

# **IMPACT OF CONTEXTUALITY ON MOBILE LEARNING ACCEPTANCE: AN EMPIRICAL STUDY BASED ON A LANGUAGE LEARNING APP**

Stephan Böhm and Georges Philip Constantine  
*Hochschule RheinMain, Unter den Eichen 5, 65195 Wiesbaden, Germany*

## **ABSTRACT**

The mobility of both the device and the learner will determine how mobile learning takes place. Mobile learning offers new educational opportunities that allow for autonomous, personalized and context aware learning. This paper focuses on contextualized features for mobile language learning apps. Context-awareness is seen as a particularly important app feature in order to create a meaningful mobile learning experience as it adapts learning activities to the learners' real world environments. The scope of this paper is to explore students' perceptions of contextualized mobile language learning. An extended Technology Acceptance Model was developed to analyze the effect contextual app features would have on students' usage intention. The suggested app applies context-triggered push notifications to initiate learning sessions based on a location-aware vocabulary. Partial Least Squares Structural Equation Modeling (PLS-SEM), was used for an empirical validation of the proposed research model. The results of the analysis revealed, that students perceived the proposed app as beneficial for their learning endeavors. The location-aware feature is essentially relevant to improve the perceived usefulness of the system, as it may increase the learning effectiveness of the app in their everyday life.

## **KEYWORDS**

Contextual Learning; Mobile Language Learning; Empirical Study; Mobile Prototyping; User Centered Design; Up-front User Research; Technology Acceptance Model.

## **1. INTRODUCTION**

Today, mobile applications (apps) are one of the main drivers of the ongoing proliferation of mobile learning. Especially apps for mobile assisted language learning evolved broadly, and have become increasingly interesting to many mobile learners due to the availability of inexpensive or even free apps for language learning. However, the full potential of mobile learning has not been fully leveraged to this point. Accordingly this paper will focus on contextualized features for mobile language learning apps. As context-awareness adapts learning activities to the learners' real world environments, it is seen as an important app feature in order to create a meaningful mobile learning experience. Although it is not a new phenomenon, Huang et al. (2013) state that, the domain of mobile learning lacks endorsement from studies that explore context-aware language learning systems and research the users' perspective on such systems (Huang et al., 2013). This paper ties in with Huang et al.'s statement and intends to contribute to empirical research on student's perceptions on contextual mobile vocabulary learning systems and the impact of this contextuality on the acceptance of such systems. The scope of this study is therefore to analyze to what extent a contextual app feature influences the students' behavioral intention to use a context-aware mobile language learning app. Building on the Technology Acceptance Model (TAM), the objective of this study is to derive empirical findings on the importance of contextuality on usage intention for mobile language applications as well as its influence on the perceived ease of use and the usefulness of such applications. Based on these findings, recommendations for the future design of mobile learning applications and the need to integrate context-aware features can be derived.

The study consists of five chapters. After this introduction, the second chapter discusses the research background on mobile language learning and context-aware mobile app features. The research approach and the proposed research model are expounded in chapter three. Chapter four presents the research findings of the study and summarizes the results of the hypotheses testing, before conclusions and implications are drawn in chapter five.

## 2. RESEARCH BACKGROUND

Contextual mobile language learning can be categorized as an advanced form of electronic learning (e-learning), which has its roots in technology enhanced learning (TEL) and the advent of information and communication technologies (ICT). The following section briefly discusses theoretical foundations and important characteristics of mobile learning. This is used as a basis for introducing and substantiating the factor of context-awareness and the role of contextual app features to mobile language learning.

