

Discriminant validity is also supported since the square root of the average variance extracted (AVE) of a construct is higher than any correlation with another construct (Table 5). Thus both convergent and discriminant validity for the proposed research model are verified (Hair, Hult, Ringle, & Sarstedt, 2014).

Fig. 3. MBA in a field trip.

Activities	A1	A2, A3, A4	A5	A6, A7
	Handheld response systems	Mobiles in classrooms	Mobile technology outside classrooms e.g. homework	Mobile technology for field trips
	Fixed settings, curriculum led			Mobile, informal

Fig. 4. Mobile activities, adopted from (Sharples, 2013).

5.2. Test of the structured model and hypotheses

Structural model and hypotheses are supported by: (a) the value and the significance (t-values) of path coefficients (bootstrapping procedure is applied to measure t-values). (b) The variance measured (R2) by the antecedent constructs. Values of 0.2, 0.13 and 0.26 are considered as small, medium and large variance respectively.

Fig. 5 and Table 6 summarize the structural model and the hypothesis testing results. Fig. 5 shows the path coefficient for each path along with its significance (as asterisks, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$) and the R^2 for each endogenous variable. Table 6 shows the statistical significance of the relations in the model.

The construct of Perceived Usefulness has the highest mean value (5.22) followed by Social Influence (5.21). This means that students perceive mobile-based assessment as a useful educational activity. Also, students' opinions are highly influenced by their teachers, parents or classmates regarding the use of MBA.

The results from the PLS analysis support eleven out of the twelve hypotheses. All standardized path coefficients (except H5: PI → PEOU) have values between 0.176 and 0.583 which are considered medium to large (Cohen, 1988).

We conclude to the following results. Perceived Ease of Use has a positive effect on Perceived Usefulness (0.432) and on Behavioral Intention to Use (0.408). Also, Perceived Usefulness has a positive effect on Behavioral Intention to Use (0.356). When the mobile-based assessment system is perceived easy and useful, students are willing to use it. Social Influence (SI) has a positive effect on Perceived Usefulness (0.233). When students consider that their teachers or classmates approve and appreciate the use of mobile devices in assessment, they perceive MBA as being more useful. Facilitating Conditions have a positive effect on Perceived Ease of Use (0.243). When the appropriate technical and administrative infrastructure for the use of mobiles in assessments exists, students perceive the procedure as easy. All the above findings are in-line with basic technology acceptance research (Davis, 1989; Venkatesh et al., 2003). The size of the estimated casual links for our model, namely PEOU → PU (0.43), PU → BIU (0.36), FC → PEOU (0.24) and SI → PU (0.23) are comparable to the average path coefficients for the same casual links i.e. PEOU → PU (0.40), PU → BIU (0.40), FC → PEOU (0.34) and SI → PU (0.25), as these have been estimated in a recent meta-analysis of e-learning technology acceptance by Šumak et al. (2011). The coefficient size for the path PEOU→ BIU (0.41) in our model is stronger compared to the corresponding path PEOU→ BIU (0.24) in the above meta-analysis. In our model, PEOU and PU both have a strong influence on BIU. This is also in-line with the findings from the meta-analysis by Khechine, Lakhal, and Ndjambou (2016). In MBAAM, PEOU is a more influential and motivating factor for students to use MBA.

Personal Innovativeness (PI) does not have any effect on Perceived Ease of Use (0.070). This result does not agree with previous research (Liu, Li et al., 2010), where personal innovativeness is positively related with Perceive Ease of Use. It seems

Table 3
Instruments and studies that MBAAM was based on.

