Understanding Continuance Intention of Augmented Reality for Mobile Learning

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Abstract — In this paper, we examine the continued intention of learners in augmented reality (AR) for mobile learning. Though various studies have investigated topics related to mobile learning in recent years, studies on users’ intention to continue using AR for mobile learning are scant. In the emerging area, the acceptance–discontinuance anomaly phenomenon occurs frequently, in which users discontinue the use of AR for mobile learning after initially accepting them. In order to explore the determinants of the anomaly phenomenon, we combined the expectation–confirmation model and technology acceptance model to establish a theoretical model for explaining and predicting learners’ intention to continue using augmented reality for mobile learning. The results indicate that user satisfaction and attitude are the primary determinants of users’ intention to continue using the augmented reality for mobile learning. In addition, the implications of the findings for research and managerial practice are presented in this paper.

Keywords - Augmented Reality; Continuance Intention; Expectation-Confirmation Model; Mobile Learning, Technology Acceptance Model

I. INTRODUCTION

Augmented reality (AR) mobile learning has attracted considerable interest among academics and practitioners. Because of its interaction feature and appealing learning experience, AR mobile learning has also attracted the attention of educators and researchers [10,13,31]. Although numerous studies have examined AR mobile learning adoption problems [8,16,20], few studies have investigated how to enhance learners’ intention to continue using AR mobile learning systems. Previous studies on AR mobile learning have applied exploratory or qualitative analyses [11,24,34]. As the pioneering study on improving consumers’ continuance intention in the context of AR mobile learning, this study focused on developing a model for measuring learners’ adoption of and intention to continue using AR for mobile learning.

Adoption in the context of AR mobile learning has garnered increasing interest in recent years [8,16,20]. Nevertheless, few studies have explored the determinants of learners on their continuance intention. Previous studies Limayem, Hirt, and Cheung [21] and K.-M. Lin [23] have also indicated that the gaps in the determination of variables continuance usage have yet to be filled. Hence, the current study involved two goals: (1) to investigate the determinants of continuance intention for AR mobile learning, and (2) to explore the paths among the determinants in the context of AR mobile learning.

From the perspective of AR mobile learning, this study proposes a model that is an extension of expectation–confirmation theory (EDT) and the technology acceptance model (TAM) for exploring the potential determinants on their intention to continue using an AR mobile learning system. To measure the direct and indirect effects on their continuance intention, five constructs were incorporated into the model: confirmation, perceived usefulness, perceived ease of use, satisfaction, and attitude. Finally, we reviewed the EDT model and TAM and attempted to adapt them by integrating them with the characteristics of AR mobile learning.
II. RESEARCH MODEL AND HYPOTHESES

A. Determinants of Continuance Intention

Studies have suggested that many determinants exert a direct or indirect effect on learners’ intention to continue using new systems or services, and such determinants include user satisfaction \([4,5,18,33]\), attitude \([6]\), perceived usefulness \([4,5,6,29]\), and perceived ease of use \([33,37]\). Nevertheless, studies that have explored the relationship between the initial acceptance and post acceptance (continuance behavior) of AR mobile learning systems are seldom.

Previous studies \([22,38]\) have suggested that the quality attributes of AR mobile learning systems comprise system quality, instructional quality, and interactive quality. Service quality refers to the difference between a user’s expectation of a service and the actual service that the user experienced, whereas system quality represents a user’s perception of an AR mobile learning system regarding the system’s ease of use, reliability, level of technical support, and response speed. Satisfaction positively influences users’ attitude and continuance intention \([33]\). Studies that have investigated the effects of determinants on users’ continuance usage intention in the AR mobile learning context have also revealed that satisfaction and perceived quality were significant factors influencing usage intention \([7,30]\).

