Computers in Human Behavior xxx (2017) xxx-xxx

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com

ELSEVIER

Full length article

Fuzzy set analysis as a means to understand users of 21st-century learning systems: The case of mobile learning and reflections on learning analytics research

Ilias O. Pappas[a, *], Michail N. Giannakos[a], Demetrios G. Sampson[b, c]

[a] Department of Computer Science, Norwegian University of Science and Technology (NTNU), Sem Sælands vei 7-9, 7491, Trondheim, Norway
[b] School of Education, Curtin University, Australia
[c] Department of Digital Systems, University of Piraeus, Greece

ARTICLE INFO

Article history:
Received 10 February 2017
Received in revised form 1 August 2017
Accepted 9 October 2017
Available online xxx

Keywords:
Mobile learning
Learning systems
Adoption
Fuzzy-set qualitative comparative analysis (fsQCA)
Configuration

ABSTRACT

Mobile technologies and their applications have the potential to benefit various learning contexts. Users' perceptions of mobile learning (m-learning) technologies are of great importance and precede the successful integration of these technologies in education. M-learning adoption has been investigated in the literature with reference to various factors and learning analytics, but largely without considering the role of different configurations (i.e., specific combinations of variables), and how these configurations might affect the adoption of various user groups. For instance, users with different backgrounds, experiences, learning styles, and so on might not be represented by the one-model-fits-all produced from the common regression approaches. In this study, we briefly review factors that have been proven important in the context of mobile learning adoption, and build on complexity theory and configuration theory in order to explore the causal patterns of factors that stimulate the use of mobile learning. To test its propositions, the study employs fuzzy-set qualitative comparative analysis (fsQCA) on a data sample from 180 experienced m-learning users. Findings indicate eight configurations of cognitive and affective characteristics, and social and individual factors, that explain m-learning adoption. This research study contributes to the literature by (1) offering new insights on how predictors of m-learning adoption interrelate; (2) extending existing knowledge on how cognitive and affective characteristics, and social and individual factors, combine to lead to high m-learning adoption; and (3) presenting a step-by-step methodological approach for how to apply fsQCA in the area of learning systems and learning analytics.

1. Introduction

Mobile applications are increasingly used nowadays to assist many and diverse scenarios (e.g., museums, formal and informal learning, outdoor activities). Those in the younger generations are familiar with the various forms and affordances of mobile technologies and their applications. They spend their leisure time playing games, taking pictures, surfing the Web, and listening to music. Many studies have shown the potential of mobile technologies and their applications to increase learning opportunities (Asif & Krogstie, 2011). Mobile technology affordances such as portability, locality, advanced augmentation, and geocaching, to mention a few (Mora, Boron, & Divitini, 2012; Niforatos, Karapanos, & Sioutas, 2012) render mobile technology suitable to support both formal and informal learning; for instance, bring your own device (BYOD) learning practices, bird-watching, plant-hunting, and museum-guiding are some of the most successful case studies (Huang, Lin, & Cheng, 2010; Wang, 2015).

Mobile technologies and their application in learning have been extensively used during the last few years, under the term mobile learning (m-learning) (Wu et al., 2012). In this paper we use the following definition of m-learning: "learning across multiple contexts, through social and content interactions, using personal electronic devices" (Crompton, 2013). As with any other educational medium, m-learning's effectiveness and users' perceptions of the medium significantly affect learning success. As the introduction of learning tools is often complex, users do not always use them as expected. For instance, students' perceptions regarding the importance of and interest in the medium are some of the most widespread barriers for effective adoption (e.g., Hsu & Lin, 2008). In addition, students' perceptions have an impact on what they have already learned and what they choose to do next (Metcalfe & Finn, 2008). Especially for mobile devices, due to their various affordances and applications, users' perceptions and adoption are among the most important aspects.

Users' perceptions and adoption have been investigated in the literature considering various factors and learning analytics, but mainly without considering the role of different configurations, and how these configurations might result in different adoption models (Liu, Li, & Carlsson, 2010). A configuration is a specific combination of causal variables that explains an outcome (Rihoux & Ragin, 2009).

* Corresponding author.
Email addresses: ilpappas@ntnu.no (I.O. Pappas); michailg@ntnu.no (M.N. Giannakos); demetrios.sampson@curtin.edu.au (D.G. Sampson)

https://doi.org/10.1016/j.chb.2017.10.010
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For instance, users with different backgrounds, experiences, learning styles, and so on might not be represented by the one-model-fits-all produced from the common regression approaches. The majority of studies in the area employ variance-based approaches (e.g., multiple regression analysis [MRA] or analysis of variances [ANOVA]) and examine net effects among variables, which offer one single solution to explain the outcome. However, focusing on net effects may be misleading because, in the real world, the opposite relation is likely to exist between the same variables in the sample (Woodside, 2014). To this end, different configurations of the examined variables may lead to the same outcome depending on how they combine with each other. Such configurations lead to multiple solutions, which in total represent a larger part of the sample, and are likely to explain a larger amount of the outcome (i.e., parts of the sample that otherwise are considered as outliers).

In this study, we briefly review factors that have been proven important in the context of m-learning adoption, and build on complexity theory and configuration theory in order to explore the causal patterns of factors that stimulate the use of m-learning. Inherent in these theories is the principle of equifinality, suggesting that multiple complex configurations of the same conditions may explain the same outcome (Fiss, 2007; Woodside, 2014), and also the principle of causal asymmetry, suggesting that the causes explaining the presence of an outcome are likely to be different from those explaining the absence of the same outcome (Meyer, Tsui, & Hinings, 1993; Ragin, 2008). In particular, this study attempts to *elucidate how cognitive and affective characteristics, together with social and individual factors, combine to lead to increased m-learning adoption*. Instead of focusing on the main effects between users' intentions and their antecedents, the goal of this study is to detect specific configurations that explain users' intentions to use m-learning. Thus, the study addresses the following research question:

RQ: What configurations of cognitive and affective characteristics, together with social and individual factors, lead to high m-learning adoption?

Identifying these configurations will help higher education institutes to create and design innovative user-centered m-learning applications and platforms, taking into consideration patterns of factors and users' needs that explain m-learning adoption among different user groups. To address the research question, we employ fuzzy-set qualitative comparative analysis (fsQCA) (Ragin, 2008), and connect configurational analysis with complexity theory in the field of m-learning, because when fsQCA is applied together with complexity theory, researchers are able to gain a better and deeper insight into their data (Fiss, 2007; Ordanini, Parasuraman, & Rubera, 2014; Woodside, 2014). Complexity theory and fsQCA are appropriate for explaining the complex interrelations existing among variables (e.g., learning analytics), since the way they combine and their interdependencies are the ones leading to the desired outcome (Fiss, 2007; Woodside, 2014; Wu, Yeh, & Woodside, 2014). As fsQCA is becoming more and more popular, to reveal its full potential further research is needed in multiple fields (El Sawy, Malhotra, Park, & Pavlou, 2010; Fiss, 2011; Woodside, 2014). Thus, we expand on the contributions of other studies from different areas, such as education (Pappas, Giannakos, Jaccheri, & Sampson, 2017; Plewa, Ho, Conduit, & Karpen, 2016), information systems (Liu, Mezei, Kostakos, & Li, 2017), e-business (Pappas, Kourouthanassis, Giannakos, & Chrissikopoulos, 2016), consumer psychology (Schmitt, Grawe, & Woodside, 2017), as well as recent promising seminal work on learning analytics (Pappas, Giannakos, & Sampson, 2016; Sergis, Sampson, & Giannakos, 2017).

The remainder of the paper is organized as follows. Section 2 presents the theoretical background and related work in the area of m-learning. Section 3 proposes the conceptual model and develops the propositions of this study. Section 4 describes the research methodology. Section 5 presents the empirical results derived, and the final section discusses the findings and conclusions, highlighting theoretical and practical implications.

2. Theoretical background and related work

The rapid technological advancement of mobile technologies is changing the landscape of how m-learning can support education (Park, Nam, & Cha, 2012). M-learning, a relatively new way of learning, occurred from the advancement of mobile, wireless, and ubiquitous technologies (Chao & Chen, 2009) and has enhanced various environments (e.g., education, business, and gaming) (Pereira & Rodrigues, 2013). M-learning is constantly evolving and helps the advancement of traditional education, since it can be offered as an alternative or complementary way to support the learning process. Further, it may be offered to students beyond the classroom, regardless of place and time, and it may easily be designed to have the user at its core. The majority of e-learning systems support mobile devices, however they are not able to fully utilize m-learning affordances, thus there is a critical need for further research in the area towards the creation of more interactive and dynamic m-learning content and systems (Pereira & Rodrigues, 2013).