Group	Construct	Instrument - Study
	Perceived Usefulness (PU)	Technology Acceptance Model -Davis (1989)
	Perceived Ease of Use (PEOU)	
	Behavioral Intention to Use (BIU)	
Environment	Social Influence (SI)	Unified Theory of Acceptance and Use of Technology
	Facilitating Conditions (FC)	(UTAUT) - Venkatesh et al. (2003)
User Profile	Mobile Device Anxiety (MDA)	UTAUT - Venkatesh et al. (2003)
	Mobile Self-Efficacy (MSE)	Compeau and Higgins (1995)
	Perceived Trust (PT)	Liu et al. (2015)
	Personal Innovativeness (PI)	Agarwal and Prasad (1998), Liu, Li et al. (2010)
Educational Content	Content (C)	CBAAM - Terzis and Economides (2011)
	Cognitive Feedback (CF)	Self-developed
Mobile Device Features	Perceived Ubiquity Value (PUV)	Self-developed
	User Interface (UI)	Liu, Chen, et al. (2010), Lee et al. (2015)

that in a high school context, personal innovativeness is not an important factor in mobile learning acceptance, since young students are already users of mobile technologies and most of them are willing to use them in their learning. Content was found to significantly relate to Perceived Usefulness (0.296), which is in line with (Terzis & Economides, 2011). With a carefully designed content, mobile-based assessment can be more useful and more likely to be used. Mobile Self-Efficacy was found to significantly relate to Perceived Ease of Use with a path coefficient of 0.478, the second largest one in the current model. Previous research has shown that computer self-efficacy plays a significant role in the adoption computer-based testing (Lu et al., 2016; Terzis & Economides, 2011).

User Interface was found to significantly relate to Perceived Ease of Use with a path coefficient of 0.307. User interface has already been recognized as an important factor that affects usefulness in e-learning acceptance (Liu, Chen et al., 2010) and mobile learning acceptance (Joo et al., 2014). When the user interface is easy to use or students' perceptions about their ability to use the mobile devices are high, students are more likely to use MBA.

A significant relationship exists between Perceived Trust and Perceived Usefulness (0.304), which is in agreement with previous research, for the role of trust in on-line exams (Chang et al., 2011). If examinees trust the examination system, their acceptance to participate in exams will be higher. Mobile Device Anxiety has a negative effect on Perceived Ease of Use (−0.218) which is in agreement with previous research (Mac Callum et al., 2014) in the context of mobile learning. The reason behind that is that students with high anxiety level about the use of mobile devices would be less likely to use mobile-based assessment. The current study introduces cognitive feedback as a new construct in the technology acceptance model. Cognitive Feedback has a positive effect on Perceived Usefulness (0.176). When students receive immediate feedback with knowledge of correct response they perceive assessment to be more useful. Also, to the best of our knowledge, the current model introduces the construct of Perceived Ubiquity Value in the context of mobile learning acceptance. Perceived Ubiquity Value has a positive effect on perceived usefulness and it is a rather highly influential factor towards acceptance (0.499), the largest one in our model. Students consider mobile devices very useful due to their embedded ubiquity characteristics offering learning and assessment services anytime and anywhere. Perceived usefulness is also highly influenced by perceived ubiquity value in the context of mobile cloud storage services as well (Arpaci, 2016).

The values of R^2 for the four endogenous variables of our model are: i) for Perceived Usefulness 0.814, ii) for Perceived Ease of Use 0.628 and iii) for Behavioral Intention to Use 0.468. According to the model, Perceived Ease of Use, Cognitive Feedback, Social Influence, Content, Perceived Ubiquity Value and Perceived Trust explain about 81% of the total variance in Perceived Usefulness. Also, User Interface, Facilitating Conditions, Personal Innovativeness, Mobile Device Anxiety and Mobile Self Efficacy explain about 63% of the total variance in Perceived Ease of Use. Finally, in MBAAM, Perceived Ease of Use and Perceived Usefulness explain about 47% of the total variance in Behavioral Intention to Use. This value belongs in a rather usual range in TAM research. It is higher than the variance found in the original TAM (Davis et al., 1989), TAM2 (Venkatesh & Davis, 2000) and in a review of one hundred and one TAM studies (Lee, Kozar, & Larsen, 2003) that explained 36%–40% of the variance in behavior intention. However, it is lower than the variance found in a research by Wang et al. (2009), that explain 58% of the variance in behavior intention to use mobile learning.

