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The Relationship among Self-Efficacy, Social Influence, Performance Expectancy, Effort Expectancy, and Behavioral Intention in Mobile Learning Service

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Abstract

The purpose of this study is to examine the structural relationship among self-efficacy, social influence, effort expectancy, performance expectancy, and behavioral intention of mobile learning, which is based on the extended technology acceptance model. We performed a study to determine the impacts that social influence, performance expectancy, and effort expectancy have on behavioral intention of mobile learning through self-efficacy. Appropriate measures were developed and tested on 226 university students of Gyeongnam province in South Korea with a cross-sectional questionnaire survey. The path relationship of the research model was analyzed by structural equation modeling (SEM) using AMOS 18.0. The results revealed that firstly, self-efficacy has positive effects on performance expectancy, social influence, and effort expectancy. Second, social influence has positive effects on performance expectancy, behavioral intention, and effort expectancy. Third, effort expectancy has positive effects on performance expectancy and behavioral intention. Fourth, performance expectancy has a positive effect on behavioral intention. Managers of mobile learning should focus on self-efficacy to enhance behavioral intention.

Keywords: *Mobile Learning, Behavioral Intention, Self-Efficacy, Social Influence, Performance Expectancy, Effort Expectancy*

1. Introduction

There have been several theoretical models employed to study user acceptance and usage behavior of emerging information technologies. While many of the models incorporate perceived ease of use as a determinant of acceptance, the Technology Acceptance Model (TAM) is the most widely applied model of user acceptance and usage [1]. TAM suggests that two specific beliefs (perceived ease of use and perceived usefulness) determine one's behavioral intention to use a technology, which has been linked to subsequent behavior [2].

Information technology (IT) acceptance research has yielded many competing models, each with different sets of acceptance determinants. Venkatesh, *et al.*, [3] suggest that the Unified Theory of Acceptance and Use of Technology (UTAUT) provides a useful tool for managers needing to assess the likelihood of success for new technology introductions and helps them understand the drivers of acceptance in order to proactively design

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interventions (including training, marketing, *etc*.,) targeted at populations of users that may be less inclined to adopt and use new systems.

Information technology (IT) acceptance and use is an issue that has received the attention of researchers and practitioners for over a decade. Successful investment in technology can lead to enhanced productivity, while failed systems can lead to undesirable consequences [4]. Availability of information technology does not necessarily lead to its acceptance. Most information system failures result from a lack of user acceptance rather than poor quality of the system [5, 6]. A greater understanding of the factors that impact user behavior could help organizations develop appropriate adoption strategies of mobile learning.

Mobile learning has unique technological attributes which provide positive pedagogical affordances. Above all, mobility enables ubiquitous learning in formal and informal settings by decreasing "the dependence of fixed locations for work and study, and consequently change the way we work and learn" [7].

Self-efficacy is the belief that teachers develop regarding their influence on student learning outcomes [8]. Teachers with high self-efficacy feel empowered to affect student success, whereas teachers with low self-efficacy have little confidence in their ability to promote students' learning [9]. Moreover, teachers with high efficacy beliefs report being more receptive to implementing new instructional practices compared to their less efficacious colleagues [10]. Self-efficacy can also play an important role in enhancing the performance of mobile learning.

The positive relationships between social influence and effort expectancy and behavioral intention have been identified in the previous studies [3], but little has been done to investigate the role of self- efficacy in mobile learning. Thus, this study proposes and tests a theoretical model incorporating self-efficacy, social influence, performance expectancy, effort expectancy, and behavioral intention of mobile learning. This study also contributes to the literature by focusing on self-efficacy and social influence, which can explain the unique pedagogical characteristics of smartphones as a clear subset of mobile devices.

2. Literature Review

A major function of intelligent thought is to enable people to predict the probability of future events, and subsequently to exercise control. Perceived self-efficacy refers to individuals' beliefs concerning their ability to meet desired outcomes in life [11, 12]. Self-efficacy has been positively related to higher levels of achievement and learning, as well as a wide variety of adaptive academic outcomes such as higher levels of effort and increased persistence on difficult tasks [13]. Thus, we propose the following hypotheses:

H1 Self-efficacy will have a positive effect on performance expectancy.

H2 Self-efficacy will have a positive effect on social influence.

