**Doi:** 10.30473/IDEJ.2022.8751 **ISSN:** 2588-4476

**Iranian Distance Education Journal**

Vol. 3, No. 1, (New Series) Winter-Spring 2021 (P 9-22), Payame Noor University

**Original Article**

# Effects of a Personalized Reading Software Program on the Development of Language Learners' Reading Comprehension

**Mehrak Rahimi [*1], Ghazal Beyzavi[2], Fatemeh Saffari[3]**

1. Associate professor of Shahid Rajaee Teacher Training University (SRTTU), Tehran, Iran

2., M.A. English Department, Shahid Rajaee Teacher Training University (SRTTU), Tehran, Iran

3. Researcher. Department of Computer Engineering, Iran University of Science and Technology (IUST), Tehran, Iran

**Received:** 2020/05/02 **Accepted:** 2021/02/14

## Abstract

The current study explored the effects of a personalized reading software program designed based on language learners' learning style on the development of their reading comprehension. Forty Iranian K-9 students were selected through convenience sampling and were assigned into control (n=20) and experimental (n=20) groups. Both groups' entry level of English reading proficiency was assessed by reading paper of Cambridge A2 Key exam. Reading was taught to both groups for 10 sessions using a researcher-developed software program. The experimental group used the reading software designed based on users' cognitive profile (visual, auditory and kinesthetic) with customized instructional scenarios. The control group used a version of the same software that did not include any user-tailored teaching materials. Both groups took part in reading paper of A2 Key again at the end of the experiment. The data were analyzed using One-way Analysis of Covariance (ANCOVA). The results revealed a significant difference between participants' reading comprehension at the end of the experiment in favor of the experimental group. The finding highlighted the role of learners' diversity in the success of computer-assisted learning environments, and has certain implications for software developers and language pedagogues.

## Keywords

personalized software; language; learners; reading comprehension

## Introduction

Some Overspread use of technology has had an immense impact on people's personal, social, and professional life in the last few decades. In particular, technology has transformed the meaning of key elements of education such as teacher, learner and instructional content and has opened myriad opportunities for personalized and life-long learning.

Computer-assisted learning environments help teachers change and adapt the content according to their students' needs and preferences; therefore, learning has become more interactive, personalized, and meaningful in recent years. The application of technology has substantially transformed instructional practices and has made teaching more effective and productive in terms of advancement and achievement [1]. Computers are now viewed as an essential instructional instrument in the classes of the 21st century in which teachers have convenient access to multiple instructional resources, are sufficiently prepared, and have more freedom in implementing the curriculum [2].

As a result of advancements in technology, teachers and learners' literacy undergoes radical changes as well. One of the advantages of using computers for learners is that they are provided with individualized instruction and become able to adjust their own learning process to the instructional content. To achieve this aim, there should be thorough consideration of learners' needs and diversity in the process of designing software to match the content to their wants, interests, and preferences. As Raschio [3] stated, the potential of computer-assisted learning is realized only after software authors begin providing material that is both self-paced and tailored to students' individual needs and preferences. Ubiquitous presence of technology and mobile devices among the nation has paved the path for such an opportunity and thus demands instructional designers to more critically pay attention to students' choice of learning media.

One of the main issues of designing educational software is considering the individual differences and people's interests for using them. For computer-supported learning environments to be effective, merely giving students access to computers for reasonable amounts of time is not sufficient; their learning strategies and styles must also be understood and exercises should be provided that are conducive to their particular cognitive style [3]. Personalized environments can adapt to students' educational demands [4] by identifying learner modality and offering content based on different scenarios and learner-based evaluation. It can store teacher and students' knowledge about the educational content and the educational strategies and avail this collection of knowledge in the appropriate time [5]. This type of instruction promotes student engagement and understanding of key concepts; and frees teachers from their routine tasks while providing them with more time to adapt the role of instructional coaches and mentors for their students [6].

Research on the implementation of personalized instruction is indicative of its positive and constructive impact on learning achievement and motivation in mainstream education [7] in general and language education in particular [8]. Within foreign language learning domain, most work has focused on teaching vocabulary with personalized instruction and research on receptive skills is still in need of further attention. The aim of the current study thus was to design a reading software program that can differentiate and categorize English as a Foreign Language (EFL) learners based on their learning style; and then provide them with customized instructional materials following the detection/prescription model. The study aims to answer the following question:

Does a personalized reading program designed based on language learners' learning style have any significant effect on the development of their reading comprehension?

## Review of Related Literature

### - *Personalized learning*

In with the advent of learner-centered approached in the second half of the 20th century, more attention has been paid to learners and their learning preferences in mainstream education. Individual differences in terms of social, cognitive, and affective domains were recognized and researched in the framework of differential psychology that is "concerned with understanding those characteristics that make individuals dissimilar to each other, exploring how and why such differences occur" [9]. The rationale behind considering individuals' personal and situational needs in instructional design and practice can be explained by the fact that learning efficiency is guaranteed when education is responsibly flexible and does not follow the premise "one-size fits all".