The current study, being in-line with previous research, confirms that the Technology Acceptance Model is valid in the context of mobile-based assessment as well. The results of the study suggest that social influence, facilitating conditions, mobile device anxiety, personal innovativeness, mobile-self-efficacy, perceived trust, content, user interface, cognitive feedback and perceived ubiquity value influence the adoption of mobile-based assessment.

6. Discussion and conclusions

The purpose of this study is to identify factors that affect secondary students' acceptance of mobile-based assessment. The study found that students' behavioral intention to adopt mobile-based assessment depends on a combination of environmental, educational, user profile and mobile device factors. The study proposes the Mobile-Based Assessment Acceptance

Table 4
Descriptive statistics and results for convergent validity for the measurement model (acceptable threshold values in brackets).

Construct Items	Mean (SD)	Factor Loading (>0.70)	Cronbach's a (>0.70)	Composite Reliability (>0.70)	Average Variance Extracted (>0.50)
Perceived Ease of Use	3.87 (0.97)		0.746	0.854	0.661
PEOU1		0.845			
PEOU2		0.849			
PEOU3		0.741			
Perceived Usefulness	5.22 (1.02)		0.789	0.875	0.701
PU1		0.840			
PU2		0.842			
PU3		0.831			
Social Influence	5.21 (0.98)		0.8837	0.921	0.745
SI1		0.942			
SI2		0.940			
SI3		0.762			
SI4		0.791			
Facilitating Conditions	4.58 (0.67)		0.8337	0.890	0.749
FC1		0.887			
FC2		0.853			
FC3		0.857			
FC4		0.850			
Perceived Trust	5.18 (0.89)		0.847	0.891	0.621
PT1		0.838			
PT2		0.721			
PT3		0.753			
PT4		0.852			
PT5		0.770			
Personal Innovativeness	5.12 (1.21)		0.7808	0.871	0.693
PI1		0.806			
PI2		0.875			
PI3		0.815			
Mobile Self-Efficacy	4.77 (0.93)		0.820	0.881	0.649
MSE1		0.749			
MSE2		0.816			
MSE3		0.842			
MSE4		0.813			
Mobile Device Anxiety	5.00 (1.22)		0.806	0.873	0.633
A1		0.707			
A2		0.793			
A3		0.837			
A4		0.838			
Perceived Ubiquity Value	4.60 (0.76)		0.799	0.881	0.712
PUV1		0.885			
PUV2		0.825			
PUV3		0.820			
PUV4		0.822			
Content	4.36 (0.45)		0.780	0.871	0.698
C1		0.811			
C2		0.834			
C3		0.852			
User Interface	4.94 (1.21)		0.794	0.829	0.619
UI1		0.837			
UI2		0.751			
UI3		0.770			
Cognitive Feedback	4.66 (0.87)		0.850	0.897	0.686
CF1		0.842			
CF2		0.878			
CF3		0.766			
CF4		0.824			
Behavioural Intention to Use	4.27 (0.65)		0.779	0.822	0.607
BIU1		0.771			
BIU2		0.716			
BIU3		0.845			

Table 5
Discriminant validity for the measurement model (values in bold: the square root of the average variance extracted for each construct).

	BIU	C	CF	FC	MDA	MSE	PEOU	PI	PT	PU	PUV	SI	UI
BIU	**0.780**												
C	0.670	**0.828**											
CF	0.642	0.766	**0.832**										
FC	0.616	0.708	0.752	**0.866**									
MDA	0.644	0.740	0.741	0.658	**0.796**								
MSE	0.588	0.787	0.732	0.656	0.760	**0.806**							
PEOU	0.626	0.803	0.712	0.674	0.628	0.714	**0.813**						
PI	0.545	0.699	0.747	0.755	0.681	0.652	0.640	**0.833**					
PT	0.664	0.774	0.688	0.611	0.556	0.745	0.575	0.615	**0.788**				
PU	0.606	0.737	0.805	0.671	0.744	0.679	0.613	0.719	0.696	**0.837**			
PUV	0.657	0.823	0.552	0.718	0.695	0.715	0.797	0.800	0.708	0.756	**0.844**		
SI	0.606	0.746	0.454	0.688	0.556	0.781	0.647	0.801	0.766	0.565	0.799	**0.863**	
UI	0.640	0.794	0.708	0.680	0.739	0.713	0.702	0.729	0.474	0.698	0.782	0.561	**0.786**

