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To Activate English Learning: Listen and Speak in Real Life Context with an AR Featured U-Learning System

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ABSTRACT

The increasing advance of mobile devices and wireless technologies has generated great interest in ubiquitous learning (u-learning) among academia, practitioners, and policy makers. However, design elements that incorporate learning styles and learning strategies into u-learning system applications in English as a Foreign Language (EFL) education are still limited. There are two objectives in this research. First, we developed a Ubiquitous Learning Instruction System with Augment Reality features (UL-IAR) to improve the performance of EFL learning with authentic situations. Second, we examined whether different learning strategies and cognitive styles affect learning performance in using UL-IAR. We conducted field experiments to investigate the appropriation of learning strategies and cognitive styles in using UL-IAR to learn EFL. The results showed that learning strategies and users' cognitive styles affect learning performance in using UL-IAR. Individuals with field dependent cognitive style fit enforcing learning strategy better than other users who are field independent and mix field cognitive styles. Our findings provide theoretical and practical insights for pedagogies that are suitable for u-learning. Our findings also contribute to the practice of AR and u-learning system development.

Keywords

Augmented Reality (AR), Cognitive Style (CS), Context-aware, Learning strategies, Ubiquitous learning

Introduction

Technological advancements in wireless applications and the popularity of mobile devices have created great advantages and opportunities for learning (Huang & Chiu, 2015; Hsieh et al., 2016). As a natural complement to ubiquitous computing, AR provides an intuitive and interactive interface to a three-dimensional information space embedded within physical reality. The application of Augmented Reality (AR) with context-aware ubiquitous learning (u-learning) systems offers considerable advantages for English as a foreign language (EFL) learning. EFL learners often confront difficulties and challenges when they need to speak English in real life settings. Contextual learning environments have been proven to improve performance in EFL learning (Sandberg et al., 2011). Context-aware ubiquitous learning (u-learning) refers to the computer systems that seamlessly integrate into our everyday life. It is a version of our future computing lifestyle in which providing services and information occurs anywhere and anytime. Researchers have found positive outcomes in the use of mobile devices for English language learners. Kolb (1984) emphasized learning is constructed and contextual which relies on an engagement with social interactions and experience from the real world (De Freitas & Neumann, 2009). Based on Kolb's arguments, we intend to design and develop a U-Learning Instruction System with Augment Reality Features (UL-IAR) to help users to learn EFL in real life contexts. Our UL-IAR allows users to learn EFL in a constructed and contextual environment that involves social interactions and experience.

Despite prior studies have considered the technical affordances of u-learning, there is an ongoing need to examine pedagogies that are suitable for u-learning to inform teacher practice, policy makers, curriculum developers, and teacher education (Pegrum et al., 2013). To implement a context-aware u-learning system for EFL learners, we further design learning strategies for different individuals. We believe that individual difference also leads to different learning performance in using u-learning systems. The individual differentiation can be discerned through cognitive styles, learning styles, cognitive control, and intelligence (Jonassen & Grabowski, 1993). The design of learning systems must consider individuals' cognitive styles which would increase the efficacy and satisfaction of the learning experience. However, the performance outcomes of distinct cognitive styles that applied to new learning technologies remain inconclusive (Dillon & Gabbard, 1998). This knowledge gap highlights the need to examine the difference between cognitive styles in u-learning systems with AR. Therefore, our research objective is to empirically examine the learning performance of u-learning system with different learning strategies and cognitive styles. Overall, this paper intends to answer the following research questions.

- What kind of learning strategy leads to better EFL learning performance when using UL-IAR?
- Do the users with different cognitive styles have different learning performance when using UL-IAR?
- Is there best alignment between learning strategies and cognitive styles when using UL-IAR?

This paper is organized as follows. We first review the definitions and studies of u-learning, augmented reality, and cognitive styles. We then show our research method which includes system design and development, experimental design and experiment participants. Last, we discuss our research results and findings and conclude theoretical and practical findings, limitations, and future research.

Literature review

This section reviews the definitions and studies of ubiquitous learning, the applications of augmented reality in education, and cognitive styles.