H3 Self-efficacy will have a positive effect on effort expectancy.

Theories applied in studies investigating technology adoption, use and attitudes towards systems, commonly employ social influence as one of the predictors for the outcome behavior or behavioral intention. Such theories are, for example, the theory of reasoned action (TRA) and the theory of planned behavior (TPB) which was developed from the TRA [13].

Prior information systems literature has investigated the social influence in a variety of contexts, such as organizational knowledge sharing [14], social networking services [15], e-learning [16], blogs [17], and e-commerce [18].

Common to many such motivational applications is the attempt to employ social influence through a user community in order to entice people to maintain their sustainable behavior. The generally increased use of social features in technologies can also be observed elsewhere [19]. In the information technology context, experiencing relatedness

through the use of a system potentially makes the user more willing to engage with the system and continue using it [20]. Venkatesh, *et al.*, [3] suggested that social influence has a positive effect on behavioral intention. Thus, we propose the following hypotheses:

H4 Social influence will have a positive effect on performance expectancy.

H5 Social influence will have a positive effect on behavioral intention.

H6 Social influence will have a positive effect on effort expectancy.

Some authors have assumed that presentation of unique reinforcers for each stimulus-response sequence is conducive to the development of a specific expectancy of a given outcome [21]. Expectancy theory proposes that when a person makes decision on whether or not to spend effort on work, s/he goes through a whole cognitive process that involves three key motivational elements namely valence, instrumentality and expectancy [22]. Venkatesh et al. [3] suggested that performance expectancy and effort expectancy have positive effects on behavioral intention. Thus, we propose the following hypotheses:

H7 Effort expectancy will have a positive effect on performance expectancy.

H8 Performance expectancy will have a positive effect on behavioral intention.

H9 Effort expectancy will have a positive effect on behavioral intention.

3. The Research

The research is designed to confirm the relationships among self-efficacy, performance expectancy, social influence, effort expectancy, and behavior intention of mobile learning. The research model is shown in Figure 1.

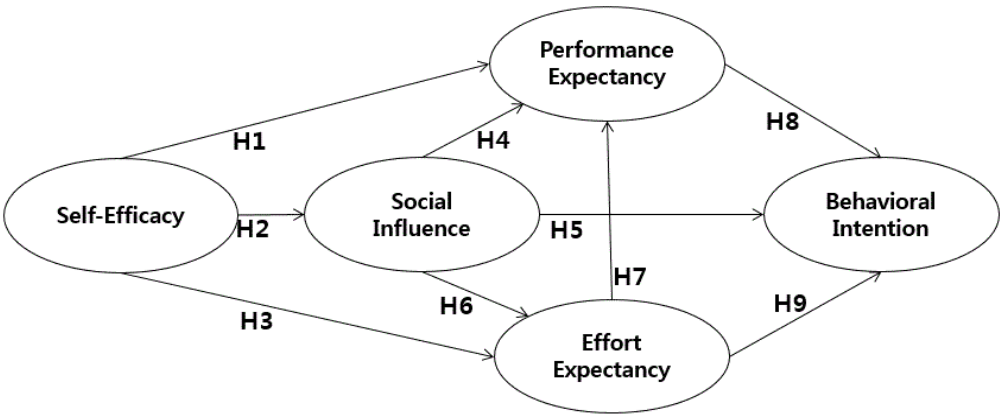

Figure 1. Research Model

A self-administered questionnaire was developed for this study. The survey included perception of self-efficacy, social influence, performance expectancy, effort expectancy, behavioral intention and demographic information.

Convenient sampling drew a sample of 300 university students who have experienced mobile learning service. A sample of university students may have a representative in this study, considering mobile learning's characteristics. For data collection purposes, a personal interview technique was used at Gyeongnam province from May 11 to 29, 2015 and of the 300 questionnaires, 74 questionnaires were eliminated due to missing data, resulting in a final sample of 226 students. The participants were asked to respond to the survey questionnaires based on their most recent experience of mobile learning.

