Mobile Learning Adoption through the lens of complexity theory and fsQCA

Ilias O. Pappas, Luka Cetusic, Michail N. Giannakos, Letizia Jaccheri
Department of Computer Science
Norwegian University of Science and Technology
Trondheim, Norway
{ ilpappas, michailg, letizia.jaccheri } @ ntnu.no, cetusic@stud.ntnu.no

Abstract— **This study aims to identify the interrelations among performance expectancy, effort expectancy, enjoyment, and satisfaction in order to predict high intention to use a mobile application for educational services. To this end a mobile application was developed which includes important services for students in one place and it was tested through feedback from questionnaires. Building on complexity and configuration theory we present a conceptual model and employ fuzzy-set qualitative comparative analysis (fsQCA) to examine how performance expectancy, effort expectancy, enjoyment, and satisfaction combine in order to explain high and low intention to use mobile learning. The results indicate different configurations of the examined factors that explain user behavior, and verify the existence of asymmetric relations among them. The study is one of the first in the area evaluating a mobile learning application, and has both theoretical and practical implications towards the development, design and provision of mobile learning applications.**

Keywords—mobile learning; adoption; complexity theory; fuzzy-set qualitative comparative analysis; configuratio)

I. INTRODUCTION

Mobile applications have become extremely popular in various contexts, one of them being mobile learning [1]. Mobile learning is defined as the "*learning across multiple contexts, through social and content interactions, using personal electronic devices*" [2]. The successful implementation of mobile learning is highly influence by the effectiveness of mobile learning applications as well as the perceptions of users towards them. Such perceptions affect the learning process and their future behavior [3], especially due to the various affordances and applications of mobile devices.

Users' behavior has been examined in the mobile learning literature considering various factors [4-7], however they do not investigate the role of multiple configurations that may lead to multiple models explaining users' behavior. Most of the work in mobile learning focuses on the net effects among variables, uses variance-based approaches (e.g., multiple regression analysis) and identifies one single best solution to explain use behavior. Nonetheless, the relations among variables are usually not fully symmetrical [8], and they can either be positive or negative for a different part of the same sample. Thus, multiple configurations of the examined variables, create multiple solutions that explain the same outcome depending on how they combine with each other.

Here we aim to investigate how well examined predictors of mobile learning adoption (i.e., gender, enjoyment, satisfaction, performance and effort expectancy) combine to better explain the use of mobile learning. To this end, we bridge complexity theory with configurational analysis, through fuzzy set qualitative comparative analysis (fsQCA) [9], in the area of mobile learning. Applying fsQCA with complexity theory offers better and deeper understanding on the examined variables [8, 10]. Further, this methodology is suitable for explaining the complex interrelations among variables, because their combinations and interdependencies lead to the desired outcome [8, 11]. Also, fsQCA is suitable because it offers valid responses in studies with small samples [11]. FsQCA is becoming very popular lately, and we expand on the contributions of other studies from the areas business management [10], learning analytics [12] and others.

II. RELATED WORK AND CONCEPTUAL MODEL

Technologies supporting mobile learning can offer possibilities to foster learning in different circumstances because of their portability [13]. Currently, applications for mobile devices have become very popular amongst young learners. M-learning applications are greatly adaptable that can be accommodated virtually to any environment [14]. Learning can take place in formal and semiformal settings, which can be of great value for students, since it gives them the possibility to stay informed, get desired notifications, and keep track of personal goals [13]. This enables the learner to have more control over the learning process, outside the formal setting. Adapting and customizing mobile learning applications provides benefits to meet educational institution's needs in terms of communication, setting learning goals and interests, accommodation of different learning styles, and anywhere and anytime learning environments [15]. Another positive aspect of m-learning, is that "*mobile learning keeps the learners engaged, and one is able to deliver learning that is authentic and informal via the mobile learning technologies*"[16].

A. Mobile learning adoption

Mobile learning literature presents various factors that may influence users' behavior [5, 6, 17]. Previous studies have identified the various effects of cognitive and affective factors, satisfaction as well as demographics on users' intention to use mobile learning applications. Performance expectancy has been identified as the main predictor of intention to use mobile learning [4, 5, 18]. Similarly, effort expectancy has been mainly found to influence positively students' behavioral intentions [5, 6]. Such findings indicate that these factors are necessary conditions in order to increase users' intention to use mobile learning applications. Nonetheless, the adoption of mobile learning may be reached through the existence of other factors. For example, experiencing positive affective characteristics will lead to high intention to use mobile learning applications [7, 19]. Furthermore, gender, among other demographics, has been identified as an important factor in forming behavioral intentions [20] and is expected to affect users' intention to use mobile learning applications [7].