Ubiquitous learning

Ubiquitous learning (u-learning) refers to a ubiquitous learning environment that enables individuals to conduct learning activities in the right place and right time. U-learning environments create a context-aware, interoperable, pervasive, and interactive learning architecture that integrates, connects, and shares learning resources among the appropriate parties (Huang et al., 2011). Context-aware u-learning environments can better understand learners' activities and the timely geographical parameters in the real world such as the locations and behaviors of the learners. In other words, context-aware u-learning environments should support personalization and the situation of instructional activities (Chen & Li, 2010). It also supports collaborative and interactive learning (Peng et al., 2008). Moreover, it can achieve constructive learning and self-regulated learning through learning activities (Chen & Chung, 2008). Thus, u-learning is a learning paradigm that takes place in a ubiquitous computing environment that enables users to learn at the right place at the right time (Shih et al., 2012). In this study, we define the context-aware u-learning environment as an environment that users access through mobile devices, wireless communications, and sensor technologies when participating in learning activities.

Context-aware u-learning has been applied in different disciplines such as natural science (Hwang et al., 2010; Chu et al., 2010; Huang & Chiu, 2015; Shih et al., 2016), museum learning (Hall & Bannon, 2006), language learning (Lan & Lin, 2016), sharing of learning resources (Yu et al., 2015), and certification tutoring systems (Huang et al., 2016b). However, the inadequate application of novel technology may lead to meaningless learning of operational techniques, rather than practical, meaningful involvement in learning (Huang & Chiu, 2015). Despite the various studies that have been conducted to examine the technical affordances of u-learning, there is an ongoing need to examine pedagogies that are suitable for u-learning to inform teacher practice, policy makers, curriculum developers, and teacher education (Shih et al., 2012; Pegrum et al., 2013). It is necessary to evaluate whether a u-learning system is able to achieve the purpose of meaningful learning (Huang & Chiu, 2015). In addition, the predictions about transformational teaching practices seem promising but the widespread and effective application of u-learning has not been realized yet. Moreover, prior studies have suggested that evaluation is critical to improve the quality of technology-supported learning environments (Martínez-Torres et al., 2008; Huang & Chiu, 2015). We apply augmented reality (AR) in our context-aware u-learning system to assist English learning in authentic situations.

Augmented reality

Augmented reality (AR) refers to technologies that enhance the sense of reality enabling the concurrence of digital information and real environments (Azuma, 1997; Sayed et al., 2011; Chang et al., 2015b). An AR system is able to combine or supplement real world objects with virtual objects or superimposed information (Azuma, 1997; Bacca et al., 2014; Sayed et al., 2011; EDUCAUSE Learning Initiative, 2005; Chang et al., 2015b). Instead of replacing reality completely, AR intends to supplement reality (Azuma, 1997). AR is not only a virtual technique but also an imbedded design characteristic that helps users retrieve the proper information at the right time and right location (EDUCAUSE Learning Initiative, 2005). An AR system has three characteristics (Azuma, 1997). First, it combines real and virtual objects in the environment. Second, it allows real-time interaction. Third, it aligns real objects or places and digital information in 3D (Azuma et al., 2001). These characteristics enable educators and designers to superimpose virtual graphics over real objects. In addition, they allow users to interact with digital content via physical manipulation (Wei et al., 2015). AR facilitates more effective demonstrations of spatial and temporal concepts, as well as the contextual relationships between real and virtual objects. It has been shown to not only increase individuals' learning motivation but also improve learning performance (Zhang et al., 2014; Wei et al., 2015). However, many of the aspects that allow learners to interact with real objects when using AR systems are still to be discovered (Zhang et al., 2014; Chang et al., 2015b).

Although AR technologies have been around for more than 50 years, the recent proliferation of mobile devices has made affordable AR systems available to the general public (Sommerauer & Müller, 2014). AR systems have been widely applied in education (Sayed et al., 2011; Ibáñez et al., 2015; Wei et al., 2015) and increasingly applied with mobile devices (such as smartphones or tablets) to assist learning (Furió et al., 2013; Hsiao et al., 2016; Huang et al., 2016a). Mobile AR applications leverage the built-in cameras, GPS sensors, Internet access, and mobile devices to embed real world environments with dynamic, context-aware, and interactive digital contents (Sommerauer & Müller, 2014). To enhance user experience, AR technologies embed digital information on objects or places in the real-world (Zhang et al., 2014; Hsiao et al., 2016). AR provides great opportunities for online teaching that emphasizes the practical training and is particularly used in non-classroom training (Hsiao et al., 2016).