Research has examined m-learning through various theoretical lenses, such as activity-based approaches, authentic learning, action learning, and experiential learning (Sharples, Taylor, & Vavoula, 2010, pp. 87–99). Independently from the selected pedagogy and approach, m-learning adoption influences heavily the learning success and user experience (Huang et al., 2010; Liu et al., 2010). During the last few years, there has been a growing body of research studies focusing on m-learning adoption. For instance, Park et al. (2012) examined the factors that influence Korean students' intention to adopt m-learning. Korean students' m-learning adoption is determined by several factors, such as its perceived usefulness, system accessibility, subjective norms, and attitude to m-learning. Liu et al. (2010) identified that Chinese students' m-learning adoption is influenced by personal innovativeness and the long- and short-term usefulness of the tool. M-learning adoption has been investigated in the literature considering factors such as perceived usefulness, perceived ease of use, system innovativeness and accessibility, subjective norms, and attitude, to mention the most common ones (Mohammadi, 2015; Yeap, Ramayah, & Soto-Acosta, 2016), but there is no research on how different configurations might result in different adoption models and relationships.

In this study, we identify critical factors from major theories of technology acceptance research and related work in m-learning, discuss their limitations, and build on complexity theory and configuration theory to explore how and what configurations of factors lead to m-learning adoption. Last but not least, we present a step-by-step methodological approach for how to apply fsQCA in the area of learning analytics, in order to leverage the capacities of contemporary learning systems and maximize their innovation potential.

2.1. Current technology acceptance research

2.1.1. Theoretical background

Various theories have been used to explain adoption and acceptance in many fields, with the most popular ones being the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1977), the Theory of

Planned Behavior (TPB) (Ajzen, 1991), Social Cognitive Theory (SCT) (Bandura, 1986), the Theory of Acceptance Model (TAM) (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003). UTAUT is the evolution of TAM-related theories and has been the most widely used in the area; this is due to its high explanatory power, since it explains users' intention to adopt technological solutions by between 40% and 70%. Especially for technology acceptance in education, the aforementioned theories are appropriate to decide what technology will be used for learning purposes and how (Teo, 2011).

Research studies have consistently proven a significant and positive relationship between beliefs and behaviors (Chang & Chang, 2009; Davis, 1989). In particular, TAM and other TAM-based theories (e.g., UTAUT) have successfully explained several issues related to the adoption of technology; the main concepts of these theories were perceived usefulness and perceived ease of use (Davis, 1989). Perceived usefulness is defined as the degree to which users believe that using m-learning will enhance their learning performance. Perceived ease of use is defined as the degree to which users believe that using m-learning will be free of effort. Both constructs have been successfully used in multiple contexts to explain user behavior and adoption (e.g., Venkatesh, Thong, & Xu, 2012). Similarly, in learning environments TAM-related theories have been applied to investigate users' intention to use e- and m-learning technologies (e.g., Park et al., 2012), and have been directly or indirectly related to various constructs such as attitude, subjective norm, self-efficacy, and system characteristics, to mention a few, reflected from various user-generated data and learning analytics (Mohammadi, 2015; Yeap et al., 2016).

TRA, and its more comprehensive version TPB, explain how individuals behave based on their pre-existing attitudes and behavioral intentions, and are among the most influential theories on human behavior (Ajzen, 1991; Fishbein & Ajzen, 1977). In this study we examine attitude and subjective norms, which are the main antecedents of behavioral intentions based on TRA/TPB and have been found to be very important in the context of m-learning (Park et al., 2012; Wang, Wu, & Wang, 2009). Attitude refers to users' positive or negative feelings towards adopting m-learning, and subjective norms describe individuals' belief that people important to them should adopt m-learning. TRA/TPB have been proven to explain a significant amount of user behavior in learning contexts (Giesbers, Rienties, Tempelaar, & Gijselaers, 2013; Shin & Kang, 2015).

SCT explains how individuals may form and maintain behavioral patterns, emphasizing cognitive, socio-environmental, and behavioral factors (Bandura, 1986). SCT incorporates the factor of self-efficacy, which is defined as the individual's beliefs about their own abilities to mobilize the motivation, cognitive resources, and courses of action needed to successfully use m-learning. Self-efficacy has been recognized as one of the most important factors, as high self-efficacy levels with respect to information technology lead to greater adoption levels (Compeau & Higgins, 1995). Self-efficacy is considered a critical factor regarding the adoption of m-learning (Park et al., 2012), and has been related to perceived usefulness and perceived ease of use, interaction with the system, and engagement (Shin & Kang, 2015).

2.1.2. Related work in m-learning

M-learning ranges from simple applications to support traditional teaching to more sophisticated systems and even eco-systems, developed specifically for the m-learning educational modality and affordances (Yeap et al., 2016). There are various possible applications of mobile technologies for both the formal and informal learning contexts. Some benefits of m-learning include the following (Milošević, Živković, Manasijević, & Nikolić, 2015):

- *Mobility and convenience* – mobile devices are light enough to be carried around and allow students to learn anywhere anytime (e.g., take notes, photos, recordings in class).
- *Interactivity* – via fast interaction between students and their lecturers/instructors (e.g., slido.com).
- *Collaboration* – among students in an ease and accessible manner (e.g., via chat as you go).
- *Environmental friendly* – with the reduction of printing materials.
- *Fun and engaging* – since the new generation of students "loves" using mobile devices.
- *Flexibility* – since students can study anytime and anywhere they like.
- *Accessibility* – by assisting students with disabilities as well as extending learning opportunities to a wider range of people in society (e.g., duolingo).

In contrast, the relatively small screen size, internet connection, and battery limitations have been identified as the main disadvantages (Ibrahim, Salisu, Popoola, & Ibrahim, 2014).

There is a long list of m-learning advantages (Milošević et al., 2015), mainly relying on the affordances of mobile technologies; some of the most significant motivators of m-learning adoption, among others, are perceived near- and long-term usefulness (Liu et al., 2010). Even if perceived near-term usefulness is a significant predictor of intention to use, more than 50% of perceived near-term usefulness can still be interpreted by the perceived long-term usefulness. In other words, students' perception of near-term usefulness is mainly derived from a positive feeling of long-term usefulness (Liu et al., 2010).

Students' attitude is another important element heavily influencing m-learning adoption (Yeap et al., 2016). Furthermore, perceived usefulness and perceived ease of use significantly affect attitude, with the effect of perceived usefulness being stronger than that of perceived ease of use (Huang, Lin, & Chuang, 2007; Tan, Ooi, Leong, & Lin, 2014). Thus, users' perception of usefulness is more important than their perception of ease of use in influencing their attitude and ultimately m-learning adoption. However, ease of use also affects usefulness (Shin & Kang, 2015), hence ease of use encourages an individual to regard m-learning as a useful technology in multiple ways. M-learning adoption has been found (Huang et al., 2007; Tan et al., 2014) to be primarily affected by usefulness and attitude, which implies that both usefulness and attitude are critical factors. Therefore, the results indicate that attitude, usefulness, and ease of use are very important factors, with attitude being also an important mediator between beliefs and user adoption.

Mobile devices and applications are associated with fun and engaging activities, and affective perceptions such as playfulness and enjoyment (Wang et al., 2009) are predictors of m-learning adoption. Also, m-learning could be used to increase social influence among students, as it may be used to share assignments and improve collaboration in the classroom (Liu et al., 2010). Social factors, such as social influence and subjective norms, are important antecedents of user behavior and adoption (Venkatesh et al., 2012), and are expected to influence intention to use m-learning (Tan, Ooi, Sim, & Phusavat, 2012; Wang et al., 2009), although this is not always the case (Tan et al., 2014). Thus, m-learning which supports enjoyable experiences is likely to result in overall positive attitudes towards m-learning and ultimately high m-learning adoption (Conci, Pianesi, & Zancanaro, 2009, pp. 63–76).

2.2. Limitations of the technology acceptance research

Theories on technology acceptance have been well established in the literature, with numerous studies, as discussed above, offering wide empirical support of their importance. However, various limitations of the technology adoption and acceptance theories have been discussed in the past decade in information systems (Benbasat & Barki, 2007) and educational contexts (Nistor, 2014), highlighting the need to move beyond traditional approaches in explaining user behavior. Indeed, to acquire an adequate theoretical grounding, it is critical to focus on the antecedents of adoption and acceptance and their interrelations. The majority of acceptance studies do not adequately capture the interrelations and the dynamic interplay that are likely to occur among behavior and its antecedents (Benbasat & Barki, 2007). One model, such as TAM or TRA/TPB, is unlikely to explain behavior fully in multiple contexts or in different situations (Bagozzi, 2007). Those models and the respective computational methods (e.g., MRA, SEM) can explain approximately half of a sample's behavior and treat the other half as outliers. In today's learning systems, half of the users might represent several thousand or even millions of users (e.g., MOOCs), who simply have different needs and expectations – and cannot be explained by the one-model-fits-all type of solutions. However, 21st-century learning technologies need to design innovative systems to cover as many users as possible. Thus, there is a need to move away from narrow models offering a single solution, towards the creation of more complex and multi-stage models (Benbasat & Barki, 2007). Technology acceptance research needs to revise the complexity of acceptance constructs and take into account multiple dimensions, in order to be able to address the real-life context and solve real-life problems (Nistor, 2014). By implementing complexity theory and configurational analysis, researchers can identify multiple solutions for their models, modeling multiple realities that highlight the asymmetric relations in real-life conditions (Woodside, 2014).