B. Conceptual model and propositions

Mobile learning behavior has been investigated in the literature considering factors, like performance expectancy, effort expectancy, satisfaction, attitude, system innovativeness and accessibility, demographics to mention the most common ones [7, 21, 22], but there is no research on how different configurations might result different adoption models and relationships. Thus, to better understand mobile learning behavior, a configurational analysis is more appropriate than examining individual causal factors. As conceptualized in Figure 1, this perspective leads to more complex causal patterns and higher-level interactions between the constructs. The Venn diagram presents five sets of constructs and their intersections, which reflect the outcome of interest (dependent variable) of this study and four sets of causal conditions to predict the outcome (independent variables).

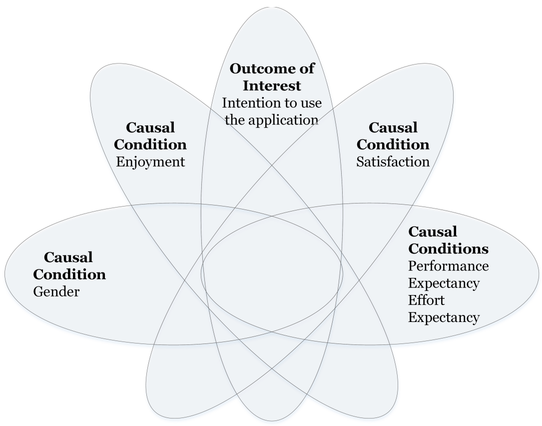

Fig. 1. Venn diagram of the conceptual model

Complexity theory builds on the principle of *equifinality* [23], which suggests that a result may be equally explained by alternative sets of causal conditions [11]. These conditions may be combined in sufficient configurations to explain the outcome [8, 24]. Enjoyment, satisfaction, performance and effort expectancy are important causal conditions for understanding students' intention to use mobile learning applications, and they may be combined with each other in various configurations. For example, students that perceive the use of the application useful and easy are likely to adopt it [5]. Further, students' that enjoy using new technologies, such as a new application, will have high intentions to use a mobile learning application.

Configuration theory proposes the principle of causal asymmetry, which means that, for an outcome to occur, the presence and absence of a causal condition depends on how this condition combines with the other conditions [8, 24]. For example, performance and effort expectancy are likely to have a positive effect on students' behavior. However, students who perceive mobile learning as less useful or hard to use may still have high intentions to use an application, if they also like it, enjoy it or feel satisfied [18]. To identify the multiple configurations among the examined variables we propose:

Proposition 1. *No single configuration of students' gender, enjoyment, satisfaction, performance and effort expectancy leads to high intention to use mobile learning applications; rather, there exist multiple, equally effective configurations of causal factors.*

Proposition 2. *Single causal conditions may be present or absent within configurations for students' high intention to use mobile learning applications, depending on how they combine with other causal conditions.*

Proposition 3*. Configurations of students' gender, enjoyment, satisfaction, performance and effort expectancy that explain high intention to use mobile learning applications, are not perfect reverses of configurations that explain low/medium intention to use the applications.*

III. MOBILE LEARNING APPLICATION DEVELOPMENT

For the objectives of this study a mobile learning application was developed. The waterfall model was selected as the appropriate development method, which is basic and easy to implement and covers the needs for developing this application. An illustration of the mobile application was created visualize it. An example of the illustration is presented in Figure 2.

Fig. 2. Mockup of the mobile application

In the requirement phase, a survey with questionnaire was used to get insight on what requirements was considered important in the mobile application. These requirements provided guidelines which could be followed to design the mobile application. Subsequently, the implementation of the mobile application takes place by using the design as a guide. Lastly, the mobile application is to go through a verification phase to ensure that the requirements has been met. In this case, the application was tested by students which provided feedback through an online questionnaire.

IV. RESEARCH METHODOLOGY

A. Sampling and measures

For the data collection, a survey of questionnaires and interviews was conducted. In this study a purposive sampling methodology is used to recruit participants. The decision in the choice of this methodology was the confidence of having a good representativeness of the target sample. Moreover, to acquire the desired results, this type of sampling focuses on particular characteristics of the target group that are of interest. To get the target sample in an efficient way, a reward of gift cards was announced to the participants.

Participants shared their insight by responding to a questionnaire. First, students' needs were collected and used to develop the application. A testing phase was planned for over a month of period. The participants got two weeks to test the application and respond to a questionnaire. The targeted sample quantity was 35 participants and 30 responded. The sample consisted of more men (66.7%) than women (33.3%). As for the age of the respondents, they were between 21 and 32 where the majority (93,34%) was between 21 and 27 years, which was expected since the target sample were university students.