Prior studies have indicated that guidance and information provided by learning partners can improve learning performance (Webb, 1982). When people feel isolated in their learning process, their learning satisfaction is reduced (Hiltz & Wellman, 1997; Rovai & Wighting, 2005). Therefore, the interactive learning environment created by AR also enhances learning satisfaction among learners (Hsiao et al., 2016; Huang et al., 2016a). AR offers a multiplicity of applications within the field of education. To complement u-learning with real-time information, AR and RFID functions were applied to create enhanced outdoor u-learning environments for the study of natural science (Liu et al., 2009). Sayed et al. (2011) developed AR student cards that incorporated brand new data-processing and interactive modes to help students visualize their learning goals. Manipulative aids were proved as an effective learning tool for interactivity and usefulness of AR (Hsiao et al., 2016).

Cognitive style

Most innovative technologies for education ignore the fact that students with different levels of achievement require different designs of learning systems and learning strategies (Huang & Chiu, 2015). Thus, we further consider the individual difference such as cognitive style in our study. Cognitive style refers to an individual's typical or habitual mode of thinking, perceiving, remembering, and problem solving (Soflano et al., 2015; Chang et al., 2015a). Cognitive style is defined as a kind of personal characteristic that processes and organizes information and experience based on personal preference (Messick, 1984). It has been considered as individual differences that can be used to affect the adoption of digital learning systems (Chang et al., 2015a). The personal differentiations of cognitive styles can be categorized into perception, thinking, learning, and problem solving (Witkin et al., 1975). Cognitive style is an approach that an individual habitually and preferentially uses to organize and present information. Individuals consistently adopt the same approach and these preferred modes of processing information differ among individuals (Witkin et al., 1975). Individuals with different cognitive styles use different approaches in learning as well. Prior studies have examined the impacts of cognitive styles on learning and found learners with different cognitive styles have different preferences (Chang et al., 2015a).

Prior studies have proved that matching cognitive styles with learning activities can lead to more efficient learning and better learning achievement (Ford & Chen, 2001). Thus, matching the cognitive styles of learners with the instruction approach contribute significantly to learning performance (Chang et al., 2015a). Because of the individual cognitive differences among learners, no one instructional method is appropriate for the array of cognitive styles. Researchers have been encouraging instructors to learn a diverse set of teaching skills so that they complement the array of cognitive styles of their students (Easton, 2003). Fitting instructional methods to learners' cognitive styles not only improves their learning performance but also attitude toward learning (Dunn & Dunn, 1994). To increase the efficacy and satisfaction of learning experience, the design of an instruction system must consider learners' cognitive styles (Hsieh et al., 2011). However, the performance designs that address diverse cognitive styles within new learning technologies remains inconclusive (Dillon & Gabbard, 1998). This knowledge gap leads us to examine the potential of an AR featured u-learning system with that integrates different cognitive styles.

There are different measures of cognitive styles. We choose "Field Dependence (FD)/Field Independence (FI) theory" (Witkin et al., 1975) among the cognitive styles because this theory fits our research context by using AR in the u-learning environment. "FD/FI theory" is the most common applied measure of cognitive styles. The word "field" can be a set of thoughts, ideas, or feelings (Witkin et al., 1975). FD learners refer to individuals that rely highly on structural format and prefer guidance in their learning process (Jonassen & Grabowski, 1993; Ford & Chen, 2000). In other words, FD learners are not good at constructing and analytical activities. The learning experience of FD individuals highly relied on the stimulus of external information and interactivity (Ford & Chen, 2000). On the contrary, FI learners prefer internal references instead of structured format and they are normally independent thinkers (Jonassen & Grabowski, 1993). That is, FI learners prefer analytical and active learning approaches (Frank & Keene, 1993). Field-mixed (FM) learners refer to individuals who do not have a clear FD or FI orientation but rather fall in the middle of the FD and FI spectrum (Liu & Reed, 1994). AR featured u-learning system intends to offer a real-life and interactive learning environment. In this case, FD/FI theory can highlight the different cognitive styles in explaining the learning performance in the AR featured u-learning environment.

Research method

This section shows our system design and development, experimental design, and selections of participants.