PEOU - Perceived Ease of Use, PU - Perceived Usefulness, SI - Social Influence, FC - Facilitating Conditions, PT – Perceived Trust, PI - Personal Innovativeness, MSE - Mobile Self-Efficacy, MDA - Mobile Device Anxiety, PUV - Perceived Ubiquity Value, C – Content, UI - Use Interface, CF - Cognitive Feedback, BIU - Behavioural Intention to Use.

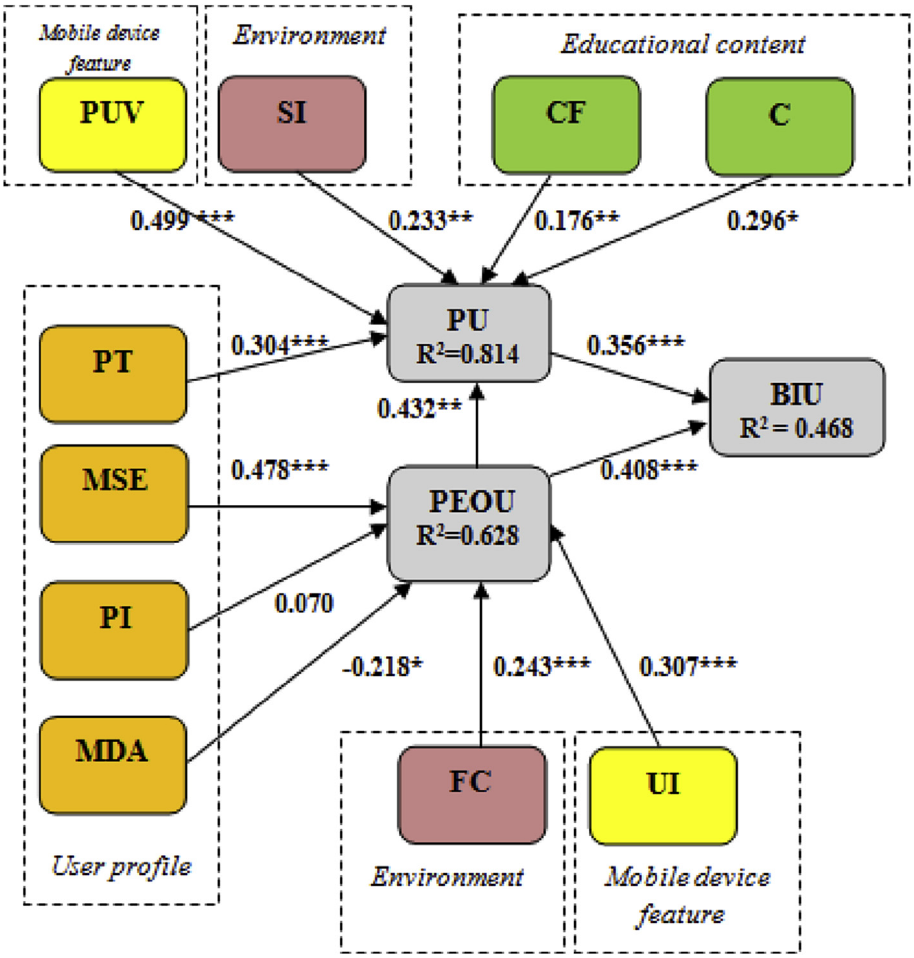

Fig. 5. SEM analysis of the research model.

Model (MBAAM). MBAAM extends TAM with a number of external variables in order to explain and predict students' acceptance of mobile-based assessment. Overall, Perceived Ease of Use and Perceived Usefulness (original TAM), Facilitating Conditions and Social Influence (environment), Mobile Device Anxiety, Personal Innovativeness, Mobile-Self-Efficacy and

Table 6
Hypothesis testing results.