Personalized learning is the "instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner. Learning objectives, instructional approaches, and instructional content (and its sequencing) may all vary based on learner needs" [10]. Following a learner-centered paradigm, personalized learning prepares the ground for learners' more engagement in learning where the teacher is the facilitator of the learning process in contrast to a teacher-fronted approach [11] where the teacher decides for everyone's learning through organizing and managing the instruction.

Through personalized instruction the learners would be provided with learning scenarios that fit their needs and wants based on their learning preferences and contexts [12].

The advancement of technologies has greatly contributed to making more personalized learning environments such as personalized websites or mobile apps. In this way the system conforms to the learners and their learning preferences rather than the learners adjusting themselves to the system [13]. Students benefit more from self-adapting learning systems where they have control over their pace of learning, the input to be processed and the activities to be done [14]. The implementation of technology to launch personalized learning environments would “provide a platform to access myriad engaging learning content, resources, and learning opportunities needed to meet each student’s needs everywhere at any time” [15]. This enables students to select those methods of online instruction that are more appropriate to their own particular learning styles [16]. This personalized and tailored instruction may utilize one of the following approaches: personalization of the content, based on learners’ preferences, educational background and experience, personalization of the delivery and form of the learning content, and full personalization, that is composed of the combination of the above approaches [17].

There are five levels of personalized learning: name-recognized, self-described, segmented, cognitive-based, and whole-person-based [18]. In name-recognized personalization the identity of the suers is acknowledged by the system. In self-described personalization the learners are capable of describing their preferences by completing gate-keeping forms or surveys. Segmental personalization divides the user based on their similarities and common shared interest. Cognitive-based personalization delivers instructional content to learners based on their cognitive attributes and profiles. The whole person personalization provides a dynamic and smart learning environment where the system collects data from the learners in the process of learning and adapt the contents to the learners based on sophisticated algorithms. From level one to level five the technology sophistication increases and more complicated programming is required.

Some studies have developed personalized applications with varying levels of technology complexity with the aim of examining the impact of these enlivenments on learning gains. Hwang, Kuo, Yin and Chuang [19], for instance, developed an adaptive learning system to assist users to learn in a real-world, authentic environment by generating several individualized learning paths based on the learning status of each student and the relationships between learning targets. Similarly, Lin, Yeh, Hung, and Chang [20] developed a personalized creativity learning system that could offer personalized learning paths for optimizing the level of creativity. The result of their study showed that personalized learning paths were effective in improving students’ creativity scores. Furthermore, they showed that incorporating personalized learning and game-based learning into a creative learning program could enhance learners' motivation and learning aims.

In a recent study, Alarmi et al. [21] reviewed the literature to provide an overview of personalized learning theory, technology, practices, and studies of implementing technology models to support personalized learning. The results are indicative of three technological models that support personalized learning within blended learning environments in higher education, an increase in personalized learning implementation in higher education with the support of the referenced technology models and platforms, and a lack of data-driven and independent research studies that investigate the effectiveness and impact of the personalized learning and technology models on student learning.

Within this framework, some studies have focused on developing personalized environments based on learning style to provide users with learning objectives, content, and activities that best suit their learning needs and preferences.

- *Personalized learning and learning styles*

One of the widely researched attributes of human being is learning styles or "an individual's preferred way of processing information and of dealing with other people" [22]. As in traditional classes it is very difficult to address all learners' learning style, researchers have shown interest in examining the way technology-based personalized learning environments can fulfill the needs of learners with different learning styles.

Zapalska and Brozik [23] recognized several teaching strategies for online instruction taking VAK learning styles into account. Their first suggestion was to deliver content in a variety of formats such as audio narration with a PowerPoint presentation, as well as a written transcription of the audio. Another recommendation of their study was to encourage active collaboration between students, with both individual and group activities. Zajac [16] explored the possibility of offering methods for personalizing the delivery of course content in a virtual learning environment. It is put forward that a learning styles questionnaire should be incorporated into the online course, so that students can assess their own personal learning style and then choose from a variety of course delivery methods in accordance to their individualized learning style.

Bachari, Abelwahed and El Adnani [24] examined teaching strategies that were matched with learner's personality using the Myers-Briggs Type Indicator (MBTI) tools. They developed an adaptive learning management system by considering learner's preferences and profiles according to the results of learning styles questionnaire that was fine-tuned during the course of the interaction using the Bayesian model. The result of the experiment conducted to evaluate the performance of this approach showed that the system was effective in improving the learning achievement. In another study, Yang, Hwang, & Yang [25] offered an adaptive learning system developed by using both learning styles and cognitive styles to modify the user interface and learning content for individual students. The results of the study illustrated that the proposed system could improve the learning achievements of the students. Additionally, it was found that the students' cognitive load was significantly declined and their belief of learning gains was augmented.