Furthermore, it is critical to address the methodological limitations that exist in the technology acceptance research, because the way a phenomenon is studied is directly linked with theory and its application, and defines (or constrains) the way a researcher thinks about it (Bagozzi, 2007). The majority of technology acceptance studies have been primarily based on symmetric tests, net effects, and regression-based models, such as multiple regression analysis (MRA) and structural equation modeling (SEM). Symmetric tests build on the assumption that a change on a predictor variable will lead to the same change on the outcome variable. Such methods compute the significance between two variables in a model or compare the effects among the variables between two or more models (Woodside, 2013). Further, regression-based models build on variance theories, which indicate that a predictor variable should be both a necessary and a sufficient condition, in order to achieve a specific outcome (El Sawy et al., 2010; Liu et al., 2017). In regression analysis, adding a variable to a model to control for this variable when working with experimental data is not the same as with non-experimental data, because variables co-vary with each other (Armstrong, 2012). The latter indicates the existence of asymmetric relations between variables and the need to perform configurational analysis, as the presence or absence of one variable will influence the presence or absence of the rest (Fiss, 2007; Liu et al., 2017). In addition, regression-based models can compute the interaction effects between variables, including moderation analysis that may address the configuration of predictors; however, the relation between the factors remains to be examined as symmetric. Focusing on symmetric and net effects may be misleading, since the observed net effects do not apply to all the cases in a dataset, and most relationships in real life are not symmetric (Pappas, Kourouthanassis, et al., 2016; Ragin, 2008; Woodside, 2014).

To overcome the limitations of the technology acceptance research, we propose the use of configurational analysis, which may offer deeper insight into the data, by identifying complex relations within a sample and explaining a larger part of it, and thus urge researchers into revisiting their acceptance and adoption models. Nonetheless, it should be noted that the aim of this paper is to highlight both the importance and the advantages of configurational analysis, as it may supplement and extend research on technology acceptance that focuses on regression-based models and symmetric relations.

2.3. Complexity theory and configurational analysis

Complexity, inherent in many phenomena in the world, examines how emergent and dynamic systems and processes interact in order to influence an outcome (Urry, 2005). “Complexity theory is destined to be the dominant scientific trend of the 1990's … This revolutionary technique can explain any kind of complex system – multinational corporations, or mass extinctions, or ecosystems such as rainforests, or human consciousness” (Lewin, 1999). To capture and explain complex phenomena, existing approaches of variance-based theories are not enough. The solution is to examine such phenomena as clusters of interrelated conditions (or elements) towards a holistic and simultaneous understanding of the patterns they create, by taking a configuration theory approach (El Sawy et al., 2010). “Relationships between variables can be non-linear with abrupt switches occurring, so the same ‘cause’ can, in specific circumstances produce different effects” (Urry, 2005). Complexity theory and configuration theory are both based on the core principle of equifinality (Fiss, 2007; Von Bertalanffy, 1968; Woodside, 2014), which states that more than one complex configuration (combination) of antecedent conditions may lead to the same outcome. In a complex system, such as that of m-learning adoption, relationships among factors are complex and, depending on how they combine, both high and low conditions of a certain factor may predict high scores for the outcome. These conditions may be combined in sufficient configurations to explain the focal outcome (Fiss, 2011; Woodside, 2014). Configuration theory is also based on the principle of causal asymmetry, which states that a cause that leads to the presence of an outcome may be different from the cause that leads to the absence of the same outcome (Fiss, 2011; Ragin, 2008). In other words, the presence of a learning analytic factor may lead to a certain outcome, but the absence of the same factor may not lead to the absence of that outcome.

In general, a variable can have an asymmetric relationship with the expected outcome; a variable may be insufficient for the outcome to occur, although it can serve as a necessary condition for the outcome (Fiss, 2007, 2011; Woodside, 2013), making it indispensable to the outcome. Such conditions may be of high interest in multiple situations, for both positive and negative outcomes. In detail, one may identify a condition as indispensable for high behavioral intentions, or a condition that is indispensable for low behavioral intentions, indicating where to focus in order to achieve or avoid the outcome. Relationships between two variables (e.g., A, B) are complex, and the presence of one (i.e., A) may lead to the presence of the other (i.e., B), suggesting sufficiency. However, at the same time, variable B may be present even when variable A is absent, suggesting that the presence of A is a sufficient but unnecessary condition for variable B to occur. Sufficiency and necessity describe subset relationships among variables (Glaesser & Cooper, 2012). Similarly, especially when additional variables exist, variable A may be necessary but insufficient for B to occur. Finally, a variable (e.g., A) may lead to a desired outcome (e.g., B) only when a third variable (e.g., C) is present or absent (El Sawy et al., 2010; Fiss, 2007). Thus, various combinations may exist that are able to lead to the desired outcome. These combinations are defined as configurations.

A configuration is a specific set of causal variables, the synergetic nature among which may lead to an outcome of interest. To identify such configurations, qualitative comparative analysis (QCA) may be employed (Rihoux & Ragin, 2009). QCA has three main variations (Rihoux & Ragin, 2009): crisp set QCA (csQCA), multi-value QCA (mvQCA), and fuzzy-set QCA (fsQCA). FsQCA is able to overcome some of the limitations of csQCA and mvQCA, and has received increased attention recently because, when it is applied together with complexity theory, researchers have the opportunity to gain deeper and richer perspectives on different data and analytics (Ordanini et al., 2014; Pappas, Giannakos, et al., 2016; Pappas, Kourouthanassis, et al., 2016; Woodside, 2014).

FsQCA, and the respective software application, was developed through the integration of fuzzy sets and fuzzy logic principles with QCA (Ragin, 2000; Rihoux & Ragin, 2009), and has been recently applied in various fields, including education and learning analytics (e.g., Pappas, Giannakos, et al., 2016; Plewa et al., 2016; Sergis et al., 2017). FsQCA is appropriate for different sample sizes, from very small to very big, as it is only a matter of time to wait until the software completes the analysis, and for different types of variables, as long as the researcher is able to transform them into fuzzy sets. Details on how to perform fsQCA are presented in the research methodology section of this paper. By using fsQCA researchers go beyond MRA, since they are able to identify multiple pathways that explain the same outcome. These pathways or combinations of independent variables also include variables that are not identified by MRA, because they influence the outcome only for a small number of cases (Woodside, 2014). The identified combinations lead to multiple solutions offered by fsQCA, and include both necessary and sufficient conditions. Such conditions may be present or absent in a solution, or they may be in a "do not care" situation. The "do not care" situation indicates that the outcome may either be present or absent and it does not play a role in a specific configuration. Necessary and sufficient conditions may be present (or absent) as core and peripheral elements. Core elements indicate a strong causal relationship with the outcome, and peripheral elements indicate a weaker relationship (Fiss, 2011). Thus, with fsQCA researchers may identify what variables are indispensable or not needed for an outcome, and what combinations of variables are more or less important than others.

2.3.1. Relevance to education and learning

QCA has recently been applied in social sciences (Schneider & Wagemann, 2012), including education and learning (Glaesser & Cooper, 2012; Mavroudi, Hadzilacos, Kalles, & Gregoriades, 2015). Although fsQCA is able to address various limitations of the other QCA variations (Liu et al., 2017), recent studies in the context of education have not chosen to employ it (Mavroudi et al., 2015). However, fsQCA and configurational analysis have been applied primarily in the last decade in organizational research, and lately in the area of information systems and business management, in order to examine user behavior (Liu et al., 2017; Pappas, Kourouthanassis, et al., 2016; Ragin, 2008; Woodside, 2014). It is thus evident that configurational analysis may offer valuable insights in the context of education and learning analytics (Pappas, Giannakos, et al., 2017; Sergis et al., 2017). Nonetheless, not many studies have employed fsQCA in education and learning analytics, indicating that many researchers are still unfamiliar with this method and its potential in understanding users of contemporary learning systems via the generated learning analytics.

This study aims to increase awareness and present the basic steps for employing fsQCA in the context of education and learning. Further, this paper presents a comparison of configurational analysis with traditional regression-based models and offers theoretical support for extending the use of fsQCA from organizational research, information systems, and management to learning systems and the learning analytics produced. Similarly, it is important to extend the present application of QCA to educational research by employing fsQCA in this area. To this end, this study contributes to the literature by applying fsQCA to educational research, and chooses mobile learning as its application context.

2.3.2. Benefits and limitations of configurational analysis

The majority of previous studies in learning analytics (and even in the wider area of education and learning) research focus on regression-based methods (e.g., linear regression, SEM) in order to examine and predict learner behavior and the learning outcome (e.g., Baker & Inventado, 2014; Elbadrawy, Studham, & Karypis, 2015). These methods are not able to identify the variables that may influence the outcome in a small subset of cases; however, they may be complemented and extended by applying configurational analysis. The benefits of configurational analysis and fsQCA mainly occur from the limitations of regression-based methods (El Sawy et al., 2010; Liu et al., 2017; Pappas, Kourouthanassis, et al., 2016; Woodside, 2013, 2014). Regression-based methods take a net effect approach in examining the effects among factors of interest, and the variables are examined in a competing environment. The covariance among the variables in a model suggests that the presence or absence of one variable influences their effect, both on the other variables and on the rest as well as on the expected outcome, adding to the importance of applying configurational analysis, which is based on this notion (Fiss, 2007).