System design and system development

In recognition of Kolb's (1984) idea that mature learning environments combine both learning and life, we developed a Ubiquitous Learning Instruction System with Augmented Reality Features (UL-IAR). The design incorporated AR technology and extensive computing power within a context-aware u-learning system to provide adaptive learning strategies to assist English learning. Figure 1 shows the system structure of UL-IAR.

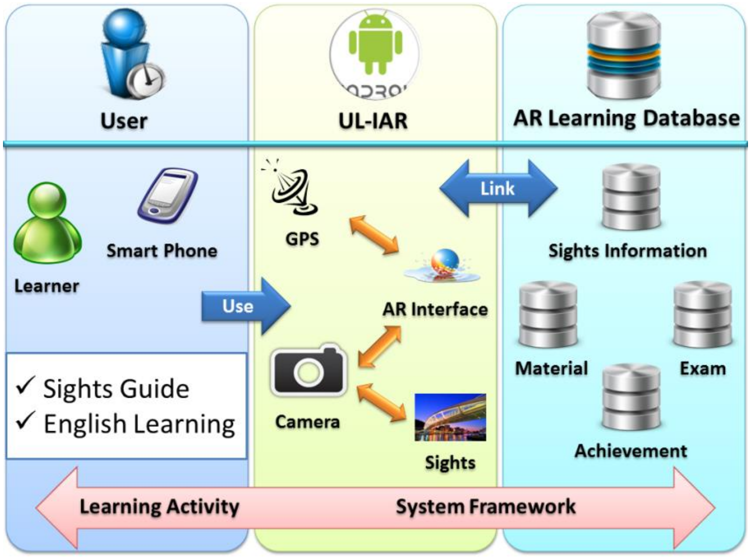

Figure 1. System structure

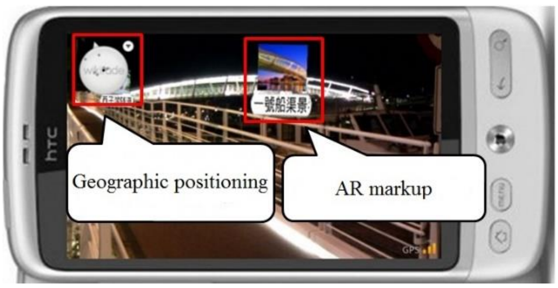

Figure 2. Display of AR markup in a scenery spot

UL-IAR is an English learning system which integrates AR and Wikitude World Browser (See Figure 2). This system was developed on the Android smartphone using Wikitude SDK and Android SDK. The Wikitude World Browser was a mobile software that integrates AR technologies, GPS, and mobile networks which allowed users to retrieve the information relevant to their surroundings (Wikitude, 2016). The primary features of UL-IAR include GPS positioning, the highlighting of local features, mark-up, scaffolding instruction, and real-time tests. Current applications of Wikitude World Browser were commonly employed in business contexts such as providing shopping information and popular scenic spots. However, applications within educational contexts were rare. This UL-IAR system which integrated learning strategies and real-time quizzes helped users to learn English in real life contexts was one of the pioneering applications in the field of education.

Figure 3. English Vocabulary in the smartphone

Figure 4. Real time exam

Figure 5. Result (Scores) of real-time examine

The system structure of UL-IAR can be illustrated as following. First, users must turn on their GPS function in their mobile devices to increase the precision of geographic positioning (See Figure 3). After that, when users turned on UL-IAR, they can choose their current location to start learning English. UL-IAR connected the database through GPS or wireless Internet to provide scenery related instruction and attendant learning materials such as vocabulary or sentences that applicable in real-life contexts (See Figure 4). Third, users can evaluate their learning performance through real-time tests which were served as the pretest in this study. Based on the results of pre-tests, UL-IAR will provide different learning strategies (enforcing, semi-enforcing, and non-enforcing instructions) to assist users' prior learning (See Figure 5). Last, after the scaffolding instructions, there will be another test to investigate users learning achievements when using different learning strategies.