In this study, items used to operationalize the constructs were mainly adapted from previous studies and modified in the context of mobile learning. Self-efficacy is the degree to which an individual believes that he or she has the ability to perform a specific task/job using the mobile learning [23]. Performance expectancy is the degree to which a person believes that using mobile learning system would enhance his or her learning

performance [1]. Effort expectancy is the degree to which a person believes that using mobile learning system would be free of effort [3]. Social influence is the degree to which an individual perceives that most people who are important to him think he should or should not use mobile learning system [24]. Behavioral intention is an individual's positive or negative feelings about performing the target behavior [3]. All items used in this study were measured on a seven-point Likert-type scale (1 = strongly disagree and 7 = strongly agree).

Table 1. Measurement Scales

Variable	Items	references
Self-Efficacy	I could complete the job using a mobile learning …if there was no one around to tell me what to do as I go. …if I had just the built-in help facility for assistance. …if someone showed me how to do it first.	[23]
Performance Expectancy	Using mobile learning system in my job would enable me to accomplish tasks more quickly. Using mobile learning system would improve my job performance. Using mobile learning system would make it easier to do my job.	[1], [3]
Effort Expectancy	Learning to operate mobile learning system would be easy for me. I would find it easy to get mobile learning system to do what I want it to do. I would find mobile learning system easy to use.	[1], [3]
Social Influence	People who influence my behavior think that I should use mobile learning system. People who are important to me think that I should use mobile learning system. The acquaintance of this business has been helpful in the use of mobile learning system	[1], [3]
Behavioral Intention	I like the idea of using mobile learning system. Using mobile learning system is pleasant. I have fun using mobile learning system.	[1], [3]

In order to test the proposed interrelationships among perception of self-efficacy, social influence, performance expectancy, effort expectancy, and behavioral intention, structural equation modeling (SEM) was performed using analysis of moment structure (AMOS). Structural equation modeling allowed us to examine the causal relationships among concepts in the model and to test the model against the obtained measurement data to identify how well the proposed model fits the data [25]. SEM is an appropriate statistical method to examine hypothesized relationships among constructs proposed in this study.

4. Findings

Examination of demographic characteristics is as follows. Among 226 university students, 53.1 percent were male and 46.9 percent were female. Most of the students were in the 20-29 age range. Two times of experience frequency of mobile learning accounted for 40.3 percent and one times accounted for 35.8 percent. SAT accounted for 56.2 percent and foreign language accounted for 21.9 percent in the areas of mobile learning.

Table 2. Sample Characteristics

Gender	Freq.	Percent	Job	Freq.	Percent	Area of mobile learning	Freq.	Percent
male	120	53.1	student	226	100	SAT	136	56.2
female	106	46.9	total	226	100%	foreign language	53	21.9
total	226	100%	Experience	Freq.	Per.	public official	4	1.7
Age	Freq.	Per.	1 times	81	35.8	certificate	17	7.0
20~29	226	100	2 times	91	40.3	etc	32	13.2

total	226	100%	3 times	23	10.2	total *plural response	242	100%
Education	Freq.	Per.	4 times	9	4.0			
undergraduate	226	100	more than 5 times	22	9.7			
total	226	100%	total	226	100%			

Table 3. Reliability & Convergent Validity of Measurement Model

Variables	Items	Estimate	Std. Estimate	S.E.	t-value	Composite reliability	AVE	Cronbach's α
Self-Efficacy	1	.978	.879	.053	18.629	.895	.759	.901
	2*	1.000	.917					
	3	.880	.814	.054	16.279			
Performance Expectancy	1*	1.000	.844			.855	.663	.852
	2	.939	.772	.074	12.746			
	3	.932	.804	.070	13.399			
Effect Expectancy	1	.727	.752	.064	11.405	.800	.573	.798
	2*	1.000	.825					
	3	.793	.702	.075	10.574			
Social Influence	1	.917	.852	.064	14.326	.856	.667	.852
	2*	1.000	.892					
	3	.751	.694	.066	11.424			
Behavioral Intention	1	.973	.864	.057	17.094	.852	.659	.878
	2*	1.000	.894					
	3	.950	.773	.066	14.279			

Model Fit Indices: $\chi 2(80)=126.798$, p=0.001, GFI=0.932, AGFI=0.898, NFI=0.943, CFI=0.978, TLI=0.971, RMR= 0.040, RMSEA=0.051, *Reference variables