Configurational analysis focuses on the asymmetric relations among the examined variables and the outcome of interest, which may be achieved in different ways (i.e., different combinations of variables). For instance, different learning analytics representing students' activity (e.g., material views), background knowledge (e.g., results from previous tests), attitudes (e.g., results from attitudinal surveys), and teachers' digital skills can predict the future learning outcome or mobile learning adoption only if they are examined in combination (Pappas, Mikalef, & Giannakos, 2016; Sergis et al., 2017). It is not as efficient to predict the learning outcome based only on students' activity, background knowledge, or attitudes. Finally, configurational analysis may be more robust than regression-based methods as it is not sensitive to outliers, because fsQCA divides the sample into multiple subsets, thus creating multiple combinations of configurations. Each configuration represents only a subset of the sample, hence the representativeness of the sample does not affect all configurations (Fiss, 2011; Liu et al., 2017). Thus, the outliers will not influence all solutions (i.e., configurations), but only specific ones.

However, configurational analysis has some limitations, to be taken into account when employing fsQCA (Liu et al., 2017; Pappas, Kourouthanassis, et al., 2016; Woodside, 2014). Specifically, substantial knowledge of the examined variables, the outcome of interest, and the underlying theory is needed, in order to transform variables into fuzzy sets (i.e., data calibration), to simplify the solutions, and to interpret the results. Nonetheless, it should be noted that this may lead to a subjective bias in the results. Furthermore, fsQCA is not able to measure the unique contribution of each variable to the solution; instead, its objective is to identify complex solutions and combinations of independent variables. Lastly, fsQCA does not account for the validity and reliability of latent variables, since it was initially designed to be used with single-item variables. Nonetheless, before applying fsQCA, the measurement model may be tested for reliability and validity through traditional SEM techniques (Liu et al., 2017; Pappas, Kourouthanassis, et al., 2016). Once reliability and validity are established, configurational analysis may be employed by transforming the variables into fuzzy sets.

3. Conceptual model and research propositions

3.1. Conceptual model

Prior research on m-learning implements symmetric tests to examine the hypotheses and calculates net effects on the desired outcomes. Such tests focus on estimating the significance of the effects between two variables that do not apply to all of the cases in the dataset, and do not account for the cases that support the existence of an asymmetric relation between the variables (Woodside, 2013, 2014). In other words, two variables may have both positive and negative relations for different parts of the same sample. For example, users of m-learning applications may have high intentions to use this medium because their friends and colleagues use it as well, regardless of how useful they find it. Similarly, intention to use m-learning will be higher for those who like such technologies and enjoy implementing them in their everyday coursework. Further, it is expected that users who find m-learning useful, easy, and that it increases their performance will have a high intention to use it. Nonetheless, users may feel capable of using m-learning applications and consider it an easy task, without intending to use them. In such cases, one would expect that users need motivation to adopt m-learning, such as increased performance, or the presence of an affective or social factor. Thus, multiple complex relationships exist among variables that, depending on how they combine, may or may not explain users' high m-learning adoption. In order to conceptualize these relationships, a Venn diagram is proposed (Fig. 1) that accurately reflects them.

The Venn diagram presents five sets of constructs and their intersections. The five sets of constructs reflect the outcome of interest (dependent variable) of this study and the four sets of causal conditions predict the outcome (independent variables). In detail, the outcome of interest is users' m-learning adoption, and the four sets of causal conditions are the cognitive characteristics (i.e., perceived usefulness, perceived ease of use), affective characteristics (i.e., m-learning attitude), individual factor (i.e., perceived self-efficacy), and social factor (i.e., subjective norm). The intersections represent factor configurations, which are higher-level interactions, and show the areas in which one factor may exist together with the others. To detect such configurations of factors in a complex system such as m-learning adoption, the formulation of research hypotheses may not be enough. When employing variance-based methods, it is common to develop hypotheses which are framed as correlational expressions. However, this does not offer the holistic approach that will allow the identification of multiple configurations and solutions. Indeed, in configuration theory approaches, research propositions are developed as causal recipes to capture the different combinations among factors, and theoretically specify which should be present or absent from the causal recipe (El Sawy et al., 2010; Fiss, 2007; Ragin, 2008).

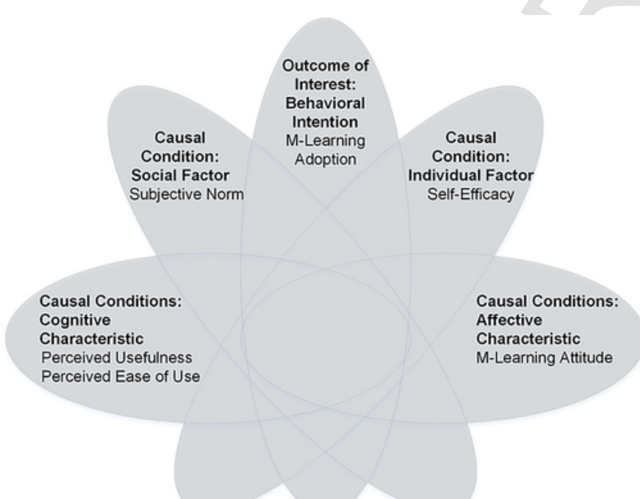

Fig. 1. Conceptual model of m-learning adoption.

3.2. Research propositions

Research in the area of m-learning has identified various factors that may influence users' behavior (Cheon, Lee, Crooks, & Song, 2012; Park et al., 2012; Tan et al., 2012, 2014). Findings from previous studies indicate different effects of cognitive and affective characteristics and social and individual factors on users' behavioral intention, and at the same time offer one single best solution that predicts the adoption of m-learning. Perceived usefulness has been identified as the main predictor of m-learning adoption (e.g., Park et al., 2012). Similarly, perceived ease of use has been mainly found to influence positively students' behavioral intentions (e.g., Park et al., 2012). These findings indicate that cognitive factors are necessary conditions in order to achieve high m-learning adoption, although the desired outcome may be reached through the existence of other factors. For example, experiencing positive affective characteristics, such as a positive attitude towards m-learning (Huang et al., 2007; Wang et al., 2009) or increased satisfaction (Pappas, Cetusic, Giannakos, & Jaccheri, 2017), will lead to increase adoption of the medium. Indeed, different combinations of variables will explain high and low m-learning adoption for students (Pappas, Cetusic, et al., 2017). Furthermore, studies have identified contradictory effects of social factors on behavioral intention (Tan et al., 2012, 2014). This suggests that the effect of subjective norms on behavior differs based on the other factors that are present and how they combine with each other. Thus, in order to better understand m-learning adoption, a configurational analysis may be more appropriate and useful than examining individual causal factors. As conceptualized in Fig. 1, this perspective leads to more complex causal patterns and higher-level interactions between the constructs.

As already discussed, complexity theory builds on the principle of equifinality, suggesting that a result may be equally explained by alternative sets of causal conditions (Fiss, 2007). These conditions may be combined in sufficient configurations to explain the outcome (Fiss, 2011; Woodside, 2014). Cognitive characteristics, affective characteristics, social factors, and individual factors are important causal conditions for understanding students' intention to adopt m-learning, and they may be combined with each other in various configurations. For example, students who perceive the use of m-learning as useful and easy are likely to adopt it (Park et al., 2012). In addition, students who enjoy using new technologies, such as m-learning, and feel capable of using them will have high intentions to adopt m-learning.

Proposition 1

No single configuration of students' cognitive characteristics, affective characteristics, social factors, and individual factors leads to high m-learning adoption; rather, there exist multiple, equally effective configurations of causal factors.

Further, configuration theory proposes the principle of causal asymmetry, which means that, for an outcome to occur, the presence and absence of a causal condition depend on how this condition combines with other conditions (Fiss, 2011; Woodside, 2014). *For example, although cognitive characteristics are likely to have a positive effect on students' behavior, students who perceive m-learning as less useful or not so easy to use will still have high intentions, depending on how the cognitive characteristics combine with affective ones, and social and individual factors. Also, students may not think that m-learning is very useful or easy to use, but may still express high intentions to use it if they like it or if their friends and colleagues use it as well, since social factors affect attitude and behavior* (Tan et al., 2012; Venkatesh et al., 2012).

Proposition 2

Single causal conditions may be present or absent within configurations for students' high m-learning adoption, depending on how they combine with other causal conditions.

Proposition 3

Configurations with the absence of at least one cognitive characteristic that lead to high m-learning adoption will also require the presence of at least affective characteristics or social factors.

4. Research method

4.1. Data collection

In this study a survey was used, which was composed of questions on demographics as well as on the identified constructs. In order to attract respondents, the questionnaire was distributed to students using mailing lists, online forums, and social media. The research instrument controls the prospective participants for their experience with m-learning, and the participants were asked to answer based on their reflection after using the medium. It was made clear that there was no reward for the respondents, that participation was voluntary, and that the study was confidential. First, a few examples of m-learning were presented, followed by questions regarding respondents' experience with m-learning. Respondents with no previous experience with m-learning were excluded from participating in the remainder of the study. In the end 243 responses were collected out of which 180 had previous experience with m-learning.