In a recent study Horváth [26] examined the impact of 3D VR platforms as personalized educational environments on learning efficiency. The learners' learning style was assessed based on Kolb's model. The results indicated that the 3D spaces have a high potential for personalizing VR education and would lead to better test performance in comparison to traditional teaching. Also, Martin, Dominic, and Francis [27] developed a system that classified the learners based on the time they spent on learning content of different types. The learning style based on VARK model (Visual, Auditory, Read/Write and Kinesthetic) was used to classify the learners. The system classified the learners and recommended the learning objects based on their learning preferences. No follow-up experimental study, however, was performed to examine the effectiveness of the system on learning gains.

- *Personalized language learning with technology*

Individual differences are viewed to be a part of language learners' characteristics that can predetermine a successful language learning experience [28]. By the ubiquitous presence of technology in everyone's lives, probing into the issue of personalized language learning environments with technology has attracted the attention of the researchers. The reason lies in the fact that the benefit of personalized instruction would be amplified in computer assisted language learning (CALL) environments as technological systems let the users achieve the most efficient learning in the least time [29]. In this framework, "personalization is not only about new ways of distributing learning resources, but also about finding ways to understand the skills, resources and interests of the learner outside the classroom" [30].

Despite a rather strong theoretical underpinning for the application of personalized systems in language learning and teaching, a few empirical studies are available on the effectiveness of such systems on learning gains. Chen and Chung [29] for instance, developed a personalized mobile English vocabulary learning system based on Item Response Theory and learning memory cycle. The system was implemented on personal digital assistant (PDA) for personalized English vocabulary learning among English teaching majors in a university in Taiwan. The results showed that the personalized system promoted learning performances and interests. In another study, Petersen and Markiewicz [30] developed the PALLAS system that provided language learners with real life language learning scenarios by giving them personalized and contextualized access to learning resources. The system was mobile based and could be integrated into a Content Management System. The system was evaluated by three teachers and the results showed that the teachers agreed that PALLAS increased the flexibility of learning for the students and it was a suitable means of providing personalized learning. Jung and Graf [31] made a cognitive-based personalized web-based vocabulary learning framework utilizing word association games for teaching English as a foreign language. The system had a personalized engine that tailored the words to the current level of learners' vocabulary knowledge. Su, Yu, Su, and Lee [32] presented the design and experimental results of a cloud-based personalized recursive dialogue game system for computer-assisted language learning. A real cloud-based system was implemented and the experimental results demonstrate promising outcomes and the effectiveness of the approach.

As the review of literature shows, the development of personalized systems for teaching reading English as a Foreign language is scarce. Xu, Wijekumar, Ramirez, Hu, and Irey [33] reviewed a number of intelligent tutoring systems (ITSs) designed for teaching reading among K-12 students. The result of examining 19 studies on the theme showed that ITSs produced a larger effect size on reading comprehension when compared to traditional instruction but a small effect size when compared to human tutoring. However, no such research is available to examine these learning conditions in the context of second or foreign language learning.

Due to scarcity of research on the impact of personalized CALL environments on EFL learners' development of reading comprehension, the current study aims at probing into the effectiveness of a personalized software program designed based on learning styles of EFL learners on the development of their reading comprehension. As for computer assisted language learning (CALL), it should be noted that a careful observation of individual differences to assess human computer interaction would help language experts and educationists understand the performance and behavior of language learners in technology-based learning environments better to design personalized instructional content [34]. Admittedly, this leads to a more effective CALL environment that is capable of taking into consideration the language learners' diverse needs.

## Method

### - *Participants*

Forty K-9 female students participated in this study. They were selected based on convenience sampling (CS) from all K-9 female students who were studying in district 16 of Tehran in the academic year 2019-2020. There were eight K-9 classes in the school, two classes were selected as the sample and they were divided into experimental (n=20) and control (n=20) groups using simple random sampling. The study utilized a pretest-posttest control group design.

The participants spoke Persian as their native language and English was regarded as a foreign language for them. They attended English class once a week and each session lasted for 90 minutes. All students attended the same public school and their entry-level reading proficiency was checked prior to the study. 2.2. Instruments

A2 Key: To assess participants' English reading comprehension, reading paper of A2 Key (Key English Test) was used. A2 Key is a test among Cambridge English Qualifications, a group of examinations developed by Cambridge ESOL at Cambridge University.