Confirmatory factor analysis (CFA) was performed to assess the overall model fit of the measurement model (see Table 3). The model fit indices showed that chi-square = 126.798, df = 80, p = 0.001, chi-square/df = 1.585, GFI = 0.932, NFI = 0.943, CFI = 0.978, TLI = 0.971, and RMSEA = 0.040, which suggests that the measurement model reasonably fits the current data. Further, the results of the reliability test showed that the alpha values of all four constructs used in this study exceeded the minimum requirement for reliability of 0.70, indicating that multiple measurement items were highly reliable for measuring each construct [25]. Also, convergent validity was examined with the factor loadings in the measurement model. All confirmatory factor loadings exceeded the accepted level of 0.5, and all factor loadings were significant at the alpha level of 0.01 [26]. Furthermore, average variance extracted (AVE) of all constructs exceeded the recommended 0.5 threshold [25]. Discriminant validity was also assessed by comparing the AVE with the squared correlations between constructs [25]. All of the squared correlations between the two constructs were less than the AVEs, which suggests that the constructs were distinct.

Table 4. Discriminant Validity of Measurement Model

Variables	Correlation								AVE
	(1) SE (ρ^2)		(2) PE (ρ^2)		(3) EE (ρ^2)		(4) SI (ρ^2)		
(1) Self-Efficacy	1								.759
(2) Performance Expectancy	.664	(.441)	1						.663
(3) Effort Expectancy	.644	(.415)	.732	(.536)	1				.573
(4) Social Influence	.336	(.113)	.472	(.223)	.481	(.231)	1		.667
(5) Behavioral Intention	.661	(.437)	.749	(.561)	.726	(.527)	.545	(.297)	.659

A structural model was estimated to test H1 through H9. The goodness-of-fit statistics of the proposed model showed that the model reasonably fits the current data (Chi-square

= 134.6, df = 81, Chi-square/df = 1.662, GFI = 0.928, NFI = 0.939, CFI = 0.975, TLI = 0.967, and RMSEA = 0.054).

Support was found for all nine hypotheses. Path coefficients are seen in Table 5 that indicate the relationship between the variables tested in the hypotheses. H1 was supported indicating that self-efficacy of mobile learning is positively associated with performance expectancy. H2 was supported, indicating that self-efficacy is positively associated with social influence. H3 was supported, indicating that self-efficacy is positively associated with effort expectancy. H4 was supported, indicating that social influence is positively associated with performance expectancy. H5 was supported, indicating that social influence is positively associated with behavioral intention. H6 was supported, indicating that social influence is positively associated with effort expectancy. H7 was supported, indicating that effort expectancy is positively associated with performance expectancy. H8 was supported, indicating performance expectancy is positively associated with behavioral intention. Finally, H9 was supported, indicating that effort expectancy is positively associated with behavioral intention.

Table 5. Results of Hypothesis Testing

Hypothesis: Path	Estimates	S.E.	t-value	p-value	Results
H1: Self-efficacy →Performance expectancy	.306	.075	4.061	0.00	support
H2: Self-efficacy →Social influence	.279	.062	4.481	0.00	support
H3: Self-efficacy →Effort expectancy	.487	.069	7.056	0.00	support
H4: Social influence →Performance expectancy	.160	.074	2.153	0.03	support
H5: Social influence →Behavioral intention	.328	.084	2.830	0.00	support
H6: Social influence →Effort expectancy	.306	.077	3.996	0.00	support
H7: Effort expectancy →Performance expectancy	.455	.105	4.340	0.00	support
H8: Performance expectancy →Behavioral intention	.520	.118	4.416	0.00	support
H9: Effort expectancy →Behavioral intention	.429	.125	3.442	0.00	support
Model Fit Indices: $\chi 2(81)=134.6$, p=0.000, GFI=0.928, AGFI=0.893, NFI=0.939, CFI=0.975, TLI=0.967, RMR= 0.044, RMSEA=0.054					

5. Conclusions

In this study, we investigated the roles of self-efficacy and social influence in mobile learning service with the aim of examining how the two constructs affect behavioral intention through performance expectancy and effort expectancy. The effect of self-efficacy on social influence was also examined in order to identify whether or not self-efficacy can be starting point for enhancing behavioral intention. The main findings indicated that self-efficacy could affect behavioral intention through social influence, performance expectancy, and effort expectancy.

