Health Professional Students' Acceptance of Mobile Information Communication Technologies for Learning -

a Study Using the Unified Theory of Acceptance and Use of Technology (UTAUT)

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***Abstract*— The aim of this study was to examine what factors affect the acceptance behavior of mobile information communication technologies for learning by students in a MSc Occupational Therapy program in a Canadian university. The study addresses mobile and distance education, specifically, the function of mobile learning in higher education. A self-administrated paper-based survey was created by adapting scales used in previous research based on the Unified Theory of Acceptance and Use of Technology (UTAUT). Our research model was tested using the Partial Least Squares (PLS) technique. *Social Influence* was the strongest salient construct for *behavioral intention* to use mobile information communication technologies for learning, followed by *performance expectancy* of mobile information and communication technologies. *Effort expectancy* was not a salient construct for behavioral intention to use these technologies.**

Keywords-m-learning; UTAUT; health sciences; education.

I. INTRODUCTION

Occupational therapists are regulated health professionals that work in a variety of public and private settings to address physical and psychiatric (mental health) issues to help people or populations maintain or return to their regular activities including work, leisure and self-care. In 2011, there were approximately 1,532 occupational therapists practicing in Alberta and 13,501 practicing in Canada [1]. The occupational therapy program is about two years (26 months) and located in Edmonton. In 2012, the Department of Occupational Therapy created a satellite program in Calgary which is 300 Km away south of Edmonton. At any one time, there are two cohorts (year one and year two). Each cohort has 98 students in Edmonton and 22 students in Calgary. The program uses distributed learning approach where students at both sites receive instruction at the same time and follow the same curriculum through the use of high definition videoconferencing and other information and communication technologies.

Information and communication technologies have the potential to enhance education and professional networks between healthcare professional including occupational therapists [2]. Our aim as educators is to prepare future generations of health professionals to perform their jobs in the community and in clients' home environments. In essence, we wish to apply information and communication technologies to create meaningful, context-specific, community-based learning for our students who will work in teams or communities of practice. Information and communication technologies have been used for learning in a variety of disciplines. E-learning is based on the use of wired and wireless Internet. Mobile learning (or m-learning) is a part of e-learning. Mobile learning is defined as "any sort of learning that happens when the learner is not at a fixed predetermined location, or learning that happens when the learner takes advantage of the learning opportunities offered by mobile technologies" [4, p. 6]. Mobile learning refers to learning activities facilitated by the use of mobile information and communication technologies, such as cell phones, smart phones, palmtops, tablet personal computers, personal digital assistants and portable multimedia players [3]. Mobile information and communication technologies have the potential to provide educational opportunities for students in higher education because they can facilitate students' access to information and interaction with instructors, peers and colleagues regardless the place where they are located [5]. Mobile information and communication technologies are expected to support the learning experience in several ways. They can: support, guide, and extend the students' thinking process within and out of the classroom; enhance learner creativity, exploration and problem solving; facilitate the process for students to express their opinions; and enable learning with students' preferred approach and

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speed of communication, making learning more autonomous and self-reliant [6].

University students value the portability and immediacy of smart phones and tablets for obtaining and sharing information with peers [7]. Mobile information and communication technologies have been accepted by students in university lectures and are perceived as useful and easy to use. Additionally, students' attention and motivation are higher with metacognitive supports provided via mobile technologies during class [8]. Research has revealed that the use of technologies for learning activities depends on students' perception towards technologies [9]. However, little research has investigated the factors that determine students' acceptance of mobile information and communication technologies for learning [3]. Much less attention has been given to the study of factors associated with adoption behavior of mobile information and communication technologies by occupational therapy students.

Theories from the social sciences have explained how and why people adopt technologies, calling this construct as the behavioral intention to use technology [10]. The Unified Theory of Acceptance and Use of Technology (UTAUT) [11] integrates previous models with the behavioral intention perspectives and use of technologies. The UTAUT model has six constructs: 1) Performance expectancy (PE) defined as the degree to which a person believes that using the technology will help him or her to attain gains in job performance. 2) Effort expectancy (EE), the degree of ease associated with the use of the technology. 3) Social influence (SI), the degree to which a person perceives that important others believe he or she should use the technology under study. 4) Facilitating conditions (FC), the degree to which a person believes that an organizational and technical infrastructure exists to support use of the technology. 5) Behavioural intention (BI), the intention to do some Behavior and 6) Use, the overt behavior [10].