In the context of AR mobile learning, perceived usefulness is defined as the extent to which a person believes that AR mobile learning can be a driving force toward achieving a favorable shopping experience \([25,33]\) or service (e.g., using the AR mobile shopping system, e.g. I can increase my shopping performance). Similarly, perceived ease of use is defined as the extent to which a person believes that using an AR mobile learning system is free of effort \([17]\). Numerous TAM-related studies have indicated that perceived ease of use directly and indirectly affects attitude \([2,3,18,36]\). In addition, a previous study suggested that perceived usefulness directly affects attitude \([6]\). A study Kaplan \([19]\) suggested that attitude is a learned tendency in response to an object in a consistently favorable or unfavorable manner. Another study indicated that satisfaction causes a significant and positive effect on people’s attitude toward services such as e-shopping \([12]\). From a theoretical perspective, the theory of reasoned action and the theory of planned behavior suggest that beliefs affect attitude, which in turn influences users’ behavioral intention. In addition, the findings of previous studies have indicated that attitude significantly influences users’ continuance intention in an AR mobile learning context \([7,30]\).

Moreover, a study on user acceptance and use of technology reported that continuance intention is dependent on users’ attitude toward information technology \([27]\).

B. Model and hypotheses

The literature review suggested that in the context of AR mobile learning with different perceptions (perceived usefulness and perceived ease of use), satisfaction, attitude, and continuance intention. Therefore, in this paper, we propose an extended model for investigating the determinants of continuance intention and explain the different effects of determinants in AR mobile learning on continuance intention. The proposed model is an extension of the TAM and EDT. Fig. (1) illustrates the research model, indicating that it comprises six constructs: (a) confirmation, (b) user satisfaction, (c) perceived ease of use, (d) perceived usefulness, (e) attitude, and (f) continuance intention. The research model was used to examine the primary determinants of continuance intention in the AR mobile learning context and to investigate the effects of determinants on continuance intention by validating the following hypotheses.
Introduction

The perceived usefulness of the AR mobile learning system has a direct and positive effect on the intention to continue using the system.

H10. User satisfaction with the AR mobile learning system has a positive effect on attitude toward the adoption of the system.

H11. User satisfaction with the AR mobile learning system has a direct and positive effect on the intention to continue using the system.

III. METHOD

A. Instrument Development

For measuring the research model, a survey instrument was developed by adopting existing validated instruments. The measurement items for the EDT were adopted from two studies [5,6], and those for the TAM were adopted from Davis [9]. Questions were anchored on a 7-point Likert scale, with scores ranging from 1 (strongly disagree) to 7 (strongly agree). To improve the content reliability of the scale, the list of categorized measures was subsequently screened by an academic in charge of an e-commerce student interest group. In addition, we assessed the construct validity by determining convergent and discriminant validity according to the level of consistency within the categorized items Moore and Benbasat [28]. A pilot study involving 40 users with AR mobile learning at Shu-Te University was then conducted by sending the users an e-mail containing a hyperlink to the questionnaire on web site.

B. Data Collection and Sample

To test the hypotheses, we administered surveys to the recruited users. A total of 250 responses were obtained, of which 236 were complete, representing in a valid response rate of 94%. The results of the pilot test were evaluated using Cronbach’s reliability coefficient and factor analysis. The reliability coefficient was first calculated for the items of each construct, and the standard lower bound for Cronbach’s α was set to 0.7 [1]; items that did not significantly contribute to the reliability were eliminated. A factor analysis was then conducted to examine whether the items produced the anticipated number of factors and whether the individual items were loaded on their appropriate factors. The analysis results (Table 1) revealed that all items had high loadings on their corresponding factors and low cross-loadings on other factors, indicating high convergent and discriminant validity.

IV. ANALYSIS AND RESULTS

We used partial least squares (PLS) regression as our analytics tool for several reasons. First, a confirmatory covariance-based analysis, such as that implemented in LISREL software, was not appropriate for the proposed model and measures. Second, PLS regression can be used to test the psychometric properties of indices and effectively confirm the relationships among constructs. Third, our study framework was exploratory rather than confirmatory. Fourth, PLS regression has three vital intrinsic attributes: less rigorous standards regarding sample size, distribution parameters, and levels of correlation between variables. In this study, SmartPLS [32] and the bootstrap resampling approach were used to test the measurement model and structural models. Subsequently, data analysis was conducted according to a two-stage methodology proposed by [1] by using PLS regression. The initial phase of the data analysis involved establishing the convergent and discriminant validity of the constructs by using the measurement model. The second phase entailed testing the structural models.