While in prior studies performance expectancy, effort expectancy, social influence, and facilitating conditions have been used as individual reactions to using information technology [3], in our paper we tested the hypothetical relationships among performance expectancy, effort expectancy, and social influence, as well as examined the relationship between self-efficacy and the constructs. The results showed that self-efficacy is a meaningful antecedent of social influence, performance expectancy, and effort expectancy. Social influence is also an important antecedent of performance expectancy and effort expectancy. Furthermore, it was identified that effort expectancy has a positive effect on performance expectancy.

As verified in both this study and previous studies, it was identified that social influence, performance expectancy, and effort expectancy can be important influence factors of behavioral intention in mobile learning. Performance expectancy had the most impact on positive behavioral intention, such as positive word of mouth or reuse intention.

Thus, the managers should make an effort to meet performance expectancy through self-efficacy and social influence, which can lead to actual use of mobile learning.

With smartphones becoming increasingly more affordable, these devices have assumed increasing importance in people's everyday lives and their significance is seen in their use for learning, leisure activities, social interaction and identity formation [27]. Most research literature reveals generally positive outcomes and attitudes to m-learning [28]. This study showed that higher level of self-efficacy results in higher levels of performance expectancy, social influence, and effort expectancy, which support higher behavioral intention. University students in this study viewed the value of mobile learning to help them in their studies, careers and, to make friends and contacts are confirming their acceptance of the dominant, subliminal message sent out by these smart devices. It is very important to examine how these devices are used in everyday practices and their relationship to learning. Furthermore, under-standing the relationship between self-efficacy and social influence and behavioral intention of mobile learning is fundamental to preparing students for study and employment.

The findings of this study should be interpreted with caution because there are some limitations. First, it will be necessary for a longitudinal research to accurately track university students' perceptions of self-efficacy and social influence of mobile learning. Second, the managers should focus on e-learning lifelong education in order to grow mobile learning market. Thus, e-learning lifelong education is needed to consider in the future research of mobile learning. Third, additional studies need to consider individual characteristics to understand how people with different characteristics associate self-efficacy and social influence perceptions or actual use of mobile learning.

References

[1] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," MIS Quarterly, vol. 13, no. 3, **(1989)**, pp. 319–339.
[2] S. Taylor and P. A. Todd, "Understanding Information Technology Usage: A Test of Competing Models," Information Systems Research, vol. 6, no. 2, **(1995)**, pp. 144–176.
[3] V. Venkatesh, M. G. Morris, G. B. Davis and F. D. Davis, "User Acceptance of Information Technology: Toward a Unified View," MIS Quarterly, vol. 27, no. 3, **(2003)**, pp. 425-478.
[4] V. Venkatesh, "Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model," Information Systems Research, vol. 11, no. 4, **(2000)**, pp. 342-365.
[5] M. Igbaria, "User Acceptance of Microcomputer Technology: An Empirical Test", OMEGA International Journal of Management Science, vol. 2, no. 1, **(1993)**, pp. 73-90.
[6] A. Bandura, "Self-Efficacy", The Corsini Encyclopedia of Psychology, **(2010)**, pp. 1534-1635.
[7] F. D. Davis, "User Acceptance of Information Technology: System Characteristics, User Perceptions and Behavioral Impacts," International Journal of Man-Machine Studies, vol. 38, no. 3, **(1993)**, pp. 475-487.
[8] P. T. Ashton and R. B. Webb, "Making a difference: Teachers' Sense of Efficacy and Student Achievement", New York, NY: Longman, **(1986)**.
[9] M. Tschannen-Moran and A. W. Hoy, "Teacher Efficacy: Capturing an Elusive Construct," Teaching and Teacher Education, vol. 17, **(2001)**, pp. 783-805.
[10] T. R. Guskey, "Teacher Efficacy, Self-Concept, and Attitudes toward the Implementation of Instructional Innovation," Teaching and Teacher Education, vol. 4, **(1988)**, pp. 63-69.
[11] N. Azizli, B. E. Atkinson, H. M. Baughman and E. A. Giammarco, "Relationships between General Self-Efficacy, Planning for the Future, and Life Satisfaction," Personality and Individual Differences, vol. 82, **(2015)**, pp. 58-60.
[12] P. R. Pintrich and D. Schunk, "Motivation in Education", Theory, Research and Applications, 2nd ed., Prentice Hall, Upper Saddle, NJ, **(2002)**.
[13] J. Hamari and J. Koivisto, "Working Out for Likes: An Empirical Study on Social Influence in Exercise Gamification," Computers in Human Behavior, vol. 50, **(2015)**, pp. 333-347.
[14] G.-W. Bock, R. W. Zmud, Y.-G. Kim and J.-N. Lee, "Behavioral Intention Formation in Knowledge Sharing: Examining the Roles of Extrinsic Motivators, Social-Psychological Forces, and Organizational Climate," MIS Quarterly, vol. 29, no. 1, **(2005)**, pp. 87–111.
[15] C. M. K. Cheung, P.-Y. Chiu and M. K. O. Lee, "Online Social Networks: Why Do Students Use Facebook?", Computers in Human Behavior, vol. 27, **(2011)**, pp. 1337–1343.