According to the UTAUT model, four constructs play a role as direct predictors of behavioral intention to use the technology under study and two have a direct influence on the use. Performance expectancy (PE), effort expectancy (EE), and social influence (SI) are direct determinants on *behavioural intention* (BI); and facilitating conditions (FC) and Behavioural Intention (BI) to use the technology are the two determinants that have a direct impact on *use* of the technologies. Based on this theoretical framework, our study objectives were to develop a path model (path analysis) of mobile information and communication technologies acceptance by university students and to analyze the relationship of the UTAUT constructs, i.e., how performance Expectancy, Effort Expectancy, Social Influence determine students' Behavioural Intention to use mobile information and communication technologies for learning. In addition, some descriptive statistics related to m-learning use were also used to explain the Behavioural Intention. We think that our results might help program administrators and instructors implement strategies for m-learning. Thus, the aim of this study was to answer the following research question:

What factors affect the acceptance behavior of mobile information communication technologies for learning by students in a MSc in occupational therapy program in a University in Canada?

This paper is organized as follows: related works, the theoretical framework and the research objectives and question are presented in the first section. Materials and methods are presented in the second section. Results, discussion and conclusions are presented in the third, fourth and fifth section, respectively.

II. MATERIALS AND METHODS

In this study, we used a cross-sectional exploratory approach using a self-administrated paper-based survey. This study received approval from the University of Alberta Health Research Ethics Board. The target population consisted of all students at the occupational therapy masters program (MScOT). We tested the model using the Partial Least Squares (PLS) technique. We adopted guidelines for sample size where a minimum of 10 subjects should be surveyed per total number of dependent variable with the largest number of independent variables influencing it [12]. Therefore, the minimum sample size required for this study was 40 subjects.

We created a survey questionnaire designed to measure the constructs and relationships contained in our research model. The 36-items were grouped into three sections. In the first section (section A1, items from 1-5), we asked for participant demographics and background or previous degree. In the second section (section A2, item 6 and 7) we inquired about the students' experience using mobile information and communication technologies including mobile technology (e.g., smart phone, tablet, digital camera), and mobile applications and software (e.g., paid short message service, Skype, wiki), as well as the average daily use over the last week (in hours/day) of these technologies during personal and study time. In the third section (section B, items from 8-35), we created specific questions (items 8-35) by adapting scales and items already validated and with high levels of internal consistency in previous research for each construct of the model (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Behavioural Intention). Part B also included four items for assessing attitude towards and anxiety generated by mobile information and communication technologies [3] [11].

Under the logic of PLS modeling, the model is formed by one or more blocks, which is a structure formed by a latent variable (each UTAT construct in this study) with its manifest variables (MV) (each questionnaire item per construct). The LVs can be exogenous, endogenous, or both. A latent variable is exogenous when it is not predicted by any other latent variable. A latent variable is endogenous when it is predicted in by one or more latent variables. The structural model is composed of the relationships or paths amongst exogenous and endogenous latent variables. In this research we had one outcome (endogenous) latent variable (i.e., Behavioural Intention); and four independent latent variables (Performance Expectancy (questionnaire items 8-11), Effort Expectancy (items 12-15), and Social Influence (items 16-19) were considered as direct latent variable (independent or exogenous variables) of Behavioural Intention. We measured Facilitating Conditions (items 20-23), however, we did not use it in the path model because Facilitating Conditions is considered to be direct latent variable of use in the UTAUT model and we did not measure use behavior in this study. We measured attitude and anxiety toward using technologies, however, we did not include them in the path analysis in our study because it has been reported that these constructs are significant only when performance and effort expectancies are not included in the model [11].