**Table1.** Reading tasks of A2 key [35]

| **Part** | **Number of Questions** | **Task Type** | **What do candidates have to do?** |
|---|---|---|---|
| 1 | 6 | 3-option multiple choice | Read six short real-world texts for the main message. |
| 2 | 7 | 3-option multiple matching | Read seven questions and three short texts on the same topic, then match the questions to the texts. |
| 3 | 5 | 3-option multiple choice | Read one long text for detailed understanding and main ideas. |
| 4 | 6 | 3-option multiple-choice cloze | Read a factual and choose the correct text vocabulary items to complete the gaps. |
| 5 | 6 | Open cloze | Complete gaps in an email (and sometimes the reply too) using one word. |

There are seven tests from pre-A1 to C2 clustered in three proficiency levels (basic, independent, proficient) based on Common European Framework of Reference (CEFR). A2 Key is the third test of level 'basic' above pre-A1 and A1 and below B1 (Preliminary English). This test assesses candidates' proficiency of English communication in simple situations.

A2 Key is made up of four papers including reading, writing, listening, and speaking. For the purpose of this study, the reading paper was used. This paper has five parts and 30 questions. Details of A2 Key reading paper are provided in Table 1 [35].

The reliability coefficients of A2 Key for pretest and posttest were estimated to be .72 and .84 respectively.

VAK learning style questionnaire: VAK learning style questionnaire was used to assess the participants' learning style and portray their cognitive profile [36]. The scale has 30 items that assess individuals' preferred way of absorbing information and perceiving the outside world. The scale has three learning modalities (often identified by the acronym VAK): Visual Modality, Auditory Modality, and Kinesthetic Modality.

Each item of the scale has three options: A, B, and C by the help of which the respondents' learning style is determined:

- If the respondent chooses mostly A's, s/he has visual learning style.
- If the respondent chooses B's, s/he has an auditory learning style.
- If the respondent chooses C's, s/he has a kinesthetic learning style.

The software: The main instrument for carrying out this research was a software program for teaching reading skill designed based on learner's cognitive profile.

In the process of logging into the software, the students were asked to answer the VAK learning style questionnaire by selecting the option(s) that best described their learning preferences. Then the participants fall into one of three categories or types of cognitive modes known as visual, auditory and kinesthetic based on their answers. When the learner's preferred style of learning was identified, the individual was directed to one of the three instructional scenarios/teaching contents that matched their learning preferences in the software.

Scenario A, visual style: As a visual learning style has a preference for seen or observed things, including pictures, diagrams, demonstrations, displays, etc., the reading passages were integrated with pictures and displays. In other words, while reading the passage, the users were able to activate the hyperlinks to displays and pictures within the text.

Scenario B, auditory style: An auditory style has a preference for the transfer of information through listening to the spoken word, of self or others, of sounds and noises. Thus, the reading passages were integrated with pronunciation of words (American accent), read-aloud of the texts, and background music.

Scenario C, kinesthetic style: Someone with a kinesthetic learning style has a preference for physical experience, motion, and doing. The reading passages were integrated with gif representations or animations that included motions and movements of the concepts. Pushing the keyboard, clicking, and acting out were among the tasks required to be done.

The software consisted of six short passages revolving around the topics of the textbook Prospect 3 [37]. The flowchart of the program is shown in Fig. 1.

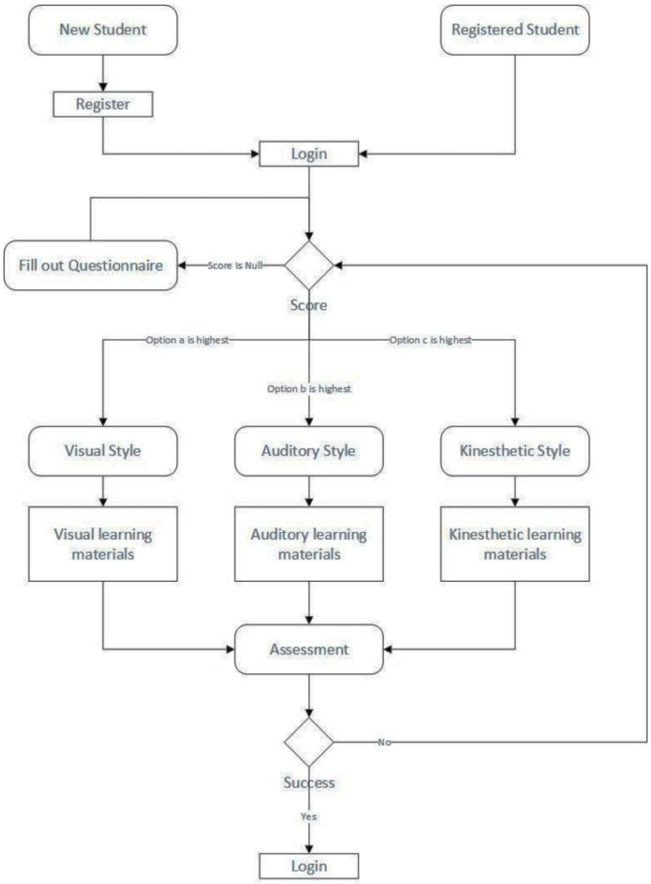


**Figure1.** The flowchart of the personalized software program

For the control group, another version of the software was developed with the same format and the same reading passages and questions but without the VAK learning style questionnaire as the gatekeeping. Thus, no specific scenario for teaching the texts was determined. The combination of displays, music, animations, and motions were used for each reading passage.