A. Measurement Model

We tested the reliability and validity of the measurement model a common approach for testing reliability is using Cronbach’s reliability coefficient. A previous study [14] proposed that the generally accepted lower limit for Cronbach’s α value is 0.70, although it may decrease to 0.60 in exploratory studies. In the current study, the Cronbach’s α values for all constructs exceeded 0.8. Moreover, to determine the convergent validity, we subjected the respondents to two tests according to the procedures presented in a previous study [14]: a composite reliability (CR) test and average variance extracted (AVE) test. The CR for each construct must be greater than 0.7, and the AVE for each construct must exceed 0.5 [14].
TABLE 1. CONSTRUCTS MEASUREMENTS

<table>
<thead>
<tr>
<th>Constructs measure and item description</th>
<th>Mean</th>
<th>S.D.</th>
<th>Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Confirmation (CON) [4,5]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>My experience with using the AR mobile learning system was better than I expected</td>
<td>4.26</td>
<td>1.21</td>
<td>0.81</td>
</tr>
<tr>
<td>The service level provided by the AR mobile learning system was better than I expected</td>
<td>4.32</td>
<td>1.23</td>
<td>0.84</td>
</tr>
<tr>
<td>The AR mobile learning systems can meet demands in excess of what I required for the service</td>
<td>4.42</td>
<td>1.23</td>
<td>0.85</td>
</tr>
<tr>
<td><strong>Perceived Usefulness (PU) [9]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using AR mobile learning can improve my learning performance</td>
<td>4.24</td>
<td>1.53</td>
<td>0.83</td>
</tr>
<tr>
<td>Using AR mobile learning can increase my learning productivity</td>
<td>4.41</td>
<td>1.12</td>
<td>0.82</td>
</tr>
<tr>
<td>Using AR mobile learning can improve my learning effectiveness</td>
<td>4.37</td>
<td>1.23</td>
<td>0.84</td>
</tr>
<tr>
<td>I find AR mobile learning to be useful to me</td>
<td>4.14</td>
<td>1.35</td>
<td>0.87</td>
</tr>
<tr>
<td><strong>Perceived Ease of use (PEU) [9]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating the AR mobile learning system is easy for me</td>
<td>4.82</td>
<td>1.62</td>
<td>0.87</td>
</tr>
<tr>
<td>Interacting with the system does not require a lot of my mental effort.</td>
<td>4.46</td>
<td>1.44</td>
<td>0.81</td>
</tr>
<tr>
<td>I find it easy to get the system to do what I want it to do.</td>
<td>4.34</td>
<td>1.75</td>
<td>0.82</td>
</tr>
<tr>
<td>Overall, the AR mobile learning system is easy to use</td>
<td>4.32</td>
<td>1.78</td>
<td>0.83</td>
</tr>
<tr>
<td><strong>User Satisfaction (SAT) [4,5]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am satisfied with the performance of AR mobile learning</td>
<td>4.12</td>
<td>1.21</td>
<td>0.81</td>
</tr>
<tr>
<td>I am pleased with the experience of using AR mobile learning</td>
<td>4.11</td>
<td>1.32</td>
<td>0.92</td>
</tr>
<tr>
<td>My decision to use AR mobile learning was a wise one</td>
<td>4.34</td>
<td>1.25</td>
<td>0.81</td>
</tr>
<tr>
<td><strong>Attitude (ATT) [9]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using AR mobile learning is a good idea</td>
<td>4.32</td>
<td>1.41</td>
<td>0.84</td>
</tr>
<tr>
<td>I like using AR mobile learning</td>
<td>4.36</td>
<td>1.42</td>
<td>0.82</td>
</tr>
<tr>
<td>It is desirable to use AR mobile learning</td>
<td>4.47</td>
<td>1.62</td>
<td>0.81</td>
</tr>
<tr>
<td><strong>Continue Intention (CI) [4,5]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I will use the AR mobile learning system on a regular basis in the future</td>
<td>4.73</td>
<td>1.46</td>
<td>0.88</td>
</tr>
<tr>
<td>I will frequently use the AR mobile learning system in the future</td>
<td>4.45</td>
<td>1.74</td>
<td>0.83</td>
</tr>
<tr>
<td>I will strongly recommend that others use it</td>
<td>4.75</td>
<td>1.45</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Falk and Miller [14] suggested that the factor loading of each indicator should be greater than 0.55. The standardized path loadings for all questions in this study were statistically significant and greater than 0.55. In addition, the Cronbach’s α values for all constructs exceeded 0.7. Therefore, the instruments used in this study achieved suitable convergent validity. Next, we tested discriminant validity by comparing the square root of the AVE for each construct with the correlations between that construct and other constructs [14]. The results revealed that the square root of the AVE for each construct exceeded the correlations between that construct and other constructs [14]. Therefore, the items used in this study exhibited favorable discriminant validity.