Experimental design

There were two steps before the experiments. First, the participants were asked to take the "Embedded Figures Test (EFT)" to identify their cognitive styles (Messick, 1962). The EFT test included two parts with each part composed of 16 questions embedded with a simple figure among numerous complex figures (Messick, 1962). The completion time was limited to 20 minutes. Second, after identifying the cognitive styles, it took around 10 minutes to introduce and allow the participants to practice the UL-IAR system. Participants were asked to use the ULIAR system as the practice before visiting Kaohsiung West Bay to conduct the experiment. Overall, there were 30 minutes in the pre-experiments steps.

The EFT test was conducted with continuous scoring with a range from 0 (FD) to 32 (FI) to discern the cognitive styles among FD/FI users. This research categorized both the top and bottom 27% of users into both the FI and FD groups wherein the 46% of learners that fall between both ends were defined as the FM users (Spanjer &

Tate, 1988). Specifically, FI and FD individuals are those who are polarized at the end of the spectrum with extremely high and low scores respectively (Liu & Reed, 1994). We found that there were more FM participants followed by FD and FI in our sample size. It is easily to have more FM users in the sample size because 46 % of the individuals that falls in the middle of the scores in EFT. The distribution is also verified in other studies (Angeli et al., 2009; Nicolaou & Xistouri, 2011). To have equal sample size for three different learning strategies, there were 30 FD, FI, and FM users selected for the experiment. Finally, we selected 90 participants to make sure there were an equal number of participants represented in each of the three cognitive styles.

Figure 6. Display of UL-IAR

There were two steps in the experiment. First, the participants were asked to use UL-IAR in Kaohsiung West Bay to experience and learn English (See Figure 6). After that, they took the first test (pre-test) to exam what they have learned from UL-IAR. Second, different learning strategies were assigned to the participants to conduct the review of what they have learned from the first round. The participants used the UL-IAR system for the review of learning contents. In the end, there was a second test. Overall, the experiments were around 60 minutes.

We conducted field experiments to investigate users' learning performance while using UL-IAR. Although field experiments can't control all variables, the experiment results are closest to the real-life learning context. We intended to find out the most appropriate learning strategies for FD, FM, and FI individuals in using UL-IAR. We chose Kaohsiung West Bay as our experiment field because it has many popular scenic spots and numerous street food vendors. The West Bay scenic spots include National Sun Yat-sen University, West Bay Beach Hall, the British Consulate, No. 1 Ship Canal Landscape Bridge, West Bay Tunnel, and Gushan Ferry Station. Our learning materials and in-app tests were developed and based on these scenic spots and street foods which provided vivid learning contents. All of the learning materials and contents were revised by English native speakers.

Figure 7. Enforcing strategy

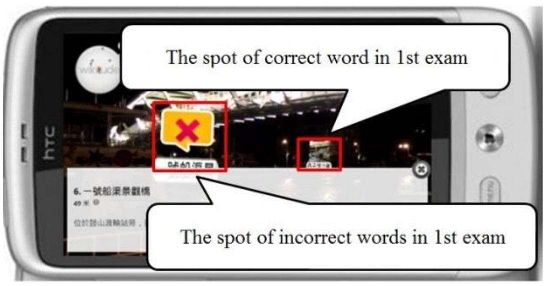

Figure 8. Semi-enforcing strategy

Learning strategies are defined as the behaviors and thoughts that individual engages during learning and that are intended to influence his/her encoding process." Enforcing learning strategy is considered as an appropriate learning strategy in our research context because it can assist individuals to accomplish their learning task more effectively (Wood et al., 1976). Enforcing strategy is defined to help leaners recapitulate and integrate what was explicitly displayed in the instructional materials and techniques that contribute to the memorization and understanding of learning contents. Enforcing strategy has been approved to be an effective learning strategy that leads to positive effects on individuals' learning performance. We applied enforcing strategy with different levels in our experiment: enforcing, semi-enforcing, and non-enforcing to explore the learning effects of users with different cognitive styles. With enforcing strategy, the UL-IAR showed the vocabulary of the scenic spots that learners did not know in the first exam. This incorrect vocabulary was linked to the scenic spots with a green "plus" mark (See Figure 7). The enforcing strategy emphasizes the vocabularies that are incorrect in the first exam. With semi-enforcing strategy, the UL-IAR would show all the scenic spots. When learners did not know the vocabulary of scenic spots in the first exam, the UL-IAR would show a read "cross" mark (See Figure 8). If learners already knew the vocabulary of the scenic spots, UL-IAR system would not have any highlight. With non-enforcing strategy, no matter learners knew the vocabulary or not, there was no specific highlight in the UL-IAR (See Figure 9). It only showed the vocabulary that is related to the scenic spot.