### 2.1 Context Awareness in Mobile Learning

Today, mobile learning is seen from a *learner-centric* perspective, which emphasizes the focus on the mobility of the learner as well as the mobility of the learning process itself. Herein, the concept of context with its different aspects for mobile learning becomes an essential factor. With the mobile device at hand, learners can learn in various different scenarios. Hence, it is important to focus on learning activities, which on the one hand are facilitated by the type of device, and on the other hand are determined by the physical and social contexts the activity takes place in. Herein, the informal and context-based learning experience evolve to important factors given by the mobility of the learner (Traxler, 2007). By means of the context notion, the mobile device becomes a mediator-tool that offers personalized learning activities adequate for the learner's mobile status. The scope of context awareness in mobile learning is, as stated by Brown et al. (2010), to connect the real world with digital media to support the learner. Context-awareness as a technological phenomenon is usually referred to as context-aware computing. According to Abowd et al. (1999) context-aware mobile computing is "... the use of context to provide task-relevant information and/or services to a user, typically [based on, notation of the authors] the location, identity and state of people, groups, and computational and physical objects". Zimmermann et al. (2007) argued that context is of dynamic nature and defined five different context categories, which they described as individuality, activity, location, time, and relations. The dynamic mesh of context information that is woven around the learner has led to a paradigm for context-awareness in the domain of mobile learning, which Sharples et al. (2005) have summarized as follows: "Context should be seen not as a shell that surrounds the learner at a given time and location, but as a dynamic entity, constructed by the interactions between learners and their environment."

In order to adapt the learning activity to the learning context, context-acquisition due to sensor technology plays an important role. Modern sensor technologies such as cellular networks, GPS, WLAN, Bluetooth/Beacons, RFID (Radio Frequency IDentification) or cameras generate important input information for contextualization (Wang, 2004). Mobile devices use these context inputs for the design and development of learning activities and functionalities, and in addition offer possibilities for the customization respectively personalization of learning activities.

### 2.2 Contextual Mobile Language Learning

In mobile language learning, the language learning process is assisted and enhanced by the use of a mobile device. Often, the acronym MALL – Mobile Assisted Language Learning – is understood to describe this approach of language learning. Kukulska-Hulme (2012) defined MALL as the use of "... mobile technologies in language learning, especially in situations where device portability offers specific advantages". The use of mobile devices in the learning process enables spontaneous and interactive learning activities across multiple contexts. For the most parts, mobile language learning occurs outside of formal learning settings, such as while commuting, instead of within a classroom. Thus, it gives way for a shift from a mainly formal oriented learning activity to a rather informal learning approach. Among the most common areas for mobile-based language learning are vocabulary learning, listening tasks, grammar tasks, phonetics

and reading comprehension (Miangah, 2012). Educational apps for mobile language learning are becoming more and more accepted and popular among mobile users. Sweeney/Moore (2012) discuss four major aspects which need to be considered for the design of such mobile language learning apps: (1) The mobile app design should allow for interactivity, (2) the learning resources should include multimedia contents, (3) utility and functionality of the learning resources should be fostered by contextual relevancy, and (4) the app design should increase autonomous and personalized learning. In this perspective, the impact of the learning context on the learning process as proposed in aspect (3) is crucial to the subject of this paper. Wang (2004) also emphasized the importance of developing context-aware, wireless and mobile learning apps. After sensing the learning context, e.g. location, activity, or learner state, the system can react to changes in the learning environment, with the scope to provide learners "...more relevant information to meet their dynamically changing contextual requirements" (Wang, 2004). Hence, the mobile device can be seen as a mediator to provide language learning opportunities in real-world interactions through context-aware app features that enable new modes of contextualized mobile learning.

### **3. RESEARCH OBJECTIVE AND MODEL**

The objective of this paper is to empirically analyze the importance of contextuality on mobile learning acceptance. For this reason, the study is based on an app concept for a "Contextual Language Learning (CoLaLe)" app. The concept of the CoLaLe app and the proposed research model are discussed in the following sections of this paper.