Confounding variables were operationalized according to [13] methods as follows: Dichotomous variables were coded as “0” or “1” (e.g., student’s gender, and student’s year in the MScOT program). All items of section B of the questionnaire (items from 8-35) related to each dependent and independent latent variables were scored on a 7-point Likert scale, ranging from “strongly disagree (1)” to “strongly agree (7)” [14]. As we had four questions per construct, the numbers of items per construct exceeded the minimum three items required for proper calculation of measurement errors [15].

Before sending out the surveys to participants we conducted a pilot study with six students (graduate and undergraduate) selected by convenience. We made minor changes to clarify some of the questionnaire items. We held a meeting with all potential study participants (230 MScOT students) where researchers distributed packages, including an information letter, informed consent form and the survey questionnaire to students. Students who agreed to participate filled out the survey at that moment. We used codes for the surveys instead of students’ names or ID in order to ensure anonymity and confidentiality. Students who were unable to attend the meeting were invited to sign the consent form and complete the questionnaire online. A list with the match between students’ identifiers and survey codes were stored in a locked file cabinet.

Before the statistical analysis, a random sample of 20% of the entered data was compared to check coding accuracy. We used descriptive statistics to summarize demographic data. We conducted correlation analysis (Pearson or Spearman Rho as appropriate) to determine whether survey responses for Performance Expectancy, Effort Expectancy, Social Influence and, Behavioural Intention to use, were correlated with students’ age, gender, city of the program, year in the program, attitude and anxiety toward technologies, and average daily hours of mobile information and communication technologies use for personal purposes, and education purposes. Missing data was handled in the following manner: (1) missing data of continuous variables such as students’ clinical experience and age were replaced by the average values of these variables; and (2) for categorical and ordinal variables such as the discipline or type of the therapists, and their educational level, missing data were replaced by the medians of these variables.

We tested the multivariate research model using the PLS technique [16]. The PLS measurement model evaluation was conducted by means of: (1) reliability measurement for each construct (Cronbach’s alpha); (2) convergent validity measurement of each set of items with respect to their associated construct will be assessed by examining the factor loadings of the items on the model’s constructs; and (3) discriminant validity was analyzed by using Average Variance Extract (AVE) indicator. PLS structural model was evaluated by means of (β) paths coefficients, the explained variance (R^2) and the effect size (f^2) for each path segment of the model. Also the Bootstrapping re-sampling method was employed to verify the statistical significance of (β) paths coefficients of the PLS model. The alpha level of significance was set at $p \leqslant 0.05$. IBM SPSS® V 22.0 and SmartPLS V 2.0 M3statistics package were used to generate descriptive, univariate and bivariate statistics, and PLS path modeling respectively.

III. RESULTS

Regarding our sample size, considering that the potential subjects to be surveyed were 230 students, and that we retrieved 213 surveys, we achieved a 93% response rate and a statistical power of 100%. The only large effect size was the one for the path Social Influence→ Behavioural Intention: (f^2=0.771) (see Table II). We achieved 99.5% of accuracy in data entering. Missing data was low (e.g., we had missing information in the students’ year (0.9% of respondents) and previous experience with of some information and communication technologies (between 0.9% and 2.2% of respondents). In part B of the survey, we had 3.8% missing data. After using missing data procedures we found negligible changes in variables.

TABLE I. STUDENTS PREVIOUS EXPERIENCE WITH TECHNOLOGIES

ICTs used	n (%)	AHP[S.D.]	AHE[S.D.]
Mobile ICTs	204 (96.2)	9.00[9.00]	6.08[4.12]
Smart phone	200 (94.3)	3.3 [3]	1.1 [1.8]
Mobile phone	6 (2.8)	2.5 [2.1]	5.5 [6.4]
Laptop computer	203 (95.8)	2.5 [2.3]	4.3 [2.3]
Tablet	56 (26.4)	1.2 [0.9]	1.7 [1.9]
GPS navigation device	49 (23.1)	0.7 [1.1]	0.1 [.31]
Audio/Video recording	12 (5.7)	0.6 [0.5]	0.0 [0.1]
Digital camera	33 (15.6)	0.7 [1.3]	0.5 [1.6]
Other device	5 (2.4)	1.3 [1.5]	0.7 [1.2]
Paid short message service	143 (67.5)	2.2 [3.9]	0.5 [2.6]
Free mobile messaging app	84 (39.6)	1.6 [3.0]	0.1 [0.8]
Goniometer App	3 (1.4)	0.0 0	0.00
Skype	64 (30.2)	1.5 [2.7]	0.0 [0.1]
FaceTime	63 (29.7)	0.8 [0.7]	0.0 [0.0]
Blogs	20 (9.4)	1.2 [1.2]	0.8 [1.3]
Wiki	35 (16.5)	0.7 [0.9]	1.0 [1.2]
Other app	5 (2.4)	1.7 [2.5]	1.3 [1.1]