### Procedure

- *Software development*

In order to develop the software first the linguistic content was prepared and then the software was designed by the developer.

Preparing the linguistic content: Appropriate reading texts were chosen and their difficulty levels were checked with two language teachers. Additional materials including pictures, animations, music, and sounds were also provided.

Designing the software: Software development methodology was incremental and the following phases were followed for designing each feature of the software.

Requirements: The flowchart of the program was developed and given to the software developer along with the list of the requirements.

Design: The software developer designed the feature(s) based on the requirements.

Implementation and testing: The software developer implemented the frontend of the software using HTML5, CSS, Bootstrap, and JavaScript. The backend was implemented by PHP. For managing the data SQL language was used.

Verification: The feature was checked by the researchers for the appropriacy of technical and pedagogical issues. Some issues were discussed with the software developer and resolved based on the researchers' suggestions. Ultimately, the feature was verified.

The software was both desktop- and mobile-based.

**- The experiment**

After selecting the participants and organizing them into control and experimental groups, all participants took part in A2 Key reading paper. Then the reading instruction was delivered based on the design of the study to both experimental and control groups.

The students of the experimental group were first introduced to the software and how it worked. Then they were asked to register and log into the program. Based on the results of the gatekeeping assessment of their learning styles, they were divided into three groups: visual, auditory, and kinesthetic learners. The teacher explained to the learners how different individuals learn concepts and skills in diverse ways and encouraged them to become familiar with their own style of learning and implement it while reading other texts.

The teacher provided the students of the control group with the second version of the software that did not observe any individual differences based on the cognitive profile of the leaners. Reading was taught to the whole class with the same materials and procedure.

After 10 sessions of teaching, both groups' reading proficiency was reassessed with A2 Key. The data were inserted into IBM SPSS 25 for further analysis.

**- Results and findings**

To compare the means of both groups' post-test scores of A2 Key reading paper, One-way Analysis of Covariate (ANCOVA) was employed. In this study, ANCOVA was preferred to neutralize the differences observed in A2 Key pretest scores of the control (mean=13.7, SD=4.48) and experimental groups (mean=12.64, SD=4.79).

Some preliminary assumptions were examined before going further with main ANCOVA analysis [38].

**- ANCOVA Assumptions**

The assumptions of reliability of the covariates, normality, linearity, homogeneity of variances, homogeneity of regression slopes, and equality of error variances underlie ANCOVA. The results of testing these assumptions are as follows:

Reliability of covariate: As Cronbach alpha coefficient of A2 Key pre-test was .72, this assumption was met.

Multivariate normality: To check for normality, Kolmogorov-Smirnov and Shapiro-Wilk statistic were used. The results of normality tests are shown in Table 2. As the results suggest, normality has not been violated ($p=.01$).

**Table2.** Tests of normality

| | | Kolmogorov-Smirnov | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|---|
| | **Group** | **Statistic** | **df** | **Sig.** | **Statistic** | **df** | **Sig.** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| A2 Key | Control | .204 | 20 | .028 | .909 | 20 | .061 |
| | Experimental | .111 | 20 | .200 | .981 | 20 | .950 |

Linearity: To check the assumption of linearity, the linear relationship between the dependent variable and the covariate for all groups was examined (Fig. 2).

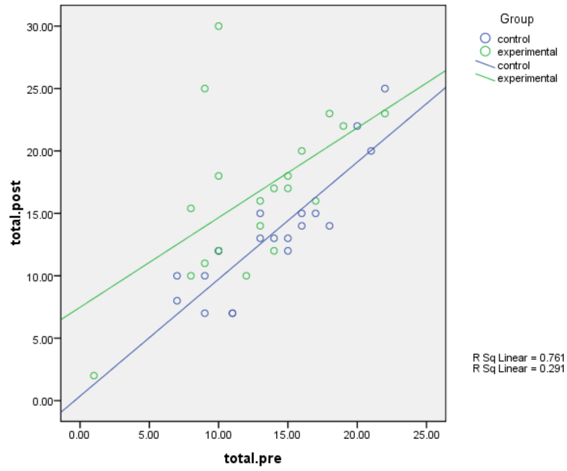


**Figure2.** The linear relationship between the dependent variable and the covariate

As Fig. 2 illustrates, there is a linear relationship between the dependent variable (post-test) and covariate (pre-test) for two groups due to the fact that the slope of two lines is quite similar. Therefore, the linearity assumption was fulfilled.