The sample of respondents consists of more females (40%) than males (60%). The vast majority of the respondents (60%) were high school graduates. In addition, about 27% were holders of a master's degree or higher, and almost 13% holders of a bachelor's degree. Further, almost 54% of the respondents were 22 years old or younger, and almost half (47%) of the sample had used m-learning over 10 times in the past six months. Table 1 presents the demographic characteristics of the sample.

4.2. Measures

The constructs used in this study were measured using scales adopted from previous studies in the area of m-learning. Table 2 presents the operational definitions of the constructs in this theoretical model as well as the studies from which the measures were adopted.

Table 1
Demographics.

	N	%
Gender		
Male	72	40
Female	108	60
Age		
18–19	42	23.3
20–21	44	24.5
22–23	20	11.1
24–25	29	16.1
25+	45	25
Education		
Secondary Education	108	60
Graduate	23	12.8
Postgraduate	49	27.2
Main method of accessing m-learning content		
Learning by downloading content	93	51.7
Real-time video lectures	46	25.6
Internal content on mobile devices	20	11.1
Streaming learning content	21	11.7
Purpose of using m-learning content		
Major courses in university	106	58.9
Language study	21	11.7
Lectures for getting certification	20	11.1
Lectures for getting a job	10	5.6
Other	20	11.1
Experience	*Median*	
Number of times (approximately) used mobile devices for learning purposes in the past six months		10

Table 2
Construct definition.

Construct	Operational Definition	Source
Perceived Usefulness	Perceived usefulness refers to the degree to which users believe that using m-learning would enhance their learning performance.	(Cheon et al., 2012; Park et al., 2012)
Perceived Ease of Use	Perceived ease of use refers to the degree to which users believe that using m-learning is free of effort.	
M-learning Attitude	Attitude refers to an enduring positive or negative feeling of users about m-learning.	
Subjective Norm	Subjective norm refers to users' perception that most people who are important to them think they should or should not use m-learning.	
Self-Efficacy	Self-efficacy refers to individuals' beliefs about their ability to mobilize motivation, cognitive resources, and courses of action needed to successfully use m-learning.	(Park et al., 2012)
M-learning Adoption	Adoption refers to users' behavioral intention to use mobile devices for learning purposes.	(Cheon et al., 2012)

A seven-point Likert scale anchored from 1 ("completely disagree") to 7 ("completely agree") was employed. Appendix 1 lists the questionnaire items used to measure each construct, along with descriptive statistics and loadings.

4.3. Data analysis

The constructs of this study were first evaluated in terms of their reliability and validity. Reliability testing, based on composite reliability and Cronbach's alpha, showed acceptable indices of internal consistency in that all constructs exceeded the cut-off threshold of 0.70. Next, establishing validity requires average variance extracted (AVE) to be greater than .50 and the correlations between the different variables in the confirmatory models not to exceed 0.8, the latter because exceeding 0.8 suggests low discrimination; in addition, the square root of each factor's AVE must be larger than its correlations with other factors (Fornell & Larcker, 1981). The AVEs for all constructs ranged between 0.55 and 0.80, all correlations were lower than 0.80, and the square root AVEs for all constructs were larger than their correlations. Table 3 displays the findings.

Further, the study tested for multicollinearity (O'Brien, 2007) along with the potential common method bias by utilizing the common latent factor technique and the CFA marker variable technique, which are better than other control procedures frequently employed in the literature (e.g., Harman's single-factor test) (MacKenzie & Podsakoff, 2012; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The variance inflation factor for each variable was below 3, indicating that multicollinearity was not an issue. The results also suggest an absence of common method bias, as the variance from the common latent factor technique and the CFA marker variable technique are 0.13 and 0.28, respectively.

4.4. FsQCA

4.4.1. Data calibration

The first step in fsQCA is to define the outcome and the independent measures. The next is to calibrate all measures into fuzzy sets with values ranging from 0 to 1 (Ragin, 2008), which shows their degree of membership in a certain group (i.e., the extent to which they are part of a certain group). Each case in the dataset has a distinct position which is determined by its fuzzy-set membership. Since all values range from 0 to 1, this means that a case with a fuzzy membership score of 1 is a full member of a corresponding fuzzy set, and a case with a membership score of 0 is a complete non-member of the set. A membership score of 0.5 is exactly in the middle, thus is both a member of the fuzzy set and a non-member, creating the intermediate set membership.

Data calibration may be either direct or indirect. In the direct method, the researcher chooses three qualitative breakpoints, which define the level of membership in the fuzzy set for each case. In the indirect method, the measurements require rescaling based on qualitative assessments. The researcher may choose either method depending on their substantive knowledge of the data and the underlying theory (Ragin, 2008; Rihoux & Ragin, 2009). The cases in the dataset should be transformed into membership scores in a careful, well-documented, and qualitatively justified manner, since variations in the calibration may lead to variations in the outcome. Studies recommend the direct method of setting three values that correspond to full-set membership, full-set non-membership, and intermediate-set membership (Ragin, 2008). Having a substantive knowledge of data and theory suggests that the researchers have sufficient knowledge and expertise of the field they are working on as well as of the type of data and the underlying theories of the examined phenomena. It is up to the researchers and their substantive knowledge to choose the three breakpoints, and there are different ways to do this.

The most straightforward way to calibrate the data is to choose as breakpoints the values of 1, 0.5, and 0. For example, in a seven-point Likert scale, the values 7, 4, and 1 would be calibrated into 1, 0.5, and 0 respectively, and the rest (6, 5, 3, 2) would follow accordingly. For seven-point Likert scales multiple studies suggest that the values of 6, 4, and 2 are used as thresholds (Ordanini et al., 2014; Pappas, Kourouthanassis, et al., 2016). In this case, the full-set membership threshold is fixed at a rating of 6; the full-set non-membership threshold is fixed at 2; and the crossover point is fixed at 4. Furthermore, the measures may be calibrated by using percentiles. Thus, the researcher may identify 80%, 50%, and 20% as the full-set membership, intermediate-set membership, and full-set non-membership, respectively. Nonetheless, since it is up to the researcher to choose the three breakpoints, these thresholds may be changed accordingly. Here, because the data are skewed to the right, data calibration is done using percentiles, as calibrating based on the survey scale might offer less meaningful results, producing only one solution with all the conditions identified as necessary (Pappas, Mikalef, Giannakos, & Pavlou, 2017; Plewa et al., 2016).

When using the fsQCA software, once the three breakpoints are decided, the values of every variable are calibrated based on the log odds of full membership, to fit into these three breakpoints. The calibration in fsQCA software is performed by using the *Calibrate* function of the software, which takes as input the variable that will be calibrated and the three breakpoints (from the highest to the lowest values). It should be noted that the researchers may use other software for the calibration part , and also it is not mandatory to calibrate all values following a logistic function; instead, other membership functions (linear or non-linear) may be used (Mendel & Korjani, 2012).

4.4.2. Identifying the configurations

Following the calibration, the researcher is ready to run the fsQCA algorithm on the menu *Analyze* and to choose *Fuzzy Truth Table Algorithm*. At this point the researcher chooses the outcome of interest (i.e., dependent variable) and all the causal conditions (i.e., independent variables). Regarding the outcome, the researcher may choose to examine the presence of the outcome, and choose *Set*, or the absence of the outcome, *Set Negated*.

Next, the fsQCA algorithm produces a truth table of 2^k rows, with k representing the number of outcome predictors and each row representing each possible combination. For example, a truth table between four variables (i.e., conditions) would provide sixteen possible logical combinations. For every combination, the minimum membership value is calculated; that is, the degree to which every case supports the specific combination. FsQCA uses the threshold of 0.5 to identify the combinations that are acceptably supported by the cases. Thus, all combinations that are not supported by at least one case with membership over the threshold of 0.5 are automatically removed from further analysis.

The final step is to sort the truth table based on frequency and consistency (Ragin, 2008). Frequency describes the number of observations for each possible combination. Consistency refers to “the degree to which cases correspond to the set-theoretic relationships expressed in a solution” (Fiss, 2011). As the truth table computes all possible combinations, it is very likely that some of the combinations

Table 3
Descriptive statistics and correlations of latent variables.