S.D: Standard deviation, **Sample size: 212**
AHP: Average hours ICTs daily use for personal purposes
AHE: Average hours ICTs daily use for education

Overall, participants had an average age of 24.81years (SD 9.93), were mainly female (90.6%), and located in Edmonton (82.5%). Table I shows the previous experience of students with mobile devices and applications as well as students' average daily hours of mobile information and communication technologies (devices and applications) for personal use in the last week. Overall: (1) almost all students had previous experience using mobile devices and applications; (2) the mobile devices most used by students were smart phones (94.3%) and laptop computers (95.8%); (3) the mobile applications most used by students were paid short message service (SMS) (67.5%), free mobile messaging app (39.6%) followed by Skype and FaceTime (30.2% and 29.7% respectively). Smart phones had the highest average weekly hours of personal use (3.3 hours), Mobile phones and laptop computers had the highest average of daily hours used for education (5.5 hours, and 4.3 hours respectively).

We used the UTAUT constructs to examine the overall perceptions of students about mobile information and communication technologies for learning: (1) students thought that mobile information and communication technologies for learning will help them to increase their academic performance and learning (Performance expectancy: 78.2% Agree (Agree-strongly agree), Mode 5.00; Mean 5.32 SD 1.20); (2) students perceived that mobile information and communication technologies for learning are easy to use or not complicated to use (effort expectancy: Agree (Agree-strongly agree: 76.7%), Mode: 5, Mean 5.30 SD 1.08); (3) students tended to be either neutral or agree with the perception that the intention to use mobile information and communication technologies for learning is influenced positively by the opinions and perceptions of peers or instructors. (Social Influence: agree (Strongly-Agree: 35.9%), Neither agree or disagree: 37.5%), Mode: 4, Mean 4.14 SD 1.20); (4); students agreed that in the academic program under study, most of the conditions such as opportunities, resources, technical support and knowledge, as well as that the mobile information and communication technologies are compatible with their educational goals (facilitating conditions Agree (Agree-Strongly: 74.6%), Mode: 5, Mean 5.07 SD 1.18); (5) there was a strong trend in Behavioural Intention to use mobile information and communication technologies for education by students (Behavioural Intention: Agree (Agree-Strongly: 72.2%), Mode: 5, Mean 5.14 SD 1.26); (6) in the same way students´ attitude towards using mobile information and communication technologies for learning is positive (Attitude: Agree (Agree-Strongly: 65.2%), Mode: 5, Mean 4.88 SD 1.14); and (6) students disagree that mobile information and communication technologies generate anxiety in terms of apprehension, intimidation, hesitation or stress (Disagree (strongly-Disagree: 53.6%), Mode: 3; Mean: 3.53, SD: 1.42).

Although the UTAUT model includes gender, age, experience with the technology and voluntary use as possible moderators in the relationship between the four main constructs and the Behavioural Intention or use of technologies [11], we did not include age because age was homogeneous in our sample. Neither did we include gender because in a bivariate analysis the correlation was not significant (Spearman Rho: 0.049, p=0.24). As a measure of experience in the use of mobile information and communication technologies, we included as confounder variable in the PLS multivariate analysis the average hours of use of mobile information and communication technologies for education whose correlation with behavioral intention was found to be significant (Spearman Rho: 0.398, p=0.02).