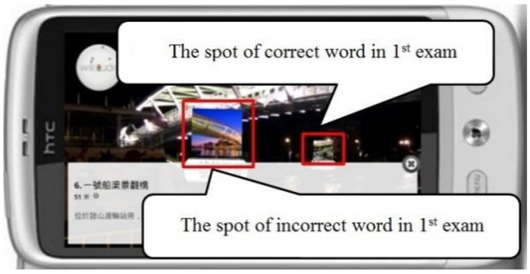

Figure 9. Non-enforcing strategy

Experiment participants

We recruited and selected participants by using convenient and snowball sampling. To ensure the variety and heterogeneity of participants, participants were selected from different ages and backgrounds. Overall, there were 90 participants in our experiment who ranged from the age of 18 to 30 years old. They were college students, medical care workers, service industry employees, social workers, and kindergarten teachers. The objective of this experiment was to separate the appropriate learning strategies for FI, FD, and FM users when using our UL-IAR. We did not employ control and experimental groups but randomly assigned participants of the three different cognitive styles into three different learning strategies. Therefore, there were 9 groups which contain 10 participants each. To measure group differences, cell size with 30 can explain for 80% power. If decreased, no lower than 7 per cell (VanVoorhis et al., 2007). We have 10 participants in each cell which is acceptable sample size.

Research results and discussion

This research aimed to investigate the learning performance of using UL-IAR system among users that have different cognitive styles (field dependent (FD), mixed field (FM), and field independent (FI)). The UL-IAR system embodied different learning strategies (enforcing, semi-enforcing, and non-enforcing) to investigate their impact on users' learning performance. Thus, the independent variables were cognitive styles and learning strategies. The dependent variable was the learning performance of using UL-IAR to learn English. We first conducted a descriptive statistical analysis of the learning performance of all users (See Table 1). The results showed that the average learning scores of FD users with enforcing strategies were the highest (Mean = 91.25). This implies that users with FD cognitive styles matched the enforcing learning strategies. Second, individuals with FM cognitive styles had the highest scores with enforcing learning strategy (Mean = 81.625). Third, the average scores of FI users with semi-enforcing learning strategy was the highest one among the other three. This implies FI users preferred a semi-enforcing learning strategy which would lead to greater learning performance.

We conducted two-way ANCOVA analysis (See Table 2) and the results showed that cognitive styles were not statistically significant (F = 1.995, p = .143). However, learning strategies were statistically significant (F = 10.426; p = .000). In addition, we found that there were interactive effects between cognitive styles and learning strategies (F = 3.493; p = .011) (See Table 2). The partial Eta Squared value indicates the effect size and should be compared with Cohen's guidelines (0.2 - small effect, 0.5 - moderate effect, 0.8 - large effect). It can be seen that effect size of the interaction between Cognitive Styles and Learning Strategies is small (0.149). This value describes how much of variance in the dependent variable is explained by the independent variable (14.9%).

This implied that the impact of cognitive styles on learning performance is affected by another independent variable (learning strategies). A statistical interaction occurs when the effect of one independent variable (cognitive styles) changed depending on the level of another independent variable (learning strategies). Thus, we need to examine how learning strategies are affected by cognitive styles. We further conducted the simple effect tests (Weinberg & Abramowitz, 2002).

Table 1. The descriptive statistics of the learning effect

Cognitive style	Learning strategy	Mean	*SD*	*N*	Total *SD*
FD	Enforcing	91.2500	5.270	10	
	Semi-enforcing	81.8750	10.396	10	16.563
	Non-enforcing	63.3725	17.348	10	
FM	Enforcing	81.8750	5.472	10	
	Semi-enforcing	80.6250	16.783	10	15.110
	Non-enforcing	71.8750	18.923	10	
FI	Enforcing	76.7500	18.049	10	
	Semi-enforcing	77.4500	13.066	10	14.252
	Non-enforcing	73.0750	12.072	10	
Total	Enforcing	83.292	12.502	30	
	Semi-enforcing	79.983	13.324	30	15.222
	Non-enforcing	69.440	16.403	30	

Note. FI = field-independent, FM = mixed-field, FD = field-dependent.