Measurement of Covariate: The researcher measured the covariate prior to the intended treatment, so this assumption was met, too.

Homogeneity of Regression Slope: As it is shown in Table 3, the significant value for the interaction of independent variable and covariate (group and pre-test respectively) is 0.467>.05, therefore, the assumption of homogeneity of regression slope was not violated.

**Table3.** Tests of between subjects effects to check homogeneityof regression

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 670.622 | 3 | 223.541 | 12.496 | .000 |
| Intercept | 63.713 | 1 | 63.713 | 3.562 | .067 |
| Group | 52.538 | 1 | 52.538 | 2.937 | .095 |
| Total pre-test | 553.944 | 1 | 553.944 | 30.965 | .000 |
| Group * total post-test | 9.647 | 1 | 9.647 | .539 | **.467** |
| Error | 644.009 | 36 | 17.889 | | |
| Total | 10177.160 | 40 | | | |
| Corrected Total | 1314.631 | 39 | | | |

Equality of error variance: The Levene's test of equality of error variances was used to examine whether the error variance of the dependent variable was equal across groups. As the value for the error variances was not significant (F=3.495, p= 0.069>.05) it can be concluded that this assumption was also satisfied.

As all assumptions underlying ANCOVA were met, ANCOVA was carried out.

**-ANCOVA**

The result of ANCOVA is reported in Table 4. As Table 4 shows, the result of Tests of Between-Subjects Effects is significant [F (1, 37) =10.00; p=0.003; partial eta squared=0.213] indicating that the performance of subjects in two groups was statistically different after the treatment. Moreover, Partial Eta Squared (0.213) shows that 21 percent of the variance in the dependent variable was explained by the independent variable. Based on Cohen's guideline [39], this value indicates a strong effect for the intervention.

**Table4.** The result of ANCOVA

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| Corrected Model | 660.975 | 2 | 330.487 | 18.707 | .000 | .503 |
| Intercept | 68.912 | 1 | 68.912 | 3.901 | .056 | .095 |
| Total pre-test | 547.406 | 1 | 547.406 | 30.986 | .000 | .456 |
| Group | 176.761 | 1 | 176.761 | 10.005 | **.003*** | .213 |
| Error | 653.656 | 37 | 17.666 | | | |
| Total | 10177.160 | 40 | | | | |
| Corrected Total | 1314.631 | 39 | | | | |

Examining the descriptive statistics showed that experimental group outperformed (Mean=16.57, SD=6.3) the control group (Mean=13.20, SD=4.8) in A2 Key posttest.

**Table5.** Descriptive Statistics of A2 Key Post-test across groups

| Group | Mean | SD |
|---|---|---|
| Control | 13.200 | 4.818 |
| Experimental | 16.570 | 6.323 |

## - Discussion

As the results of this research illustrates, integrating a personalized educational software program designed according to EFL learners' learning style can have a significant effect on the development of their reading comprehension.

The finding is first and foremost in agreement with theoretical underpinnings of second language acquisition that considering language learners' differences in the instruction can impact teaching and learning outcome. Since language learners are not homogeneous, the levels of linguistic competence to which they reach are also diverse. Among individual differences, this study addressed learner's learning styles that deal with individuals' preferred way of information processing, that is, perceiving, conceptualizing, organizing, and recalling information [40]. Considering these factors in instruction leads to improvement in the quality of language learning as learners' engagement in cognitive activities is influenced by the way their preferred ways of learning are appropriately addressed. In particular, literature shows that considering language learners' learning style during teaching and learning can contribute to deeper and more effective learning since, as shown in this study, imagers learn best from pictorial presentation, while verbalizers are superior when text processing is involved [41].

Further, when teaching methods and formats of presenting the materials are consistent with learners' learning styles, both student's learning performance and attitudes towards learning are boosted. Involving students in learning environments in which they have the chance to pursue the learning process according to their own learning style can significantly influence information processing and thereby the results of learning [42].

The findings of this study corroborate the results of other works on the benefit of personalized instructions [43] implying that when the instruction format and the learner's learning styles are consistent with each other, acquiring knowledge is more enjoyable and the learner's attitude and motivation are positively affected. The personalized learning environments can create a uniquely joyful learning atmosphere tailored to the needs and wants of every individual and thus reduce the fears and insecurities the students may feel while they experience learning new concepts. Furthermore, as technology behavior of learners is highly related to learners' diversity, particularly their cognitive style [44], their learning is promoted within this context.