Hypothesis	Path	Path Coefficient	Results
H1a	Perceived Ease of Use → Perceived Usefulness	0.432^{**}	support
H1b	Perceived Ease of Use → Behavioral Intention to Use	0.408^{***}	support
H2	Perceived Usefulness → Behavioral Intention to Use	0.356^{***}	support
H3	Social Influence → Perceived Usefulness	0.233^{**}	support
H4	Facilitated Conditions → Perceived Ease of Use	0.243^{***}	support
H5	Personal Innovativeness → Perceived Ease of Use	0.070	not support
H6	Perceived Ubiquity Value → Perceived Usefulness	0.499^{***}	support
H7	Mobile Self Efficacy → Perceived Ease of Use	0.478^{***}	support
H8	Mobile Device Anxiety → Perceived Ease of Use	-0.218^{**}	support
H9	Content → Perceived Usefulness	0.296^{*}	support
H10	User Interface → Perceived Ease of Use	0.307^{***}	support
H11	Cognitive Feedback → Perceived Usefulness	0.176^{**}	support
H12	Perceived Trust → Perceived Usefulness	0.304^{***}	support

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Perceived Trust (user profile), Content and Cognitive Feedback (Educational material), User Interface and Perceived Ubiquity Value (mobile device features) account for 47 percent of the variance in behavioral intention to use mobile-based assessment.

The findings of the study are in line with previous research about technology acceptance (Davis, 1989; Sharples, 2013; Venkatesh et al., 2003; King & Jun He, 2006; Šumak et al., 2011; Khechine et al., 2016).) and also mobile learning acceptance as well (Liu, Han et al., 2010; Park et al., 2012). The study confirms the influence of facilitating conditions and social influence on the perceived ease of use of the technology and on the perceived usefulness of the technology respectively. The study also confirms the influence of the latter constructs on intention to use MBA. Moreover, the study examines and confirms the impact of mobile device anxiety, mobile-self-efficacy and content on MBA acceptance. Only the construct of perceived innovativeness (from the mobile learning acceptance research) found not to relate significantly with intention to use mobile devices in assessment, in the high school settings.

While TAM research has already extensively studied various external factors that can influence mobile leaning adoption (such as previous experience, social influence, facilitating conditions, self-efficacy, anxiety and personal innovativeness), there are variables that have not been adequately studied so far. Perceived trust has been examined in the context of on-line exams (Chang et al., 2011) but not in the particular context of MBA. Our study demonstrates that perceived trust positively influences MBA acceptance. Research on the influence of user interface on mobile learning acceptance is rather limited (Joo et al., 2014) with no evidence to exist in the particular context of MBA. Our study considers user interface as a three dimensional construct (design, navigation and interactivity) (Lee et al., 2015; Liu, Chen, et al., 2010) and finds a positive impact on intention to use. Emotional feedback and its influence on intention to use computer-based assessment has been already investigated (Terzis et al., 2012). Our study introduces cognitive feedback confirming its positive impact on students' intention to use MBA. User perceptions about the mobility feature of mobile devices have been found to positively influence perceived usefulness (Huang et al., 2007). Our study introduces the construct of “users' perceptions about the ubiquity”, the “anywhere and anytime” distinguished feature of the mobile devices. Perceived ubiquity is introduced as a four dimensions construct: active, authentic, cooperative and personalized (Huang et al., 2011). Its role on intention to use MBA has been found to be very influential; it is the variable with the strongest impact followed by mobile-self efficacy.

The current study contributes to the mobile learning acceptance literature in the following three ways. First, it extends the current understanding of mobile learning acceptance by investigating variables, such as perceived trust, perceived ubiquity value, user interface, cognitive feedback that have not been extensively studied so far. Second, it examines mobile learning acceptance research in high schools settings, a context that has not been adequately studied (Ng & Nicholas, 2013). Higher education students are the most frequent research populations (Wu et al., 2012), followed by elementary school students (Crompton & Burke, 2015). Third, to the best of our knowledge, this study is one of the first to examine the factors influencing students' intention to use mobile-based assessment.