Table 2. Two-way ANCOVA analysis of the learning effect

Source	*SS*	*df*	*MS*	*F*	*Sig.*	Partial eta squared
Pretest	4929.881	1	4929.881	36.488	.000	.313
Cognitive Styles	538.954	2	269.477	1.995	.143	.047
Learning Strategies	2817.209	2	1408.605	10.426	$.000^{***}$	.207
Cognitive Styles x Learning Strategies	1887.817	4	471.954	3.493	$.011^{*}$	.149
Error	10808.739	80	135.109			

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

The results of the simple effect tests show that an enforcing learning strategy influenced three different cognitive styles users (FD, FI, and FM) ($F = 5.996^{**}$) (See Table 3). Since we have 3 groups of participants in three cognitive styles, the significant levels are divided by 3. It implies that the enforcing learning strategy differs in the learning performance among three different cognitive styles of UL-IAR users. On the contrary, semi-enforcing ($F = 0.500$) and non-enforcing ($F = 2.483$) learning strategies did not show statistically significant difference.

Table 3. The simple effect tests of learning strategies to cognitive styles

Learning strategies	FD	FI	FM	*F*
	Mean / *SD*	Mean / *SD*	Mean / *SD*	
Enforcing	91.250 / 5.270	76.750 / 18.049	81.875 / 5.472	5.996^{**}
Semi-enforcing	81.875 / 10.396	77.450 / 13.066	80.625 / 16.783	0.500
Non-enforcing	63.373 / 17.348	73.075 / 12.072	71.875 / 18.923	2.483

Note. FI = field-independent, FM = mixed-field, FD = field-dependent. $^{*}p < .05/3$; $^{**}p < .01/3$.

Since enforcing learning strategy differs in the users' learning performance among three cognitive styles, we further examine the simple effect tests for enforcing learning strategies. Among three cognitive styles (FD, FI, and FM users), FD users aligned with an enforcing learning strategy yield the best English learning performance ($p = .002$) (See Table 4). With enforcing learning strategy, the learning performance of FD users is better than that of FI users (Mean difference = 16.617, $p = .002^{**}$).

Alternatively, we examined whether different cognitive styles with different learning strategies lead to different learning performance (See Table 5). The results showed that FD users' learning performance was significantly different with three learning strategies (enforcing, semi-enforcing, and non-enforcing) ($F = 21.894^{**}$). On the contrary, FI and FM users' learning performance did not show significantly different with three different strategies (FI: $F = 0.764$ and FM; $F = 1.049$).

Table 4. The simple effect tests for enforcing learning strategy among three cognitive styles

(I) Cognitive Style	(J) Cognitive style	Mean Difference (I-J) / *SE*	*Sig.*	Note
FD at Enforcing	FI at Enforcing	16.617/4.876	.002**	FD > FI
	FM at Enforcing	11.069/4.838	.031	
FI at Enforcing	FD at Enforcing	-16.617/4.876	.002**	
	FM at Enforcing	-5.548/4.773	.256	
FM at Enforcing	FD at Enforcing	-11.069/4.838	.031	
	FI at Enforcing	5.548/4.773	.256	

Note. FI = field-independent, FM = mixed-field, FD = field-dependent. $^{*}p < .05/3$; $^{**}p < .01/3$.

Table 5. The simple effect tests of cognitive styles to learning strategies

Cognitive styles	Enforcing Mean / *SD*	Semi-enforcing Mean / *SD*	Non-enforcing Mean / *SD*	*F*
FD	91.2500 / 5.270	81.875 / 10.396	63.373 / 17.348	21.894**
FI	76.750 / 18.049	77.450 / 13.066	73.075 / 12.072	0.764
FM	81.875 / 5.472	80.625 / 16.783	71.875 / 18.923	1.049

Note. FI = field-independent, FM = mixed-field, FD = field-dependent. $^{*}p < .05/3$; $^{**}p < .01/3$.

To understand the interactive effect between cognitive styles and learning strategies, we conducted the simple effect tests of cognitive styles to learning strategies as the post-hoc analysis (See Table 6). Among three learning strategies, FD users with enforcing learning strategy yield best English learning performance which was better than semi-enforcing learning strategy (Mean = 81.875; p = .007) and non-enforcing learning strategy (Mean = 63.373; p = .000). FD users with semi-enforcing learning strategy was better than FD users with non-enforcing (p = .001). Overall, when users' cognitive style was FD, enforcing learning strategy was better than semi-enforcing and non-enforcing learning strategy.