The finding also shows that when students' learning style in reading instruction is addressed, processing of information is optimum. Several studies have referred to the fact that incorporating the needs of language learners in reading instruction is a must in developing instructional materials. The reason lies in the fact that individual cognitive differences among students mean that no single instructional method of teaching reading skills is suitable for the range of cognitive styles. Increased comprehension of a given knowledge set, i.e., a text, and increased satisfaction with technology use have been found to be mutually reinforcing to a certain extent [45]. Further, the presentation of reading activities in the customized computer learning environments can bring about more understanding of the text and more positive attitudes towards reading tasks [46].

The study supports the proposition that computer-based learning environments are more influential when students' needs are met and observed in design process. This promotes learning because through the incorporation of technology, learners can obtain responsible and self-directed behaviors. Research suggests that instructors need to learn a different set of teaching skills, particularly, for teaching online [47], so they can fit the design and presentation of the materials to students' needs and wants. Any reading software program along with the accompanying instructions must be adaptive to learners' cognitive styles so as to increase both the efficiency and the satisfaction of the learning experience.

## Conclusions

By the advancement of technology in recent years, particularly in the domain of artificial intelligence, personalized software programs have attracted the attention of researchers of different subject matters. Although there is empirical evidence to support the effectiveness of personalized applications in certain areas of language education such as vocabulary and grammar [31], the role of these types of learning environments in the development of language receptive skills is not yet fully addressed. To fill this gap, the current study investigated the effect of a personalized reading program designed based on EFL learners' learning style on the development of their reading comprehension. In order to achieve this aim, 40 Iranian language learners were asked to participate in the research. They took part in a mobile-based reading instruction course in which they worked on a reading program designed based on their cognitive profile. In agreement with a few research done on the effectiveness of intelligent tutoring systems (ITSs) on reading comprehension [33], the findings of the study showed a significant difference in the performance of the experimental and control groups with respect to the development of their reading comprehension.

Based on available literature, educational technology applications have positive but small effect on the development of reading skills [48] and personalized technology-enhanced environments can increase this effect size. The results of the study emphasize the pivotal role of learner-tailored instructional materials in learning and the importance of considering teaching and learning principles in designing CALL materials and environments as personalization of the instruction is not only about how learning resources are distributed, but also how different ways are formed to understand the knowledge, skills, and interests of the learners [30].

Suggestions for further research: This study can be done on other age ranges of students, on both genders and on greater number of participants to increase the validity of the findings. Also, various tools for collecting data can be employed including interviews and observations in order to provide deeper insights into the qualitative data. Due to scarcity of research on personalized software programs for teaching language macro and micro skills, it is suggested that CALL specialists design such programs and probed into their effectiveness in learning outcome. Last but not least, future studies can address other cognitive styles such as holist – analyst or reflective-impulsive using neuroscience-based research tools such as electroencephalogram (EEG) or eye-tracking technology. This further helps to investigate and estimate the amount of attention students pay to different parts of a text on their computers or mobile phones when their learning preferences are observed in designing such learning environments.

**References**

[1] Patel, C. (2013). Use of multimedia technology in teaching and learning communication skill: An analysis. IJOART, 2, 116-123.

[2] Becker. H. C. (2000). Findings from the teaching, learning, and computing survey: Is Larry Cuban right? Education Policy Analysis Archive, 8, 1-31.

[3] Raschio. A. R. (1990). The role of cognitive style in improving computer-assisted language learning. Hispania, 73, 535-541.

[4] Moundridou, M., & Virvou, M. (2003). Analysis and design of a Web-based authoring tool generating Intelligent Tutoring Systems. Computers & Education, 40, 157-181.

[5] Curilema, S. G., Barbosab, A. R., & de Azevedo F. M. (2007). Intelligent tutoring systems: Formalization as automata and interface design using neural networks. Computers & Education, 49, 545-561.

[6] Moody, R., & Bobic, M. (2011). Teaching the Net Generation without leaving the rest of us behind: How technology in the classroom influences student composition. Politics & Policy, 39(2), 169-194.

[7] West, D. M. (2011). Using technology to personalize learning and assess students in real-time. Washington DC: Governance Studies.

[8] Ismail, H. M., Harouse, S., & Belkhouche, B. (2017). Review of personalized language learning systems. Paper presented in 2016 12th International Conference on Innovations in Information Technology (IIT). Al Ain, United Arab Emirates.

[9] Dörnyei, Z., & Ryan, S. (2015). The psychology of the language learner revisited. London: Routledge.

[10] U.S. Department of Education, Office of Educational Technology, Reimagining the Role of Technology in Education: 2017 National Education Technology Plan Update. Washington, D.C.

[11] Garrick, B., Pendergast, D., & Geelan, D. (2017). Theorizing personalized education. Singapore: Springer

[12] Gómez, S., Zervas, S., Sampson, D. G., & Fabregat, R. (2014). Context-aware adaptive and personalized mobile learning delivery supported by UoLmP, Journal of King Saud University - Computer and Information Sciences, 26(1), 47-61.