[16] B. Hernandez, T. Montaner, F. J. Sese and P. Urquizu, "The Role of Social Motivations in E-Learning: How Do They Affect Usage and Success of ICT Interactive Tools?", Computers in Human Behavior, vol. 27, **(2011)**, pp. 2224–2232.
[17] C.-L. Hsu and J. C.-C. Lin, "Acceptance of Blog Usage: The Roles of Technology Acceptance, Social Influence and Knowledge Sharing Motivation," Information & Management, vol. 45, **(2008)**, pp. 65–74.
[18] J. Hamari, "Transforming Homo Economicus into Homo Ludens: A field Experiment on Gamification in a Utilitarian Peer-to-Peer Trading Service," Electronic Commerce Research and Applications, vol. 12, no. 4, **(2013)**, pp. 236–245.
[19] P. Zhang, "Motivational Affordances: Reasons for ICT Design and Use," Communications of the ACM, vol. 51, no. 11, **(2008)**, pp. 145-147.
[20] J. M. Holden and J. B. Overmier "Choice Behavior under Differential Outcomes: Sample Stimulus Control Versus Expectancy Control," Learning and Motivation, vol. 51, **(2015)**, pp. 50-61.
[21] Y. Sun, N. Wang, C. Yin and J. X. Zhang, "Understanding the Relationships between Motivators and Effort in Crowdsourcing Marketplaces: A Nonlinear Analysis," International Journal of Information Management, vol. 35, **(2015)**, pp. 267-276.
[22] N. Pachler, J. Seipold and B. Bachmair, "Mobile Learning: Some Theoretical and Practical Considerations," In Friedrich, K., Ranieri, M., Pachler, N., de Theux, P. (Eds.) The 'My Mobile' handbook. Guidelines and Scenarios for Mobile Learning in Adult Education, **(2012)**, pp.11-16.
[23] V. Venkatesh and H. Bala, "Technology Acceptance Model 3 and a Research Agenda on Interventions," Decision Sciences, vol. 39, no. 2, **(2008)**, pp. 273-315.
[24] R. L. Thompson, C. A. Higgins, and J. M. Howell", Personal Computing: Toward a Conceptual Model of Utilization," MIS Quarterly, vol. 15, no. 1, **(1991)**, pp. 124-143.
[25] J. F. Hair, R. E. Anderson, R. L. Tatham and W. C. Black, "Multivariate Data Analysis", 5th Ed., Prentice Hall, Upper Saddle River, NJ, **(1998)**.
[26] J. C. Anderson and D.W. Gerbing, "Structural Modeling in Practice: A Review and Recommended Two Step Approach," Psychological Bulletin, vol. 103, no. 3, **(1988)**, pp. 411-23.
[27] H. N. Sung, D. Y. Jeong, Y.S. Jeong, and J. I. Shin, "The Effects of Self-Efficacy and Social Influence on Behavioral Intention in Mobile Learning Service," Advanced Science and Technology Letters, vol. 103, **(2015)**, pp. 27-30.
[28] N. N. Chan, C. Walker and A. Gleaves "An Exploration of Students' Lived Experiences of Using Smartphones in Diverse Learning Contexts Using a Hermeneutic Phenomenological Approach," Computers & Education, vol. 82, **(2015)**, pp. 96-106.
[29] K. Peters, "M-Learning: Positioning Educators for a Mobile, Connected Future," International Journal of Research in Open and Distance Learning, vol. 8, no. 2, **(2007)**, pp. 1-17.

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