The constructs were measured with scales adopted from previous studies using a 7-point Likert scale, ranging from "not at all" (1) to "very much" (7). The adopted constructs are defined in Table 1 along with their source in the literature.

TABLE I. CONSTRUCT DEFINITION AND SOURCE

Construct	Definition	Source
Enjoyment	The degree that using the mobile application is perceived to be personally enjoyable	[25]
Satisfaction	The degree that a person positively feels with using the mobile application	[26]
Performance expectancy	The degree that individuals believe that using the mobile application is useful and will increase their performance	[27]
Effort expectancy	The degree that individuals believe that that using the mobile application is easy and free of effort.	[28]
Intention to use	The degree of students' intention to use the mobile application in the future	[28]

B. Data Analysis

The constructs of this study were first evaluated in terms of their reliability and validity. Reliability was examined with Composite Reliability and Cronbach alpha, with acceptable indices of internal consistency (>0.70). Table II presents the findings. Next, validity was examined by measuring the average variance extracted (AVE) (>0.50), and by examining the correlations between the variables in the confirmatory models, which should not exceed 0.8 points, because exceeding 0.8 suggests low discrimination.

TABLE II. DESCRIPTIVE STATISTICS AND RELIABILITY OF LATENT VARIABLES

Construct	Mean (SD)	Ca	CR	AVE
Enjoyment	5.12 (1.2)	0.86	0.91	0.78
Satisfaction	5.39 (0.93)	0.84	0.88	0.73
Performance Expectancy	4.10 (1.69)	0.91	0.94	0.84
Effort Expectancy	5.60 (0.87)	0.84	0.88	0.60
Intention to use	4.53 (1.51)	0.94	0.96	0.85

Also, the square root of each factor's AVE must be greater than its correlations with other factors [29]. The AVEs for all constructs ranged between 0.60 and 0.85, all correlations were lower than 0.80, and the square root AVEs for all constructs were larger than their correlations. Table III presents the findings. We tested for multicollinearity [30] along with the potential common method bias by utilizing Harman's single-factor test [31]. The variance inflation factor for each variable was below 3, suggesting that multicollinearity was not an issue. The findings also indicate the absence of common method bias in that the first factor did not account for the majority of the variance and no single factor occurred from the factor analysis.

TABLE III. VALIDITY OF LATENT VARIABLES

Construct	ENJ	STF	PE	EE	INT
ENJ	**0.88**				
STF	.66	**0.85**			
PE	0.39	0.59	**0.92**		
EE	0.08	0.34	0.47	**0.77**	
INT	0.58	0.62	0.44	0.27	**0.92**

[a] 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. ENJ; Enjoyment, STF; Satisfaction, PE; Performance Expectancy, EE; Effort Expectancy; INT; Intention to use

C. Configurational analysis

1) FsQCA

FsQCA was developed by integrating fuzzy sets and fuzzy logic with Qualitative Comparative Analysis (QCA), is appropriate for small samples [11], and helps researchers go beyond regression based techniques [e.g., Multiple Regression Analysis (MRA)]. It identifies multiple pathways that explain the same outcome, which are not identified by MRAs as they influence the outcome only for a small number of cases [8]. These combinations lead to multiple solutions offered by fsQCA, and include both necessary and sufficient conditions. Such conditions may be present or absent on a solution, or they may be on 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 on a specific configuration.

2) Data calibration

First all factors need to be calibrated into fuzzy sets with values ranging from 0 to 1 [9]. This procedure shows their degree of membership in a specific group. It shows the extent to which they are part of a certain group. Data calibration may be done either directly or indirectly. In the direct method, the researcher should choose three qualitative breakpoints, while in the indirect method, the factors should be rescaled following qualitative assessments. The researcher may choose either method depending on the data and the underlying theory [9]. The direct method of setting three values that correspond to full-set membership, full-set non-membership and intermediate-set membership is recommended [9]. The data calibration in the present study was done following the direct method, following the procedure employed by [10, 12], and the three qualitative anchors for the calibration were based on the survey scale (seven-point Likert scale). The full membership threshold was set at 6; the full non-membership threshold was set at 2; and the crossover point was set at 4. The values of every variable were calibrated based on a linear function to fit into the three aforementioned thresholds.

3) Identifying configurations

Next, fsQCA creates a truth table of 2^k rows, where k represents the number of outcome predictors and each row represents every possible combination. For example, a truth table between two variables leads to four possible logical combinations between them. For every combination, the minimum membership value is calculated. The minimum membership value is the degree to which every case supports the specific combination. In fsQCA a threshold of 0.5 is used in order to identify which combinations are supported at an acceptable level by the sample. In detail, it is needed that at least one case in the sample has a membership of at least 0.5 in a combination, for this combination to be supported. All combinations with membership level lower than 0.5 as removed from the further analysis.