B. Instrument Development Model Testing

We assessed the hypotheses by employing SmartPLS software [32] and the bootstrapping method. To estimate the significance of the path estimates, the corresponding t values for each path were calculated. The nonsignificance of several hypotheses may be due to the collinearity among the constructs, because the correlations among the variables were high and significant. A previous study [26] indicated that highly collinear variables can dissort test results. The most widely used approach for avoiding collinearity involves measuring variance inflation factors (VIFs) and condition indices [26]. Therefore, we adopted this approach in this study. To remove collinearity, VIF values and condition indices were extracted; a maximum VIF value greater than 10 signifies high collinearity, and condition indices greater than 30 indicate moderate to strong dependencies. The results revealed that the VIF values were less than 10 and that the condition indices were less than 30. This thus suggested that multicollinearity did not significantly distort our test results.

V. DISCUSSION

A. Understanding Associations between Antecedent Constructs and Continuance Intention

This study assessed the effects of satisfaction, perceived usefulness, and attitude on the adoption and intention to continue using an AR mobile learning system. The findings indicate that satisfaction is the strongest predictor of their continuance intention, followed by attitude and perceived usefulness. The satisfaction–intention path has been extensively validated in consumer behavior research and service contexts [4,5]; the revalidation of this path in the AR
mobile learning context further ensured the robustness of this association. In addition, satisfaction may be a critical factor explaining the AR mobile learning acceptance–discontinuance anomaly (i.e., user discontinuance of AR mobile learning after its initial acceptance). However, previous studies have not clearly elucidated this anomaly.

The literature suggests that satisfaction is the strongest determinant of continuance intention. Therefore, users’ satisfaction may influence their intention to continue using AR mobile learning systems; specifically, a user dissatisfied with an AR mobile learning system may stop using it, regardless of whether the user has positive perceptions of other elements. Therefore, dissatisfaction is an essential requirement for AR mobile learning discontinuance. The TAM applies perceived usefulness and attitude constructs to predict users’ intention; these constructs cannot be used to interpret the mentioned anomaly.

Our results revealed that perceived usefulness was a secondary determinant of continuance intention. However, several noteworthy patterns have been reported in TAM-related studies in the context of information system acceptance. For example, previous studies [9,35] have reported that perceived usefulness was a more informative predictor of acceptance intention in the TAM compared with attitude. By contrast, we observed that satisfaction was a more informative predictor of continuance intention compared with perceived usefulness.