Construct	Construct								
	Mean (SD)	CR	AVE	1	2	3	4	5	6
1. Perceived Usefulness	4.37 (1.23)	.944	.739	**.860**					
2. Perceived Ease of Use	4.95 (1.16)	.892	.623	.679	**.789**				
3. M-learning Attitude	4.52 (1.34)	.943	.769	.733	.650	**.877**			
4. Subjective Norm	4.60 (1.13)	.906	.617	.628	.604	.719	**.786**		
5. Self-Efficacy	5.39 (1.23)	.949	.823	.412	.472	.429	.425	**.907**	
6. M-learning Adoption	5.06 (1.31)	.940	.798	.687	.633	.735	.715	.559	**.893**

Note: Diagonal elements (in bold) are the square roots of the AVE. Off-diagonal elements are the correlations among constructs (correlations of 0.1 or higher are significant, $p < 0.01$). For discriminant validity, diagonal elements should be larger than off-diagonal elements. Learning performance and motivation are single-item variables.

will have a frequency of zero, meaning that none of the cases in the sample is represented by these combinations. As the number of variables in the analysis is increased, the combinations increase as well, thus more combinations will have zero frequency. A frequency cut-off point needs to be set in order to ensure that a minimum number of empirical observations is obtained for the assessment of subset relationships. Increasing the frequency threshold means that each combination will refer to more cases in the sample, but it will reduce the percentage (i.e., coverage) of the sample that is explained by the solutions. On the other hand, a small frequency threshold will increase the coverage of the sample, although each combination will refer to fewer cases in the sample. For small and medium-sized samples, a cut-off point of 1 is appropriate, but for large-scale samples (e.g., 150 or more cases), the cut-off point should be set higher (Ragin, 2008), and can be set at 3. It is up the researcher to decide if an even larger cut-off point should be set for very large datasets. Thus, after removing the combinations with low frequency using the option on the *Edit* menu, the truth table should be sorted based on their “raw consistency.”

A consistency threshold should be set, with the minimum recommended value being 0.75 (Rihoux & Ragin, 2009). A good indication for choosing this threshold is to identify big changes in the consistency of each combination. For example, one combination may have a consistency of 0.841 and the next one may have 0.781. Although both values are above the recommended threshold of 0.75, this is an indication of what the consistency threshold should be. Nonetheless, it is up to the researcher to choose what the exact threshold will be. It should be noted that a low consistency threshold leads to the identification of more necessary conditions, reducing type II errors (i.e., false negatives), but increasing type I errors (i.e., false positives), and vice versa (Dul, 2016). The final step is to insert the value of 1 or 0 in the column with the outcome variable. Choosing 1 or 0 depends on the consistency threshold that has been chosen. For example, for a consistency threshold of 0.75, which is set here, all combinations with a consistency larger than 0.75 should be set at 1 and the rest at 0. Once this is complete, the researcher may proceed with the option of *Standard Analyses*.

4.4.3. Obtaining the solution sets

Following the sorting of the truth table, the researcher is presented with the option to choose if a single independent variable should be present or absent at all times on the solutions. Unless otherwise needed, we suggest choosing “Present or Absent” in order to obtain all the possible combinations. Next, fsQCA provides the following three sets of solutions: complex, parsimonious, and intermediate. Here, “solution” refers to a combination of conditions that is supported by a high number of cases, where the rule “the combination leads to the outcome” is consistent. The *complex* solution presents all the possible combinations of conditions when traditional logical operations are applied. In general, because the number of configurations identified can be very large, the number of complex solutions can be large and these may include configurations with several terms. This makes the interpretation of the solutions difficult and in most cases impractical (Mendel & Korjani, 2012). For this reason, they are usually simplified further into parsimonious and intermediate solutions.

The *parsimonious* solution is a simplified version of the complex solution, based on simplify assumptions, and presents the most important conditions which cannot be left out from any solution. These are called “core conditions” (Fiss, 2011) and are identified automatically by fsQCA. Finally, the *intermediate* solution is obtained when performing counterfactual analysis on the complex and parsimonious solutions (Liu et al., 2017; Ragin, 2008). In essence, the intermediate solution depends on simplifying assumptions that are applied by the researcher, which at all times should be consistent with theoretical and empirical knowledge. The intermediate solution is part of the complex solutions and includes the parsimonious solution. The conditions that are part of the intermediate solution and not part of the parsimonious solution are called “peripheral conditions” (Fiss, 2011). A more detailed and mathematically oriented description of the steps in counterfactual analysis is provided by Mendel and Korjani (2012).

4.4.4. Interpreting and evaluating the solutions

FsQCA presents the complex and parsimonious solutions regardless of any simplifying assumptions employed by the researcher, while the intermediate solution depends directly on these assumptions. A combination of the parsimonious and intermediate solutions is recommended as the main point of reference for interpreting the fsQCA results. In detail, the researchers should create a table that will include both core and peripheral conditions (Fiss, 2011; Pappas, Kourouthanassis, et al., 2016). In order to do this, the researcher should identify the conditions of the parsimonious solution in the intermediate solution. This will lead to a combined solution, which will clearly present all core and peripheral conditions, thus helping in the interpretation of the findings. Typically, the presence of a condition is presented with a black circle (●), the absence with a crossed-out circle (⊗), and the “do not care” condition with a blank space (Fiss, 2011). The distinction between core and peripheral is made by using large and small circles, respectively. The researcher should also present the overall solution consistency as well as the overall solution coverage. The overall coverage describes the extent to which the outcome of interest may be explained by the configurations, and may be compared with the R-square reported on regression-based methods (Woodside, 2013).

4.4.5. Predictive validity

After obtaining the fsQCA findings, the researcher should test for predictive validity, which examines how well the model predicts the outcome in additional samples (Gigerenzer & Brighton, 2009; Pappas, Kourouthanassis, et al., 2016; Woodside, 2014). Predictive validity is important, because achieving good model fit does not necessarily mean that the model offers good predictions. In order to test for predictive validity, the first step is to divide the sample into two subsamples and run the same analysis for both subsamples, as was described in the previous sections. Thus, the second step is to run the fsQCA for the first sample, and then the findings obtained should be tested against the second sample.

After obtaining the findings from the first subsample, the researcher must use the second sample to proceed with predictive validity testing. From the findings of the first subsample, each solution, which contains the various combinations of present and absent variables, should be modeled as one variable by using *Compute* from the *Variable* menu. Thus, the fsQCA function *fuzzynot(x)* is used for every variable that is absent (~) in the solution. This function computes the negation (1-x) of a variable (fuzzy set). Next, in order to model each solution, the function *fuzzyand(x,..,)* is used, which takes as input all the variables that are present in each configuration and the new variables that occurred as the outcome of the *fuzzynot(x)* function. The *fuzzyand(x,…,)* function returns a minimum of two variables (fuzzy sets).

Finally, the new variable is plotted against the outcome of interest using the second subsample, from the fsQCA menu *(Graphs – Fuzzy – XY Plot)*. Consistency and coverage values are presented here, which should not contradict the consistency and coverage of the solution.

5. Results

5.1. Results of fsQCA

The results of fsQCA for high m-learning adoption are shown in Table 4. Each possible combination is a solution that explains the outcome. Specifically, the presence of a condition is depicted by a black circle (●), and its absence by a crossed-out circle (⊗) (Fiss, 2011). The blank spaces indicate a "do not care" situation, meaning that the causal condition may either be present or absent. Further, core conditions are represented with large circles, and peripheral ones with small circles. Table 4 also presents consistency values for every configuration as well as for the overall solution. All values are above the recommended threshold (>0.75). Consistency measures the degree to which a subset relationship has been approximated, while coverage assesses the empirical relevance of a consistent subset (Rihoux & Ragin, 2009). The overall solution coverage indicates the extent to which high intention to use m-learning may be determined from the existing configurations, and is comparable to the R-square value reported in traditional MRAs (Woodside, 2013). An overall solution coverage of .844 suggests that the eight solutions account for a substantial proportion of the outcome. FsQCA also estimates the empirical relevance of every solution, by calculating raw and unique coverage. The raw coverage describes the amount of the outcome that is explained by a certain alternative solution, while the unique coverage describes the amount of the outcome that is exclusively explained by a certain alternative solution. The solutions presented in Table 4 explains a vast amount of users' m-learning adoption, ranging from 13% to 65% of cases associated with the outcome.

For high m-learning adoption, solutions 1–6 present combinations in which at least one of the cognitive characteristic factors is present (i.e., high), and solutions 5–8 present combinations in which at least one of them is absent (i.e., low). In detail, the presence of both perceived usefulness and ease of use may lead to m-learning adoption when, regardless of subjective norm, either m-learning attitude is also present (solution 1), or self-efficacy is present (solution 2). Further, the combination of perceived usefulness with m-learning attitude leads to high intention to use m-learning, regardless of perceived ease of use, when m-learning attitude is present (solution 3) or self-efficacy is absent (solution 4). Next, when perceived ease of use is absent, the combination of perceived usefulness and subjective norm will lead to high m-learning adoption, as long as m-learning attitude is also absent and regardless of subjective norm (solution 5). On the other hand, if perceived usefulness is absent, the combination of perceived ease of use with subjective norm will lead to high intentions, and indifference of both m-learning attitude and self-efficacy (solution 6). However, if perceived usefulness is absent and perceived ease of use is neither present or absent (i.e., do not care), high m-learning adoption may be achieved with high subjective norm, high self-efficacy, and low m-learning attitude (solution 7). Finally, if perceived ease of use is absent, and both subjective norm and self-efficacy are also absent, high m-learning attitude may lead to high m-learning adoption, regardless of perceived usefulness (solution 8).

Table 4
Configurations for high m-learning adoption.