The results of the structural model estimate are shown in Table II. We ran the PLS structural model using the bootstrap procedure with 500, 1000, 2000, and 5000 times of resampling and the magnitude and significance of the structural paths were consistent. The multivariate model in PLS structural model showed that: (1) that there is statistically significant and positive correlation between Performance Expectancy (PE) and Behavioural Intention (BI) to use mobile information and communication technologies for learning (PE→BI=+0.237, p<0.000); (2) there is no statistical evidence to support the assertion that Effort Expectancy (EE) has a positive influence on Behavioural Intention (BI) to use mobile information communication technologies for learning (EE→BI=+0.090, p<0.119); and (3) there is a strong statistically significant and positive correlation between Social Influence (SI) and Behavioural Intention (BI) to use mobile information communication technologies for learning (SI→BI =+613 p<0.000). Thus, Performance Expectancy and Social Influence constructs matter in Behavioural Intention to use mobile information communication technologies for learning by students, and whereas Effort Expectancy construct did not.

TABLE II. STRUCTURAL MODEL. (PERFORMANCE EXPECTANCY (PE), EFFORT EXPECTANCY (EE), SOCIAL INFLUENCE (SI), BEHAVIOURAL INTENTION (BI), AVERAGE DAILY HOURS ICTS USE FOR EDUCATION (AHE))

Path	Path Coefficient β	t-value	f^2	Q^2	R^2
PE→ BI	0.237	3.369**	0.073	0.475	0.521
EE→ BI	0.090	1.561	0.011		
SI→ BI	0.613	6.361**	0.771		
AHE→ BI	0.108	1.809	0.024		

Endnotes

* p<0.05; **p<0.01; **f^2**: effect size

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{excluded}}};$$

Q^2: Stone Geisser indicator ; **GoF:** Goodness of fit

$$GoF = \sqrt{\overline{Communality} * \overline{R^2}}$$

Regarding the model validity and reliability, all item loadings were statistically significant at the 0.001 level and all item loadings were greater than 0.70, indicating good convergent validity at the indicator level. All internal composite reliability (ICR) values were greater than 0.70, indicating acceptable reliability. The square root of each average variance extracted (AVE) (shown on the diagonal in

Table III) is greater than the related inter-construct correlations in the construct correlation matrix, indicating adequate discriminant validity for all of the reflective constructs.

TABLE III. CONSTRUCT CORRELATIONS (PERFORMANCE EXPECTANCY (PE), EFFORT EXPECTANCY (EE), SOCIAL INFLUENCE (SI), BEHAVIOURAL INTENTION (BI), AVERAGE DAILY HOURS ICTS USE FOR EDUCATION (AHE)) SD= STANDARD DEVIATION; CA=CRONBACH'S ALPHA.

Construct	Mean	SD	CA	ICR	AVE	BI	EE	PE	SI	AHE
BI	5.14	1.26	0.97	0.98	0.93	0.96				
EE	5.30	1.08	0.85	0.90	0.69	0.26	0.83			
PE	5.32	1.20	0.86	0.91	0.71	0.34	0.61	0.84		
SI	4.14	1.20	0.85	0.90	0.69	0.65	0.04	0.07	0.83	
AHE	6.08	4.12	1.00	1.00	1.00	0.20	0.05	0.06	0.11	1.00

The explained variance of the model (R^2) was 0.521 for Behavioural Intention to use mobile information communication technologies for learning which do appear to be strong according to [17] criteria. The Stone–Geisser's Q^2 value for Behavioural Intention to use mobile information communication technologies for learning construct was 0.475, indicating good predictive relevance of our model ($Q>0$ indicates good predictive relevance).