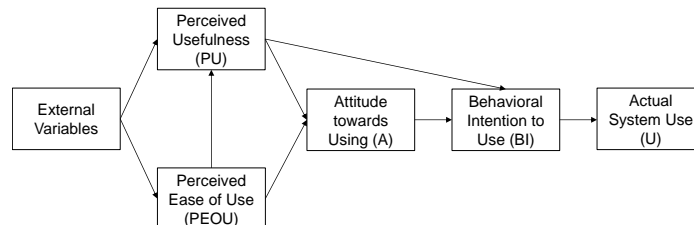
#### **3.1 CoLaLe App Prototype**

The proposed app intends to use the location-context dimension to provide language vocabulary learning activities for German and Thai. The motivation to implement such a feature in a language learning app was to utilize the advantages of personalized learning (Duo and Ying, 2012) and make the app usage more independent from the learners' initiative by introducing an external and context-aware trigger. Another aim was to increase the user acceptance of such an app by providing learning content with a high relevance to the user and his or her actual usage context. For this reason the app concept introduced location triggers that induct game-based vocabulary learning activities. The learning activities are based on sessions with flashcards containing textual, visual and audible representations of the vocabulary. The flashcards are deposited in predefined categories (e.g., study, home, food etc.), which are linked to certain contexts, such as location dependent learning sessions (e.g., home, university, restaurants). The linkage of those sessions to the app's location-filtering function can be personalized via a map-based user interface. In a first step this contextual feature allows the user to localize the actual position (e.g., GPS based). In a second step the user can then define an area around this position as relevant for the selected session. This area is then used as a "geo-fence" to trigger learning sessions by sending a push notification on the smartphone each time the user is entering this area. This context-aware feature of the app provides a new learning experience in which the learning content is directly coupled with the actual user context. However, at the time of the study at hand, the CoLaLe app was in the concept phase and not available as a market-ready mobile application to be tested in the field. For this reason, a high-fidelity prototype was developed to present the study participants with the intended user interface design and functionality. To expose the participants to the CoLaLe prototype, they were shown a short video that demonstrated the key features mentioned above. The video allowed a very realistic presentation of the visual design and a simulation of the app usage. The prototyping approach was also chosen to provide a standardized stimulus in order to prevent bias from usability problems or varying app usage in the test situation.

#### **3.2 Proposed Research Model**

In order to answer the research question in this study, a structural equation modelling (SEM) approach was chosen. In SEM, a path model illustrates the hypothesized relationships among the variables of the research subject. The constructs of the structural model and their hypothesized relationships derived in this paper are adopted from the use of Davis' (1989) TAM in prior mobile learning acceptance studies. TAM has

successfully been implemented to predict behavioral intention of mobile learning usage and is therefore the basis of the structural model development in this paper. TAM uses the two main constructs perceived usefulness (PU) and perceived ease of use (PEOU) as the accounting determinants of the actual system use (U), which is further predicted by the key constructs user attitudes towards use (A) and behavioral intention to use (BI) in Davis' model. Figure 1 illustrates the TAM and the relationships between the different constructs. In his initial survey to verify the influence of TAM's key factors PU and PEOU, Davis (1989) found that PU as well as PEOU are indeed key determinants of BI to use an information system.



Source: Davis et al., 1989.

Figure 1. Davis' Technology Acceptance Model

Lee/Jun's (2007) provided the first impulse for the derivation of a perceived contextual value (PCV) construct to extend Davis' TAM. Lee/Jun added the context dimensions of personalization, location, and time to measure PCV, though not specifically applied in a mobile learning context. A similar construct in the mobile learning context was proposed by Huang et al. (2007) who created the perceived mobility value (PMV) construct in order to evaluate BI to use a mobile learning system. Huang et al. postulate that efficiency and availability of mobile learning services are perceived as main advantages of mobile services, and conclude that PMV is "...a critical factor of individual differences affecting users' behaviors" (Huang et al., 2007). In line with this PMV construct is Akour's perceived mobile convenience (PMC) construct to measure the impact of contextual app features. Akour proposed to add the dimensions of mobility, convenience, and ubiquity (Akour, 2009). Thus, this study proposes to add PCV as a mobile learning specific construct to predict BI in the mobile adapted TAM. As a result, the research model in this paper was based on three exogenous latent variables which were perceived usefulness (PU), perceived ease of use (PEOU), and perceived contextual value (PCV). The model was also based on an endogenous latent variable which was behavioral intention (BI) of learners towards using the CoLaLe app. Figure 2 illustrates the structural model, which depicts the research hypotheses and illustrates the relationships between the assigned exogenous and endogenous latent variables.