Previous studies have suggested that attitude and satisfaction reflect users’ preacceptance and postacceptance (i.e., continued usage) of a service or system, whereas the perceived usefulness construct is a cognitive notion. Regarding users’ postacceptance of a system or service, satisfaction is based on their first-hand experience, which is more realistic, unbiased, and less likely to change. By contrast, regarding preacceptance, attitude is based merely on cognitive beliefs, which are possibly based on second-hand information from other sources such as the media or advertisements. Such beliefs may be biased and, thus, user attitude may be inaccurate, unrealistic, or uncertain. These findings indicate that perceived usefulness is closely related to acceptance intention, whereas satisfaction is closely related to continuance intention. Therefore, we suggest that AR mobile learning practitioners introduce a dual strategy for increasing learners’ adoption rate and intention to continue using their services: First, practitioners should provide richer multimedia Internet features to improve learners’ understanding and recollection of course information. Learners are more likely to adopt and continue to use AR for mobile learning systems if they perceive that such systems can enhance their learning experience. Practitioners can use social networking services and online forums to improve learners’ learning synergism. For example, researchers in a previous study [15] in the context of e-learning proposed the concept of “dynamic loop” and suggested that the higher the number of users using an e-learning system is, the higher the amount of exchanged user-generated experiences becomes, enabling the system to attract more new users. Therefore, we suggest that practitioners implement Internet marketing strategies to increase number of users and improve their mobile learning with AR technology.

VI. IMPLICATIONS

A. Implications for Academics

This study has several implications. First, from the theory establishment perspective, we attempted to establish an innovation theory by incorporating new variables into an integration of two models, namely the TAM and EDT model, and then applying them to a new context: AR mobile learning. Second, the proposed model has a strong theoretical basis, thus providing a stable foundation for theory development. Therefore, the presented model can effectively contribute to the emerging literature on AR mobile learning.

This study involves two implications for future research. First, the empirical tests revealed that the unified model exhibited excellent explanatory power, implying that combining the TAM and EDT provides an extended model with a solid theoretical basis for conducting studies in the context of AR mobile learning. This model may serve as a foundation for integrating other theoretical acceptance models.

B. Practical Implications

AR mobile learning practitioners and system designers should provide richer multimedia Internet features to improve learners’ understanding and recollection of course information. Learners are more likely to adopt and continue to use AR for mobile learning systems if they perceive that such systems can enhance their learning experience. Practitioners can use social networking services and online forums to improve learners’ learning synergism. For example, researchers in a previous study [15] in the context of e-learning proposed the concept of “dynamic loop” and suggested that the higher the number of users using an e-learning system is, the higher the amount of exchanged user-generated experiences becomes, enabling the system to attract more new users. Therefore, we suggest that practitioners implement Internet marketing strategies to increase number of users and improve their mobile learning with AR technology.

VII. CONCLUSION

In this paper, we proposed a research model that combined EDT and TAM models for understanding the potential determinants effects on learners’ intention to continue using augmented reality (AR) for mobile learning. The results indicated that there are five external variables vary influence directly or indirectly effects on users’ continuance intention in these variables containing: confirmation, perceived usefulness, perceived ease of use, satisfaction, and attitude. The results reveal that satisfaction
and attitude are the critical constructs influencing continuance intention in the AR for mobile learning context. This study has several limitations that might be addressed in future studies. First, the present findings indicate that the perceived usefulness and perceived ease of use of AR for mobile learning are crucial. Therefore, future studies should focus on establishing the period required for users to familiarize themselves with AR for mobile learning so that the ease of use of AR for mobile learning systems becomes less of a barrier to continued usage. Second, in this study, the effects of AR for mobile learning were controlled only for learners’ continuance intention. Therefore, we recommend that researchers examine whether other factors have moderating effects on continuance intention (e.g., gender, Internet experience, educational background, cultural factors, and socioeconomic status). Finally, we investigated AR for mobile learning continuance intention with five constructs; nevertheless, other potential determinants of continuance intention may exist. Hence, we suggest that future studies establish a more solid theoretical basis with other possible effects of exogenous variables such as social network influence and stimulating conditions.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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