Configuration	Solution							
	1	2	3	4	5	6	7	8
Cognitive Characteristic								
Perceived Usefulness	●	•	●	●	●	⊗	⊗	
Perceived Ease of Use	•	●			⊗	•		⊗
Affective Characteristic								
M-learning attitude	●		●	●			⊗	●
Social Factor								
Subjective Norm			●		●	●	●	⊗
Individual Factor								
Self-Efficacy		●		⊗	⊗		•	⊗
Consistency	.907	.893	.924	.800	.859	.859	.803	.764
Raw Coverage	.617	.558	.651	.267	.157	.196	.140	.127
Unique Coverage	.011	.031	.049	.005	.014	.035	.015	.003
Overall Solution Consistency	0.801							
Overall Solution Coverage	0.844							

Note: Black circles (●) indicate the presence of a condition, and circles with "x" (⊗) indicate its absence. Large circles indicate core conditions, and small circles indicate peripheral conditions. Blank spaces indicate "don't care" conditions. All circles with an "x" (⊗) are peripheral conditions. Here, all absent conditions are peripheral conditions.

The results offer support for all three propositions. First, more than one configuration leads to high m-learning adoption, which indicates equifinality (Proposition 1). Second, the results reveal configurations of high m-learning adoption in which one condition could be either present or absent depending on its combination with the other conditions, indicating causal asymmetry (Proposition 2). Third, when one cognitive characteristic is absent, at least an affective characteristic or social factor needs to be present to lead to high m-learning adoption (Proposition 3).

5.2. Testing for predictive validity

The present study tests for predictive validity, in order to identify if the model is able to predict equally well the same dependent variable on a different sample (Gigerenzer & Brighton, 2009; Pappas, Kourouthanassis, et al., 2016; Woodside, 2014). Testing for predictive validity is important, because even a model with good fit may not always predict the outcome well. To test for predictive validity, first the sample is divided into a subsample and a holdout sample. Then the analysis is executed for the subsample, and its findings (Table 5) must be tested against the holdout sample. Table 5 shows that the patterns of complex antecedent conditions are consistent indicators (overall solution consistency was 0.869) of high intention to use m-learning for the subsample.

Every one of the four configurations in Table 5 represents a model that needs to be plotted against the outcome variable (i.e., intention to use m-learning). This requires that each configuration (i.e., model) is represented as a variable in fsQCA, which can be done by using the functions provided by the software. More details on the procedure may be found on the work of Pappas, Giannakos, et al. (2016). Once the new variable is created it is plotted against m-learning adoption (Fig. 2).

As shown in Fig. 2, the findings for testing model 1 against m-learning adoption with data from the holdout sample indicate high consistency (0.985) and coverage (0.515), similar to those from the subsample 1 (Table 5). Predictive tests for all models suggest that the highly consistent models for the subsample have high predictive abil-

Table 5
Complex configurations indicating high m-learning adoption for the subsample.

Models from Subsample 1	Raw Coverage	Unique Coverage	Consistency
1. SEF*PU*SN*ATT	.564	.050	.947
2. PU*PEOU*ATT	.668	.147	.886
3. SEF*PEOU*SN*ATT	.551	.045	.943
4. ~SEF*PU*~PEOU*SN*~ATT	.107	.013	.772
Overall Solution Consistency	.869		
Overall Solution Coverage	.786		

PU: Perceived usefulness; PEOU: Perceived ease of use; ATT: M-learning attitude; SN: Subjective norm; SEF: Self-efficacy.

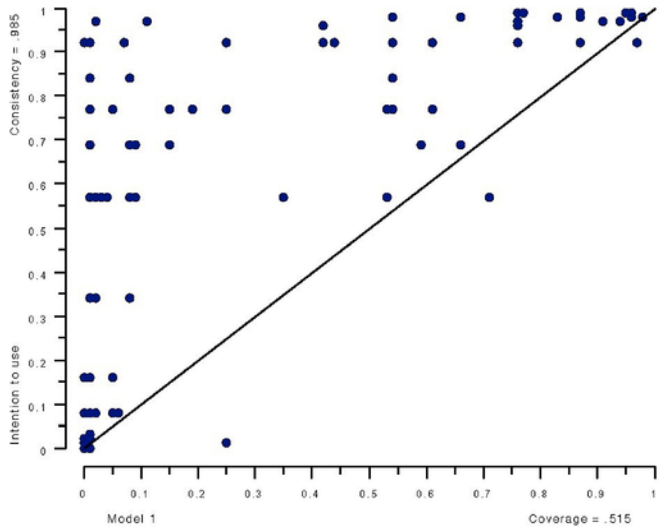

Fig. 2. Testing model 1 of the subsample using data from the holdout sample.

ity for the holdout sample and vice versa. All results are available upon request.

6. Discussion, implications, and conclusion

The present study takes a different approach from traditional technology acceptance research, builds on complexity theory, employs configurational analysis, and proposes that in m-learning environments, cognitive characteristics, affective characteristics, and social and individual factors combine to form configurations for predicting m-learning adoption. By considering the role of different configurations, this study offers an alternative approach to examining technology adoption, and sheds light on how different user groups may have high m-learning adoption, even if they lack some of the factors identified in the literature as key (e.g., ease of use, usefulness). To this end, a conceptual model is constructed along with research propositions, which serve as the basis for identifying the aforementioned configurations.

Of particular interest in the findings was the role of perceived usefulness. In fact, perceived usefulness is present in five out of the eight solutions (solutions 1–5), and when perceived usefulness is absent, high m-learning adoption may be achieved only with the strong presence of a subjective norm (solutions 6 and 7). Interestingly, users with lower self-efficacy, social norm, and perceived ease of use may still have high m-learning adoption as long as they have high m-learning attitude (solution 8).

The results revealed that cognitive characteristics (e.g., usefulness), affective characteristics (e.g., m-learning attitude), social influences, and self-efficacy do indeed play important roles in m-learning adoption. The finding coincides with prior studies that adopted a TAM-related approach (e.g., Kim, Kim, & Han, 2013; Park et al., 2012) as well as related work in social influences on m-learning adoption (e.g., Shin & Kang, 2015; Yeap et al., 2016). In this study, by employing fsQCA we found that if perceived usefulness and perceived ease of use are not present, users definitely need to have a strong presence of m-learning attitude or social influences in order to attain m-learning adoption. On the other hand, if users have strong perceived usefulness and perceived ease of use, there is no need for m-learning attitude or social influences in order to have m-learning adoption (e.g., see solution 2).

Besides the impact on m-learning environments, this paper contributes by employing configurational analysis, and presenting a step-by-step methodological approach on how to apply fsQCA in the context of learning analytics. The step-by-step approach allows researchers and practitioners to 1) make sense of diverse learning phenomena happening simultaneously; 2) better understand how users interact with 21st-century learning systems; 3) design learning technology for users with diverse needs and capabilities; and 4) contribute towards user-centered learning innovation. This approach is of particular interest in heterogeneous learning analytics, coming from datasets consisting of learners with different learning styles, backgrounds, needs, and so on. FsQCA can help us to better understand and further develop teaching and learning approaches enhancing learners' dynamics and personalized needs in an era of ubiquitous learning. Thus, this study introduces fsQCA to researchers working with learning systems and learning analytics, and provides a spring-board to utilizing this promising technique.

6.1. Implications

These findings contribute to the literature in a number of ways. The study adds to the technology acceptance literature by providing an alternative view on the adoption process, and shows how important antecedents of users' behavioral intentions can combine with each other, creating multiple solutions that explain m-learning adoption. Following the need to extend and evolve technology acceptance theories and models to better capture real-life phenomena, which are by definition complex and multi-dimensional (Benbasat & Barki, 2007; Nistor, 2014), we propose taking a different methodological approach that enables researchers to identify such complexities inherent in real-life situations. Methodology is essential, as it not only defines how we study a phenomenon, but also affects how we think about it (Bagozzi, 2007). To this end, we propose employing complexity theory along with configurational analysis, to better explain the complex relationships among variables. Since such relationships are more likely to be asymmetric, researchers with fsQCA are able to identify different configurations (i.e., combinations) of the same variables predicting the same outcome, explaining, for example, the behavior of different parts of a sample – which otherwise would have been considered as outliers and removed from further analysis. Identifying such configurations can help in theory building with fsQCA (Woodside, 2014), as configurations that appear frequently in different contexts provide support for their importance, increasing researchers' knowledge about their role in predicting behavior (Liu et al., 2017). Thus, we differentiate from traditional hypothesis building and assumptions of symmetric tests between individual variables, as the proposed approach can lead to the evolution of existing theories on technology acceptance and behavior of individuals (e.g., TAM, TRA/TPB). In detail, identifying important configurations of existing variables, in multiple contexts, will offer more knowledge on their interrelations and guide researchers to the creation of new variables, and potentially hypotheses, answering the call for incorporating more complex and multi-dimensional variables into the field (Benbasat & Barki, 2007; Nistor, 2014).