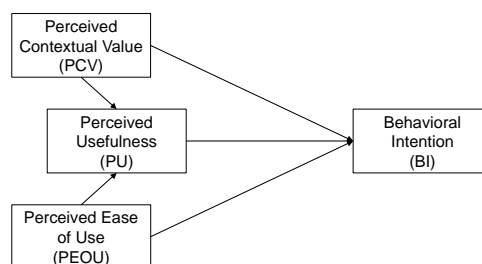


Figure 2. Proposed Research Model

The operationalization of PU, PEOU, and BI was based on reference questionnaires as applied in Venkatesh/Davis' (2000) TAM study. The PCV construct used manifest variables that were adapted from different studies that investigated contextual factors in mobile learning acceptance, i.e., from Akour (2009), Huang et al. (2007), as well as Lee/Jun (2007). Each of the four constructs were based on reflective measurement models. The items had to be translated into German in order to be applicable for the survey and were measured on a five-point Likert-scale. All the TAM-related questions were included in a section of the questionnaire which was presented to study participants following the demonstration of the CoLaLe app by the video prototype as discussed in Section 2 of this paper.

#### 4. EMPIRICAL FINDINGS

The online survey was published on June 1<sup>st</sup> 2014 and accessible for three weeks until June 21<sup>st</sup>. The survey focused on students and young professionals between 18-29 years who were familiar with mobile technology. After the data collection phase, the data was examined for potential collection issues, such as missing data, followed by data distribution for the path model evaluation. At first, the total sample (n=92) was checked for aborted cases, which resulted in a reduced net sample size of 45 completed cases (n=45). Almost 96 percent of the survey participants indicated that they use a smartphone, whereby 51 percent own an Android phone and 47 percent an iPhone. Fifty three percent of the participants have already used their smartphone for mobile learning purposes. When asked about the area of application, the participants reported they used mobile learning for study purposes (58 percent), private purposes (33 percent), or job related purposes (4 percent). Eighty three percent of the mobile learning users reported installing a mobile app dedicated to mobile learning on their devices. When asked about their perceptions towards the effectiveness of language learning supported by a mobile language learning app, 50 percent of the respondents were indecisive, twenty five percent had a positive attitude towards mobile supported language learning and the same percentage disagreed with this statement. Mobile assisted language learning seems to play a rather subsidiary role in the participants' language learning approaches. From the 31 percent of the respondents who already used a mobile language learning app, vocabulary learning is the most supported language skill (93 percent), followed by comprehension (71 percent), reading (57 percent), and speaking (50 percent).

The software package *SmartPLS 2.0* was used for the empirical validation of the research model (Ringle et al., 2005). Before being imported into *SmartPLS*, the net sample was examined for missing values and non-normality of the data. Missing data was not an issue, but the tests on *skewness* (distribution symmetry) and *kurtosis* (distribution summits), as suggested by Hair et al. (2014), revealed conspicuous indicators with values exceeding the acceptable range. Hence, the respective indicators measuring the reflective constructs PCV and PEOU were removed from the measurement model. The model evaluation in PLS-SEM was based on a two-step process. The first step intended to assess the quality of the measurement model. The second step contained the assessment of the predictive ability of the structural model (Hair et al., 2014). Unlike other methods in multivariate SEM analysis, PLS-SEM cannot be assessed by a single goodness-of-fit criterion to indicate the predictive ability of the model or its quality. Rather the evaluation of measurement and structural models rely on a set of nonparametric evaluation criteria and procedures to indicate the model quality. The first step in evaluating the reflective measurement model was to attest construct reliability which shows how well a construct is measured by its assigned indicators (Götz et al., 2010). For construct reliability, the outer loadings of each indicator should be higher than 0.70. All outer loadings of the 13 measurement items were tested and the results were above this threshold value. The reliability of the measurement model is evaluated based on its *composite reliability* (CR), which assumes that all construct indicators jointly measure the respective construct adequately. The CR values can vary between 0 and 1. CR values above 0.70 are acceptable (Hair et al., 2014). As Table 1 indicates, the CR values exceeded the threshold value 0.70, whereby all reflective constructs possess acceptable levels of internal consistency reliability. The measurement model was also tested for convergent validity by the consideration of the *average variance extracted* (AVE) on the construct level. AVE threshold values of 0.50 or higher indicate that the respective construct explains more than half of the variance of its assigned indicators. AVE values lower than 0.50 are considered insufficient, because more error variance remains in the items than indicator variance explained by the construct. As shown in Table 1 the AVE for all latent variables are well above the level of 0.50. Hence, all indicators in the reflective measurement model have high levels of convergent validity. Finally, the *discriminant validity* was assessed based on the Fornell-Larcker criterion. The *discriminant validity* describes the extent to which a construct in the measurement model is indeed dissimilar to other constructs by empirical standards (Hair et al., 2014).