IV. DISCUSSION

The aim of this study was to examine what factors affect the acceptance of mobile information and communication technologies for learning by students in a MSc program in occupational therapy at a University in Canada. We found statistical support to assert that performance expectancy (PE) and social influence (SI) affect the behavioural intention (BI) to use mobile information and communication technologies for learning. In our study, effort expectancy was not a determinant of Behavioural Intention to use mobile information and communication technologies. Previous research in acceptance of mobile information and communication technologies for learning are mixed. On one hand, a study using the UTAUT model with university students found that Performance Expectancy, Social Influence and Effort Expectancy were determinants of Behavioural Intention to use the free mobile messaging app for learning purposes [18]. However, another study using the Technology Acceptance Model (TAM) found that neither perceived usefulness (Performance Expectancy in the UTAUT) nor perceived ease of use (Effort Expectancy in the UTAUT) had an effect on the Behavioural Intention of students who were taking e-learning courses [3]. In our case, our results that Performance Expectancy and Social Influence determine Behavioural Intention are aligned with the UTAUT model. The fact that Effort Expectancy did not determine the Behavioural Intention in our model can be explained by the fact that the constructs Effort Expectancy and Performance Expectancy were significantly correlated (Spearman Rho: 0.579, $p=0.000$), thus, these two constructs showed collinearity. In order to control this collinearity, we calculated a structural model in which Performance Expectancy was eliminated. This resulted in Effort Expectancy to become in a statistically significantly predictor of Behavioural Intention; however, without Performance Expectancy the model prediction was reduced in 8% ($R^2=0.487$) which is not convenient. Thus, we decided to keep in our model both Performance Expectancy and Effort Expectancy with a R^2 of 0.521.

Students in our sample thought that mobile information and communication technologies have the potential to help them to increase their academic performance and learning. This result is consistent with previous research where university students in Canada and the USA tend to believe that mobile information and communication technologies such as cell phones, smart phones, and tablets are important to their academic success and use their devices for academic activities [5]. Students in our study also believed that mobile information and communication technologies for learning were easy to use, or not complicated to use (EE). This positive perception can be explained by the previous experience with the use of mobile information and communication technologies (mainly smart or mobile phones, laptops, SMS, WhatsApp and Skype) by students as we found a statistically significant correlation between effort expectancy (EE) and the average hours students used information and communication technologies for personal use (Spearman Rho: 0.213, $p=0.005$). In the same way, students demonstrated a positive attitude towards using mobile information and communication technologies for education and felt that they have the conditions (e.g., resources, opportunities and technical support) for using mobile information and communication technologies for learning. These results are encouraging for academic purposes because we can assume that students perceived that they have the basic skills and conditions for using mobile information and communication technologies. This can ease the implementation of learning strategies using information and communication technologies. Regarding location, we found a statistically significant negative correlation between city and Behavioural Intention, i.e., students in Calgary had higher behavioural intention (BI) to use the mobile information and communication technologies for learning. This result is not surprising because Calgary is a satellite program, Calgary students have the need to do more remote interactions with their instructors in Edmonton than those students living in Edmonton.

On the other hand, we found that students in our study used mobile phones and laptop computers for education more than four hours per day. Other technologies such as tablets, smart phones, free mobile messaging apps, Skype, blogs and wikis were used less than 2 hours per day for education activities despite the literature reporting that these types of mobile information and communication technologies increases collaborative learning, leadership [19], immediacy for obtaining and sharing information with peers [7], and enhancing attention and motivation during lectures [8]. Therefore, our results invite reflections about the need for universities to increase the academic activities

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where students have opportunities to benefit from the use of information and communication technologies.

We propose further research to examine the additional mobile information and communication technologies to investigate how these strategies can facilitate small group learning approaches and interactions across distances. These strategies include the use of mobile technologies and apps for development of competencies in interviewing simulated clients with mental health conditions, and physical assessments of activities of daily living.

V. CONCLUSION

This study shows that performance expectancy (PE) and social influence (SI) affect the behavioural intention (BI) to use mobile information and communication technologies for learning by students in a MSc in occupational therapy program at a University in Canada. Our structural model achieved a strongly explained variance of Behavioural Intention, good convergent validity and acceptable reliability. In general, students had a positive attitude towards the use of mobile information and communication technologies for learning. However, currently they are using few mobile information and communication technologies devices and applications for academic purposes. Our results support the development of strategies to increase the use of mobile information and communication technologies for teaching and learning with university students in a health profession program.

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REFERENCES

[1] Canadian Institute for Health Information, "Occupational Therapists in Canada, 2011 Occupational Therapist Provincial Reports [Online]. Available: https://secure.cihi.ca/estore/productFamily.htm?locale=en&pf = [Accessed 20 May 2015].