Previous studies in the area of m-learning adoption explain users' behavior by examining various antecedents (Cheon et al., 2012; Huang et al., 2010; Park et al., 2012; Shin & Kang, 2015; Tan et al., 2012; Wu et al., 2012). Nonetheless, they take a net effects approach by employing symmetric and variance-based tests, and oversee the interrelations and interdependencies among the examined variables (Woodside, 2014). The present study builds on complexity theory and configuration theory, employs fsQCA, and contributes to the literature of m-learning by showing how four sets of causal conditions (i.e., cognitive characteristics, affective characteristics, social factors, and individual factors) combine to form configurations that predict high m-learning adoption. Furthermore, this method provides a deeper and better understanding regarding specific patterns of cognitive and affective characteristics, and social and individual factors that lead to increased m-learning adoption. It also adds to the literature by providing conditions under which the aforementioned factors coexist. The findings indicate that cognitive characteristics are the most important predictors of m-learning adoption, and their absence may be compensated for by the existence of affective characteristics or social factors.

This paper is one of the first to perform configurational analysis based on individual-level data from users of m-learning. Employing complexity theory together with configurational analysis has been proven appropriate for theory building (Leischnig & Kasper-Brauer, 2015; Woodside, 2014). Accordingly, we create propositions that aim to explain high m-learning adoption, and test them through fsQCA. Configurational analysis with fsQCA is a method that is increasingly applied lately in various fields (Mendel & Korjani, 2012; Ordanini et al., 2014; Pappas, Giannakos, et al., 2017; Pappas, Giannakos, et al., 2016; Pappas, Kourouthanassis, et al., 2016), and our findings extend the literature by confirming the importance of examining complex causal patterns of m-learning adoption antecedents, and asymmetric relations among m-learning adoption and its predictors. FsQCA identifies combinations among variables, thus it is not able to quantify the effect of each variable independently on the outcome.

The present study provides useful insights for designers of m-learning technologies, instructors, and e-learning practitioners, since it explains how critical factors of m-learning adoption combine to better predict high intention to use m-learning. The findings verify the importance of cognitive characteristics, and especially perceived usefulness in m-learning adoption. In order to showcase the usefulness and increase the usage of m-learning, its designers should focus on the development of valuable functions, affordances, and content of m-learning systems for their potential users. Furthermore, social factors should be implemented in the design of both m-learning content and systems, so that students may adopt m-learning even if they find it less useful. For example, students may be urged to collaborate in the classroom by using their mobile devices. In addition, the integration of social media into m-learning systems will increase adoption, if for example students log in and interact with their classmates inside those systems. Finally, since affective characteristics may increase m-learning adoption when cognitive characteristics are not high, instructors should also try to present m-learning in a way that users will like and enjoy using. For example, it should not be imposed on them; instead, the advantages of its use should be highlighted so they can choose to try it out and ultimately adopt it.

Finally, one of the most important implications of this paper is related to how educational technology and user experience researchers and practitioners can utilize the fsQCA method to make sense of diverse learning analytics and take design decisions for various user groups. In the 21st century learning systems are in need of becoming more flexible, thoughtful, and adaptive (e.g., Khan Academy, Udacity) as well as incorporating "smart behavior" (e.g., Adaptemy, Dreambox, SmartSparrow) (Giannakos, Sampson, & Kidziński, 2016). However, there is a lack of empirical analytics-based research, utilizing state-of-the-art approaches to identify what designs can increase effectiveness, efficiency, and engagement. Taking an fsQCA approach provides a unique opportunity to researchers and practitioners to make sense of different learning analytics, such as click-stream interactions and learning paths (e.g., material views), background knowledge (e.g., results from previous tests), and attitudes (e.g., results from attitudinal surveys), and to offer optimal learning designs for different user groups, needs, and circumstances. This will allow contemporary learning systems to leverage the capacities of their learning analytics and maximize their innovation potential.

6.2. Limitations and future research

This empirical work has some limitations. First, users' general perceptions of m-learning are examined, without focusing on a specific system. Future studies may choose certain types of m-learning systems or content in order to provide more specific guidelines for professors and designers. In addition, the study examines users' intentions in adopting m-learning, common in technology acceptance research, but without investigating actual use behavior. Although user intention is considered as a powerful predictor of actual behavior (Fishbein & Ajzen, 1977), combing data from actual use of learning systems and applications would provide more insight into the role of cognitive characteristics, affective characteristics, social factors, and individual factors in predicting m-learning adoption. Future studies should build on learning analytics, and incorporate data from big learning analytics providers (e.g. Moodle), reflecting the use of complex learning ecosystems and offering a holistic understanding of the technology acceptance process in learning. Further, the study controls for m-learning experience by offering to the respondents specific and detailed examples of m-learning. Nonetheless, in order to increase the reliability of the sample, future studies should ask the respondents to provide an example of what they believe is m-learning. Additionally, more predictors of m-learning adoption should be examined in the future, as well as various demographic characteristics, which have been proven to influence acceptance of m-learning (Wang et al., 2009). Finally, we should mention that fsQCA does not identify the unique contribution of each variable for every solution. Instead, the goal of fsQCA is to identify combinations of the independent variables. Future studies should combine fsQCA with regression-based techniques to gain a deeper insight into the data, and integrate knowledge from both methods towards extending current theories or developing new ones. As this study is among the first to employ configurational analysis with fsQCA in education and learning environments (Pappas, Cetusic, et al., 2017; Pappas, Giannakos, et al., 2017; Pappas, Giannakos, et al., 2016; Plewa et al., 2016), further innovative research is needed to identify complex and important configurations that will move the field forward, and also reveal the full potential of configurational analysis.

Appendix 1.

Scale items with mean, standard deviation, and standardized loading.

	Mean	SD	Loading
Perceived Usefulness (CA = .929)			
1. I believe that using mobile devices would improve my ability to learn.	4.30	1.43	.827
2. I believe that mobile devices would allow me to get my work done more quickly.	4.82	1.56	.794
3. I believe that mobile devices would be useful for my learning.	4.67	1.48	.853
4. M-learning would improve my learning performance.	4.13	1.39	.901
5. M-learning can improve efficiency of learning.	4.17	1.37	.879
6. M-learning gives me high effects of learning.	4.12	1.40	.898
Perceived Ease of Use (CA = .849)			
1. I believe that mobile devices would be easy to use for learning purposes.	4.79	1.45	.806
2. I believe it would be easy to access course material with my mobile device.	4.95	1.45	.788

3. I believe that mobile devices would be easy to assist learning.	4.81	1.51	.786
4. It is easy to download and save learning content with mobile devices.	5.16	1.56	.733
5. It is easy to use mobile devices for accessing learning content.	5.02	1.39	.830
M-Learning Attitude (CA = .924)			
1. I would like my coursework more if I used m-learning.	4.09	1.69	.869
2. Using m-learning in my coursework would be a pleasant experience.	4.50	1.53	.912
3. Using m-learning in my coursework is a wise idea.	4.51	1.50	.915
4. I like to search learning content that downloads in mobile devices for learning.	4.59	1.43	.808
5. I am positive toward m-learning.	4.89	1.55	.876
Subjective Norm (CA = .875)			
1. Most people who are important to me think that it would be fine to use a mobile device for university courses.	4.18	1.37	.818
2. I think other students in my classes would be willing to adapt a mobile device for learning.	4.64	1.36	.734
3. Most people who are important to me would be in favor of using a mobile device for university courses.	4.28	1.38	.788
4. M-learning has significant meaning as a university student.	4.56	1.44	.848
5. It is necessary to perform m-learning according to recent social needs.	4.86	1.41	.800
6. I need to experience m-learning for my future job.	5.07	1.64	.717
Self-Efficacy (CA = .928)			
1. I have the necessary skills for m-learning.	5.41	1.32	.896
2. I am a skillful user in menu or software for m-learning with mobile devices.	5.33	1.32	.926
3. I have confidence in complementarily using computer and mobile devices for m-learning.	5.39	1.37	.907
4. I understand computer and mobile device terms well for m-learning.	5.43	1.37	.899
Intention to Use (CA = .915)			
1. I predict I would use a mobile device for my courses.	5.11	1.34	.882
2. I plan to use a mobile device if a course has m-learning functions.	5.14	1.45	.907
3. I intend to adopt a mobile device for university courses.	4.81	1.56	.885
4. I expect my use of a mobile device for my courses to continue in the future.	5.19	1.48	.899

CA: Cronbach's alpha.

Appendix 2.

Calibration of the variables.

Variable	Percentage	Value	Fuzzy-set membership
Perceived Usefulness	80	80.56	Full-set membership
	50	51.67	Intermediate-set membership
	20	19.56	Full-set non-membership
Perceived Ease of Use	80	81.39	Full-set membership
	50	55.00	Intermediate-set membership
	20	19.72	Full-set non-membership
M-learning Attitude	80	78.61	Full-set membership
	50	53.06	Intermediate-set membership
	20	20.83	Full-set non-membership
Subjective Norm	80	77.50	Full-set membership
	50	49.44	Intermediate-set membership
	20	23.06	Full-set non-membership
Self-Efficacy	80	78.33	Full-set membership
	50	48.61	Intermediate-set membership
	20	19.72	Full-set non-membership
Intention to Use	80	82.50	Full-set membership
	50	50.56	Intermediate-set membership
	20	23.61	Full-set non-membership

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