Table 1. Measurement Model Reliability and Validity Analysis

Latent Variable	Measured Item	Outer Loadings	Composite Reliability	AVE
BI	BI_1	0.9664	0.9664	0.9349
	BI_2	0.9675		
PCV	PCV_1	0.7719	0.914	0.6805
	PCV_2	0.8583		
	PCV_3	0.8310		
	PCV_5	0.8017		
	PCV_7	0.8584		
PEOU	PEOU_1	0.8960	0.8969	0.8131
	PEOU_2	0.9073		
PU	PU_1	0.9062	0.9362	0.7859
	PU_2	0.8578		
	PU_3	0.9119		
	PU_4	0.8688		

According to the Fornell-Larcker criterion, a latent construct's AVE has to be higher than the highest squared correlation of this construct with any other latent construct in the measurement model (Götz et al., 2010). Table 2 depicts the results of the Fornell-Larcker assessment. The AVE's square root values of each latent construct (on the diagonal) are higher than the correlation coefficients (lower left triangle) between the latent constructs in the path model. This supplies evidence that the measurement model's measures are reliable and valid. A revision of the measurement model was not necessary.

Table 2. Results of the Fornell-Larcker Criterion Assessment

	BI	PCV	PEOU	PU
BI	<b>0.9669</b>			
PCV	0.5976	<b>0.8249</b>		
PEOU	0.3101	0.2819	<b>0.9017</b>	
PU	0.7351	0.5582	0.4582	<b>0.8865</b>

In a second step the structural model, comprising the hypothetical relationships among the proposed constructs, needs to be evaluated. The examination of the structural model will concentrate on the assessment of the  $R^2$  measures and the evaluation of the significance of the path coefficients as the primary evaluation criteria. In our path model, the two endogenous constructs are PU and BI. Following the threshold value of 0.20 (Hair et al., 2014), the  $R^2$  values for PU (0.401) and BI (0.593) can be considered moderately high. Hence, the predictive capability of the parsimonious model, in general terms, can be interpreted as acceptable. Path coefficients, corresponding to the hypothesized relationships among the constructs, are expressed by standardized values between -1 and +1. In order to determine the quality of the structural model, the path coefficients' significance has to be assessed. Here the significance was tested based on an error probability of five percent ( $p < 0.05$ ), assuming a critical value of 1.96 for the two-tailed t-test. The standard error in PLS-SEM is obtained by bootstrapping in order to compute t-values to apply the two-tailed test. The results in Table 3 indicate that all path coefficients in the structural model, besides PEOU towards BI, are significant.

Table 3. Path Coefficients' Significance Testing (Bootstrapping Results)

	Path Coefficients	t-Value	Significance
PCV → BI	0.2737	2.2317	*
PEOU → BI	-0.0428	0.3594	n.s.
PU → BI	0.6019	4.8197	*
PCV → PU	0.4660	4.3288	*
PEOU → PU	0.3269	2.6545	*

Note: n.s.=not significant; \* $p < 0.05$

In summary, the path model showed satisfactory explanatory power for the behavioral intention (BI) to use the CoLaLe app. All path coefficients showed sufficient values that exceeded the zero-mark for rather weak relationships, except the relationship of PEOU on BI. However, the significance testing of the path coefficients in the path model revealed high significance, besides the aforementioned path of PEOU on BI being non-significant. Overall, the results of the analysis showed that PU had the strongest magnitude on BI with a path coefficient of 0.6019, followed by the high impact of PCV on BI with 0.2737. In contrast, PEOU has very little bearing on BI (-0.0428). Moving on in the model, PCV (0.4660) was the primary driver for PU compared to the influence of PEOU (0.3269) on PU. After having conducted the acceptance study, the findings provided sufficient evidence for the viability of the path model, and showed mostly consistent correlation with the proposed theoretical foundation.