[2] T. Hoffmann, L. Desha, and K. Verrall, "Evaluating an online occupational therapy community of practice and its role in supporting occupational therapy practice," Australian Occupational Therapy Journal, vol. 58, p. 337–345, 2011.

[3] S. Park, M.-W. Nam, and S.-B. Cha, "University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model," British Journal of Educational Technology, vol. 43, no. 4, p. 592–605, 2012.

[4] C. O'Malley, G. Vavoula, J. Glew, J. Taylor, M. Sharples, and P. Lefrere, "Guidelines for learning/teaching/tutoring in a mobile environment," MOBIlearn/UoN,UoB,OU/D4.1/1.0, n.p., 2003.

[5] J. Gikas and M. Grant, "Mobile computing devices in higher education: Student perspectives on learning with cellphones, smartphones & social media," Internet and Higher Education, vol. 19, p. 18–26, 2013.

[6] J. Rikala and M. Kankaanranta, "The Nature Tour Mobile Learning Application Implementing the Mobile Application in Finnish Early Childhood Education Settings," in 6th International Conference on Computer Supported Education CSEDU 2014, Barcelona, Spain, April 2014, vol. 3, pp. 171-178,.

[7] P. Rebaque-Rivas, E. Gil-Rodríguez, and I. Manresa-Mallol, "How to Design a Mobile Learning Environment Recommendations Based on Student Perceptions," in 6th International Conference on Computer Supported Education CSEDU 2014, Barcelona, Spain, April 2014, vol. 3, pp.145-152.

[8] F. Kapp, I. Braun, H. Körndle, and A. Schill, "Metacognitive Support in University Lectures Provided via Mobile Devices How to Help Students to Regulate Their Learning Process during a 90-minute Class," in 6th International Conference on Computer Supported Education CSEDU 2014, Barcelona, Spain, April 2014, vol. 3, pp.194-199.

[9] S. Hadjerrouit, "Wiki-mediated collaborative writing in teacher education assessing three years of experiences and influencing factors," in Proceedings of the 6th International Conference on Computer Supported Education CSEDU 2014, Barcelona, Spain, April 2014, vol. 1, pp.5-14.

[10] I. Ajzen, "The theory of planned behavior," Organizational Behavior and Human Decision Processes., vol. 50, no. 2, pp. 179-211, 1991.

[11] V. Venkatesh, M. Morris, G. Davis, and F. Davis, "User Acceptance of Information Technology: Toward a Unified View.," Mis Quarterly, vol. 27, no. 3, pp. 425-478., 2003.

[12] D. Peng and F. Lai, "Using partial least squares in operations management research: A practical guideline and summary of past research.," Journal of Operations Management, vol. 30, pp. 467-480, 2012.

[13] E. Biddis and T. Chau, "Multivariate prediction of upper limb prosthesis acceptance or rejection," Disability and Rehabilitation: Assistive Technology, vol. 3, no. 4, pp. 181-192, 2008.

[14] P. Ifinedo, "Technology acceptance by health professionals in Canada: An analysis with a modified UTAUT model," in 45th Hawaii International Conference on System Sciences, Grand Wailea, January 2012, pp. 2937-2946.

[15] W. Chin, B. Marcolin, and P. Newsted, "A partial Least Squares Latent Variable modeling approach for measuring interactions effects: Results from a monte Carlo siulation study and an electronic-main emition / adotion study.," Information systems research, vol. 14, no. 2, pp. 190-217, 2003.

[16] W. Chin, "The partial least squares approach to structural equation modeling," in Modern Methods for Business Research, Mahwah, NJ, Lawrence Brlbaum Associates, 1998, p. 295–336..

[17] J. Hair, G. Hult, C. Ringle, and M. Sarstedt, A primer on partial least squares structural equation modelling (PLS-SEM), L.A.: Sage, 2014.

[18] A. Bere, "Exploring Determinants for Mobile Learning User Acceptance and Use: An Application of UTAUT," in 2014 11th International Conference on Information Technology: New Generations, Las Vegas, 2014.

[19] C. Davis and H. Goodman, "Virtual Communities of Practice in Social Group Work Education," Social Work with Groups, vol. 37, no. 1, pp. 85-95, 2014.