Finally, the truth table is sorted based on frequency and consistency [9]. Frequency describes the number of observations for each possible combination, and consistency refers to "*the degree to which cases correspond to the set-theoretic relationships expressed in a solution*" [24]. A frequency threshold should be set to ensure that a minimum number of empirical observations is acquired for the assessment of the relationships. For samples smaller than 150 cases the threshold should be set at 2 [9, 24], thus all observations with frequency of 1 or 0 are removed from further analysis. Also, the threshold for consistency is set at the recommended threshold of 0.75 [32].

4) Obtaining solutions

FsQCA presents the researcher three solutions, namely complex, parsimonious and complex solution. Solution refers to a combination of conditions that is supported by a relatively large number of cases, which describe the combinations that lead to the outcome of interest. The *complex* solution presents all the possible combinations of conditions when traditional logical operations are applied. Complex solutions are simplified into parsimonious and intermediate solutions, which are simpler and up for interpretation. In detail, the *parsimonious* solution is a simplified version of the complex solution and it includes at least one parsimonious solution. The parsimonious solution presents the most important conditions, those that cannot be left out from any solution. These conditions are called *"core conditions"* [24] and are identified automatically but fsQCA .

The third solution, the *intermediate* solution is obtained when performing counterfactual analysis on the complex and parsimonious solution [9]. This means that 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 included in the complex solution and also includes the parsimonious solution. The conditions that are part of the intermediate solution and not part of the parsimonious, are called *"peripheral conditions"* [24].

5) Interpreting solutions

Although fsQCA presents all three solutions, it is up to the researcher to interpret and evaluate the results. Since, as we mentioned above the solutions are linked with each other, it is suggested that the researchers create a combination of the parsimonious and intermediate solution in order to make it easier, simpler and more straightforward to interpret and present the results. The complex solution is not included, because it is usually very large making its interpretation rather difficult , and because the parsimonious solution is a simpler version of the complex one. The researchers should create a table that will include both core and peripheral conditions [10, 24]. 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 the interpretation of the findings.

V. FINDINGS

The results of fsQCA for high and low/medium intention to use mobile learning are shown in Fig. 4. Each possible combination is a solution that explains the outcome. Specifically, the presence of a condition is presented with a black circle (●), while its absence with a crossed-out circle (⊗) [24]. The blank spaces indicate a "do not care" condition (i.e., either present or absent). Fig. 4 also shows consistency values for every configuration and for overall solutions. 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 [32]. The overall solution coverage indicates the extent to which high or low/medium intention to use mobile learning applications may be determined from the existing configurations, and is comparable to the R-square value reported in traditional MRAs [33]. Overall solution coverage of 0.59 and 0.60 indicate that the solutions account for a substantial proportion of the outcome.

FsQCA estimates also the empirical relevance for every solution, by calculating raw and unique coverage. Raw coverage is the amount of the outcome is explained by a certain solution, and the unique coverage is the amount of the outcome that is exclusively explained by a certain solution. The solutions identified in this study explain a vast amount of users' behavior, ranging from 29% to 49% cases associated with the outcome.

Solutions 1-3 presented in Table 2 show combinations for high intention to use the mobile learning application, and solutions 4-6 show combinations for low and medium intention to use the application. In detail, females with high performance expectancy will also have high intention to use the application (solution 1). On the other hand, for males, the findings offer two different solutions, (i) the combination of high enjoyment with low performance expectancy regardless of satisfaction and effort expectancy (solution 2), and (ii) the combination of high satisfaction with low performance expectancy regardless of enjoyment and effort expectancy (solution 3).

	Solution						
Configuration	1	2	3		4	5	6
	High intention				**Low/medium intention**		
Gender (Male)	⊗	●	●				●
Enjoyment		●				⊗	⊗
Satisfaction			●		⊗		
Performance expectancy	●	⊗	⊗			⊗	
Effort expectancy							
Consistency	.97	.83	.78		.87	.93	.94
Raw Coverage	.29	.31	.29		.40	.49	.44
Unique Coverage	.29	.03	.05		.04	.03	.07
Overall solution consistency	0.81				0.86		
Overall solution coverage	0.59				0.60		
Note: Black circles (●) indicate the presence of a condition, and circles with "x" (⊗) indicate its absence. Both circles indicate core conditions. Blank spaces indicate "don't care".							