The overall capability of the model to predict BI echoes the results of prior mobile adapted TAM studies as cited by Huang et al. (2007) and Akour (2009). In fact, the results revealed that PU possessed the strongest predictive relevance for BI relative to the other independent constructs PCV and PEOU. Thus, the findings indicate that PU is a key driver for the prediction of the user's intention to use the system, as suggested by Davis (1989) or subsequent studies on mobile learning systems. However, the analysis also revealed that PCV has a strong relationship to BI and is a key predictor for PU as well. As hypothesized, increased PU and positive BI to use the contextual mobile language learning service can be traced back to a perceived contextual value (PCV). According to that, it can be assumed that the proposed contextual value delivered by the contextual app feature does indeed contribute positively to the overall intention to use the app. The observation confirms the findings by Huang et al. (2007) who recommended that to maximize the usefulness of mobile learning, system features should be added to increase the perceived mobility value of the user. With regards to the CoLaLe app, this would increase the users' intention to use the app as well as their perceived learning effectivity. The findings indicate that the students understood that the location-aware feature of the CoLaLe app was a driving factor in their perceived usefulness of the system. The perceived easiness of the system plays no significant role in the adoption and use of the contextual mobile language learning service. Additionally, the predictive relevance of PEOU for PU in comparison to PCV was rather meager. Venkatesh et al. (2003) made a similar observation, and found that the predictive importance of PEOU in the model diminishes over time.

## 5. CONCLUSION

The scope of this paper was to explore students' perceptions of contextualized mobile language learning. Therefore, mobile adopted TAM models were used to construct the research model. The main interest of the study was to evaluate the extent to which the contextual app feature would contribute to the prediction of the students' intention to use the proposed CoLaLe app. The results of the PLS-SEM analysis revealed, on the one hand, that students perceived the proposed CoLaLe app as beneficial for their learning endeavors, while the targeted students in the sample were mainly concerned about the perceived usefulness of the system. Herein, the a priori hypothesized strong impact of the students' perceived usefulness on their intention to use the CoLaLe app was found to be a major influencing factor in the model. The students aspired to support their language learning routine with technology only when it offered genuine assistance. On the other hand, the results emphasized the overall magnitude of the perceived contextual value in the model. The students expressed that the location-aware feature of the CoLaLe app was essentially relevant in regard to their perceived usefulness of the system, as it may increase the learning effectiveness and contribute to usage scenarios in their everyday life. Moreover, situated learning activities that pervasively transfers language learning into the immediate informal learning context of the student may increase the motivation of the student to engage in a learning activity. As a next step, it would be interesting to survey whether the perceived effectiveness of the students when using the CoLaLe app for language learning factually results in increased learning success. It is persistently believed by the authors of this paper that contextual app features applied in mobile language learning can impact the success of, in this case vocabulary learning, if applied appropriately.

The study presented in this paper was subject to a range of limitations. One major constraint was the collection of the survey data. The survey solely took place among technology- and media-affine students, which inevitably resulted in quite a homogenous population in the sample that otherwise would not be desirable. Moreover, the sample size of the survey was rather small ( $n=45$ ). Although this was enough to run the PLS-SEM analysis of the path model in *SmartPLS*, the net sample size should be increased for future

research. Further limitations that have to be noted regard to the deduction of the path model. Although in the spirit of Davis' (1989) to treat TAM as a parsimonious model, the path model in this paper excluded further external variables in the adoption of the TAM model that have been validated in prior mobile learning studies. Further research may tie in to this and include external variables in the path model that refer to social, cognitive, or environmental factors in the context of mobile learning.

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