Mobile technologies and devices can also open new windows of opportunities when used in assessment. Mobile technologies and mobile devices in education have been used so far both as a content-delivery tool and as a tool to stimulate motivation and engagement as well (Sung et al., 2016). The NMC Horizon Report - 2016 Higher Education Edition reports that education institutions increasingly adopt Bring Your Own Device (BYOD) policies (Johnson et al., 2016). Therefore, studying MBA adoption is of great importance. MBA acceptance research cannot be placed in the same research agenda with other mobile learning activities, since previous research has raised numerous issues regarding students' perceptions about MBA (Cheon et al., 2012; Huff, 2015; Thamadharan & Maarop, 2015; Wang et al., 2009). Despite the affordances that MBA provides, student's negative perceptions and concerns about intention to use may introduce extra barriers to MBA adoption. Since there is a lack of empirical evidence about the factors that influence intention to use mobile-based assessment, the current study fills this gap in the literature by investigating these factors and proposing and verifying the Mobile-Based Assessment Acceptance Model (MBAAM).

The current study is aiming at modeling mobile-based assessment acceptance across a wide range of high-school education activities featuring formal and informal assessment that spans across multiple contexts and also cannot be easily separated from instruction (Wong & Looi, 2011). According to Shute and Rahimi (2017), “the choice and use of an assessment should depend on the educational purpose”. Therefore, the assessment format depends each time on the specific assessment used. For example, students in a classroom response system, answer multiple choice or yes/no questions, while students participating in performance assessment may use their mobiles to upload artifacts (e.g. photos) onto their portfolio. In our study, students have been involved in various mobile-based assessments (formative, summative, in-class and outside class, etc), in order to acquire an “extensive” experience in MBA. Their answers to the survey questionnaire reflect their general perceptions about mobile-based assessment across the aforementioned spectrum of educational activities. Therefore, MBAAM models the overall students' attitudes towards using mobiles for assessments, integrating this way learning and assessment goals across a variety of contexts. However the study cannot conclude on the effects of specific MBA-types and formats. This is a limitation of the study. For a detailed analysis of the acceptance of different assessment formats and types, a different research design should be implemented and this is in our future research plans. According to our preliminary findings, K-12 students prefer to answer multiple choice or Yes/No questions in their mobiles. They also like to answer questions providing photos as evidence.

Future studies also should reach more and larger audiences (not only high school students but also University students and life-long adult learners) in order to investigate MBA adoption under different contexts and for a variety of assessment types. An interesting approach could be to identify the type of students that are most likely to adopt different types of mobile assessments and under which conditions. Also, the validity and reliability of the constructs of Cognitive Feedback and Perceived Ubiquity Value may need to be studied further and confirmed from other researchers too. One of the main challenges in mobile learning is to avoid information overload and the additional cognitive load imposed on learners' working memory (Hung, Hwang, Lin, Wu, & Su, 2013). It is in our plans to investigate the influence of cognitive load on students' acceptance. Furthermore, Use Context, a construct introduced by Liu and Li (2011) describing the environment where a technology is used, will be incorporated into our mobile learning research. Another construct that could be interesting to investigate is perceived learning performance (MacGeorge et al., 2008) (vs. actual performance) and its relation to Behavioral Intention to Use. Furthermore, it is in our research plans to investigate MBA adoption form the teachers' perspective, since teachers' intention to use MBA constitute a critical factor towards its widespread adoption.

The current study triggers a discussion about the acceptance of mobile-based assessment. Assessment has a key role in learning due to its close relation to instruction and learning outcomes (Goodrum, Hackling, & Rennie, 2001). Studies have shown that students' perceptions -and intention to use-about assessment can affect their learning approach which in turn affects the extent to which students are successful in their classrooms (Dhindsa et al., 2007). These concerns should not be ignored when trying to implement mobile-based assessment.

Based on the empirical evidence the current study provides, educational practitioners can develop more acceptable, motivational and successful mobile-based assessments by taking into consideration the factors that influence students' intention to use. Higher levels of intention to use learning technologies can lead to better learning outcomes (Park, Ko, & Kim, 2007; Shin & Kang, 2015). An educational system that appropriately supports students' needs, it is not only easier adopted but it can ultimately improve students' learning (Hwang, Sung, Hung, & Huang, 2013). Our study provides a better understanding towards developing mobile-based assessments that support learners, enhance learning experience and promote learning. Moreover, it raises the overall level of awareness about mobile-based assessment towards the establishment of a new agenda for assessment research.