Table 6. The simple effect tests for FD users among learning strategies

(I) Learning strategies	(J) Learning strategies	Mean difference (I-J) / *SE*	*Sig.*	Note
FD at Enforcing	FD at Semi-enforcing	13.110/4.511	.007*	Enf. > Semi-enf.
	FD at Non-enforcing	29.148/4.416	.000***	Enf. > Non-nf.
FD at Semi-enforcing	FD at Enforcing	-13.110/4.511	.007*	Semi-enf. < Enf.
	FD at Non-enforcing	16.037/4.451	.001**	Semi-enf. > Non-enf.
FD at Non-enforcing	FD at Enforcing	-29.148/4.416	.000***	Non-enf. < Enf.
	FD at Semi-enforcing	-16.037/4.451	.001**	Non-enf. < Semi-enf.

Note. FI = field-independent, FM = mixed-field, FD = field-dependent. $^{*}p < .05/3$; $^{**}p < .01/3$; $^{***}p < .001/3$.

Conclusion

Researchers have been interested in promoting context-aware u-learning to improve learning performance. How to better apply new technologies to create vivid learning environment and experience is a critical research issue. This paper has two main objectives. The first objective of this study is to develop a u-learning system that incorporates AR technology (UL-IAR) to improve English learning performance and to animate English learning experience. Based on this UL-IAR system, we further developed English learning content with different learning strategies (enforcing, semi-enforcing, and non-enforcing). The second objective is to examine whether cognitive styles and learning strategies affect learning performance when using UL-IAR. We further tested the optimum alignment of learning strategy and cognitive style for the UL-IAR application. Our main findings can be summarized as following. First, different learning strategies with different cognitive styles lead to different learning performance when they use UL-IAR to learn English in real life contexts. Second, field dependent users aligned with an enforcing learning strategy yield the best English learning performance by using UL-IAR. Applying an enforcing learning strategy for FD users in UL-IAR is more productive than applying either a semi-enforcing or a non-enforcing learning strategy. Third, FD users benefit more from an enforcing learning strategy than users who have FI or FM cognitive styles. The results show that using the UL-IAR with an enforcing learning strategy can positively improve FD users' learning performance. Our findings are consistent with Dunn and Dunn's (1994) argument that an individual's learning performance or learning attitude can be positively improved when teaching and learning resources match an individual's cognitive style.

Overall, our contributions can be summarized as following. First, we developed a context-aware u-learning system with augmented reality technology (UL-IAR) to allow users to animate their English learning experience in a real life context. UL-IAR allows users to listen, to speak, and experience English learning in the real life context. This study provides practitioners a reference to develop and implement learning system in education field. Second, the UL-IAR allows individuals to learn English in a real life context which improves the understanding of English vocabulary and enlivens learning experience. This study echoes Kolb's idea that mature learning environments combine both learning and life (Kolb, 1984). Third, applying learning strategies to users with different cognitive styles leads to different learning performance in using UL-IAR. Applying enforcing learning strategy in UL-IAR to FI users leads to best learning performance. This finding suggests the best alignment of learning strategies with users of different cognitive styles. Forth, if we apply learning strategies in the learning processes by using UL-IAR, users immediately recognize areas of difficulty and are able to address them when they arise. This finding implies that applying learning strategy in UL-IAR system can contribute to better learning performance. Our findings also echo prior research that suggests that context-aware u-learning can improve individuals' learning performance (Sandberg et al., 2011, Cheng et al., 2010).

There are a few limitations in this research. First, we didn't find adaptive relationships in some learning strategies and cognitive styles. Future research may test different learning strategies for different cognitive styles to find out better alignments for different users. Second, as AR technologies mature, to create authentic language u-learning environment with AR is emerging as a promising approach for improving learning performance. This study demonstrates such design and finds the relationships between learners' cognitive styles, learning strategies and learning performance in the UL-IAR usage. Future research can provide a broader and deeper view of how different learners can be adaptively supported in using UL-IAR to learn English effectively.

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