Fig. 3. Configurations for achieving high and low/medium mobile learning adoption

Further, the results clearly demonstrate the asymmetrical relation between the examined variables since the configurations for high intention to use the application are not the equivalent ones for not having high intention to use the application (i.e., low or medium). Specifically, low/medium satisfaction from using the application is enough to explain low/medium intention to use, regardless of all the other factors as well as the gender (solution 4). Similarly, for the combination of low/medium enjoyment and performance expectancy, regardless of gender, satisfaction and effort expectancy (solution 5). Finally, the findings show that males with low/medium enjoyment will also have low/medium intention to use the application, indifferent of satisfaction and performance and effort expectancy (solution 6).

Findings provide support for all three propositions. First, more than one configuration leads to high intention to use the mobile learning application, indicating equifinality (proposition 1). Second, the results reveal configurations of high intention to use the application in which one condition could be either present or absent depending on its combination with the other conditions, indicating causal asymmetry (proposition 2). Third, the configurations that explain high intention to use the application are not perfect reverses of the configurations that explain low/medium intention to use the application.

VI. Discussion

This study proposes that in order to explain intention to use mobile learning applications, enjoyment, satisfaction, performance expectancy, effort expectancy and gender may combine with each other to form multiple configurations. In order to examine its propositions a mobile learning application was created and tested with students, and by employing complexity theory and configuration theory a conceptual model was constructed that serve as the basis for identifying the aforementioned configurations. We employ fsQCA, a novel analysis approach, and provide complex patterns, on which conditions are present or absent, that explain students' behavior. The findings show how users with different perceptions towards the application may have either high or low/medium intentions to use it.

When female students are able to identify the usefulness of the application and if the application is able to increase their performance, then they will have high intention to use it, without being affected by their other perceptions. Furthermore, male students who do find the application useful, will still have high intention to use it as long as they enjoy using or feel satisfied. However, if male students do not enjoy using the application they will probably not use it, regardless of any other factors. It is also interesting to note that effort expectancy is never present or absent indicating that it is not important for the students how easy or hard is the system to be used. This may be explained by the fact that the majority of the students are experienced with using mobile phones and mobile applications.

The present study adds to the literature by identifying specific conditions for explaining high intention to use mobile learning. The majority of the studies in the area of mobile learning employ regression based methods and focus on the net effects among the examined constructs. Only recently literature has started examining the asymmetric relations among variables, in different areas such as business [10, 34] and learning analytics [15]. The different variables may coexist and different combinations may lead to the same result. For example, a very useful application may not lead to high behavioral intention depending on how gender, enjoyment, and satisfaction combine with each other. Our findings extend the mobile learning literature by showcasing the necessity of examining complex causal patterns as well as asymmetric relations of m-learning behavior antecedents. FsQCA identifies combinations among variables, thus it is not able to quantify the effect of each variable independently on the outcome.

This paper is one of the first to employ configurational analysis using fsQCA in mobile learning adoption based on individual-level data from the CS students. Complexity theory and theory of configuration may help theory building when examining individual phenomena. Further, based on complexity theory and the theory of configuration we make propositions and test them empirically with fsQCA. The paper confirms the existence complex causal patterns of predictors and asymmetric relationships between antecedents and outcomes. FsQCA aims to identify multiple combinations of factors which can explain a specific outcome. Hence, different combinations of independent factors are able to explain the same result. Further, since the methodology investigates combinatorial effects, the influence of every independent factor on the outcome is not quantified.

The present study has certain limitations. Firstly, using a survey to test the application would require a larger sample, however fsQCA is designed to be effective is small samples as well. Further, more predictors of m-learning behavior should be examined by future studies, combined with demographic characteristics, that have been proven to influence acceptance of m-learning [7]. Finally, fsQCA does not measure the unique contribution of each variable for every solution. Instead, the goal of fsQCA is to identify combinations of the independent variables. Future work may run together fsQCA and regression-based methods to get a deeper insight on the data.

VII. CONCLUSION

The present paper investigates combinations of students' gender, performance expectancy, effort expectancy, enjoyment, and satisfaction, to explain and predict students' intention to adopt mobile learning. To this end, a mobile learning application is developed to address the goals of this study. Further, complexity theory and theory of configuration is used to showcase the need to examine asymmetric relationships as well as complex patterns among the predictors of variables. Different factors will lead male and female students to high or medium/low mobile learning adoption. We posit that not all gender, performance expectancy, effort expectancy, enjoyment, and satisfaction, need to be present for students to adopt or not adopt mobile learning. Complex but parsimonious patterns occur in which the different antecedents may be present or absent, indicating that various factors may combine to predict students' behaviour towards mobile learning.

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