APPPENDIX

Table 7
Questionnaire Items used.

Constructs	Items	Descriptions	Sources
Behavioural Intention to Use	BIU1	I indent to use MBA in the future.	Davis (1989)
	BIU2	I plan to use MBA in the future.	
	BIU3	I predict I would use MBA in the future.	
Social Influence	SI1	People who influence my behaviour think that I should use MBA.	Venkatesh et al. (2003)
	SI2	People who are important to me think that I should use MBA.	
	SI3	My teacher has been helpful in the use of MBA.	
	SI4	In general my educational institution has supported the use of MBA.	
Facilitating Conditions	FC1	I have the resources necessary to use MBA.	Venkatesh et al. (2003)
	FC2	I have the knowledge necessary to use MBA.	
	FC3	MBA is not compatible with other systems I use.	
	FC4	Someone is available for assistance with system difficulties.	
Perceived Ease of Use	PEOU1	My interaction with MBA is clear and understandable.	Davis (1989)
	PEOU2	It is easy for me to become skilful at using MBA.	
	PEOU3	I find the system easy to use	
Perceived Usefulness	PU1	Using MBA enhances my effectiveness.	Davis (1989)
	PU2	MBA is useful for my study.	
	PU3	Using MBA increases my productivity.	
	PI1	I like to experiment with new information technology	

Table 7 (*continued*)

Constructs	Items	Descriptions	Sources
Personal Innovativeness	PI2	If I heard about a new information technology, I would look for ways to experiment with it.	Agarwal and Prasad (1998), Liu, Li et al. (2010)
	PI3	Among my peers, I am usually the first to try out new information technology.	
Mobile Self-Efficacy	MSE1	I could complete a job or task using a mobile-device	Compeau and Higgins (1995)
	MSE2	I could complete a job or task using a mobile device if someone showed how to do it first.	
	MSE3	I was fully able to use a mobile device before I began using MBA.	
	MSE4	I can navigate easily through the Web using a mobile device to find any information I need.	
Mobile Device Anxiety	MDA1	I feel apprehensive about using the system.	Venkatesh et al. (2003)
	MDA2	It scares me to think that I could lose a lot of information using the system by hitting the wrong key.	
	MDA3	I hesitate to use the system for fear of making mistakes I cannot correct.	
	MDA4	The system is somewhat intimidating to me.	
Perceived Trust	PT1	I think that MBA is reliable in identifying examinees' identities.	Liu et al. (2015)
	PT2	I feel that the strategies used to prevent cheating behaviours in MBA are trustworthy.	
	PT3	I think that evaluations of my learning outcomes through MBA are fair.	
	PT4	I feel that the information security of online exam is creditable.	
	PT5	Overall, I think that MBA is trustworthy to me.	
Perceived Ubiquity Value	PUV1	I can interact with the environment during the MBA	Self-developed
	PUV2	I like to participate in MBA during real world tasks in authentic environments.	
	PUV3	I like to share experiences and knowledge with my peers during the MBA.	
	PUV4	MBA can provide personalized and adaptive information.	
Cognitive Feedback	CF1	Feedback was clear and understandable.	Self-developed
	CF2	Feedback was relevant to the procedure.	
	CF3	Feedback enhanced my learning by immediately providing me the correct answer.	
	CF4	Feedback made me to be more engaged.	
User Interface	UI1	The screen design of the MBA is comfortable to read.	Based on Liu, Chen, et al. (2010) and Lee et al. (2015)
	UI2	Navigation through the MBA questions is easy.	
	UI3	I like the interactivity the MBA provides me.	
Content	C1	MBA's questions were clear and understandable.	Terzis and Economides (2011)
	C2	MBA's questions were relative with the course's syllabus.	
	C3	MBA's questions were useful for my course.	

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