[13] Green, H., Facer, K., Rudd, T., Dillon, P., & Humphreys, P. (2005). Personalization and digital technologies. UK: Futurelab.

[14] Jung, I. S. (2001). Building a theoretical framework of Web-based instruction in the

context of distance education. British Journal of Educational Technology, 32(5), 525-534.
[15] Wolf, M. (2010). Innovate to educate: System [re]design for personalized learning. A report from the 2010 symposium. Washington, DC: Software & Information Industry Association.
[16] Zajac, M. (2009). Using learning styles to personalize online learning. Campus-Wide Information Systems, 26(3), 256-265.
[17] Papanikolaou, K.A., Grigoriadou, M., Kornilakis, H., & Magoulas, G. D. (2003). Personalizing the interaction in a Web-based educational hypermedia system: the case of INSPIRE. User Modeling and User-Adapted Interaction., 13(3), 213-267.
[18] Martinez, M. (2002). Designing learning objects to personalize learning. In Wiley, D. (Ed), The instructional use of leaning objects (pp. 151-171). Bloomington, Indiana: AIT/AECT
[19] Hwang, G. J., Kuo, F. R., Yin, P. Y., & Chuang, K. H. (2010). A heuristic algorithm for planning personalized learning paths for context-aware ubiquitous learning. Computers & Education, 54(2), 404-415.
[20] Lin, C. F., Yeh, Y. C., Hung, Y. H., & Chang, R. I. (2013). Data mining for providing a personalized learning path in creativity: An application of decision trees. Computers & Education, 68, 199-210.
[21] Alamri, A., Watson, S., & Watson, W. (2021). Learning technology models that support personalization within blended learning environments in higher education. TechTrends, 65, 62-78.
[22] Ellis, R. (2008). The study of second language acquisition (2nd ed). Oxford: Oxford University Press.
[23] Zapalska, A., & Brozik, D. (2006). Learning styles and online education. Campus-Wide Information Systems, 23(5), 325-335.
[24] Bachari, E., Abelwahed, E. H., & El Adnani, M. (2011). E-learning personalization based on dynamic learners' preference. International Journal of Computer Science & Information Technology, 3(3), 200-216.
[25] Yang, T.-C., Hwang, G.-J., & Yang, S. J.-H. (2012). Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles. Educational Technology & Society, 16(4), 185-200.
[26] Horváth, I. (2021). An analysis of personalized learning opportunities in 3D VR. Frontiers in Computer Science, 3, Article 673826.
[27] Martin, A. J., Dominic, A. M., & F. S. Francis (2021). Learners classification for personalized learning experience in e-learning systems. International Journal of Advanced Computer Science and Applications, 12(4), 690-697.
[28] Skehan, P. (1991) Individual differences in second language learning. Studies in Second Language Acquisition, 13, 275-98.
[29] Chen, C. M., & Chung, C. J. (2008). Personalized mobile English vocabulary learning system based on item response theory and learning memory cycle. Computers & Education, 51, 624-645.
[30] Petersen, S. A., & Markiewicz, J. K. (2009). Personalized and contextualized language learning: Choose when, where and what. Research and Practice in Technology Enhanced Learning, 4(1), 33-60
[31] Jung, J. Y., & Graf, S. (2008). An approach for personalized web-based vocabulary learning through word association games. Paper presented in the International Symposium on Applications and the Internet.
[32] Su, P., Yu, T., Su, Y., & Lee, L. (2013). A cloud-based personalized recursive dialogue game system for Computer-Assisted Language Learning. In Proceedings of SLaTE 2013 (pp. 37-41). Grenoble, France.
[33] Xu, Z., Wijekumar, K., Ramirez, G., Hu, X., & Irey, R. (2019). The effectiveness of

intelligent tutoring systems on K-12 students' reading comprehension: A meta-analysis. British Journal of Educational Technology, 50(6), 3119-3137.
[34] Rahimi, M. (Ed). 2015. Handbook of research on individual differences in CALL. US: IGI Global.
[35] A2 Key handbook for exams from 2020. Retrieved January 2021 from 504505-a2-key-handbook-2020.pdf. 2020
[36] Barbe, W. B., Swassing, R. H., & Milone. M. N. (1979). Teaching through modality strengths: concepts practices. Columbus, Ohio: Zaner-Bloser.
[37] Alavimoghaddam, B., Kheyrabadi, R., Rahimi, M., & Alavi, M. (2019). Prospect 3. Tehran: Ministry of Education.
[38] Pallant. J. F. (2020). SPSS survival manual; A step by step guide to data analysis using IBM SPSS (7th ed). UK: Routledge.
[39] Cohen, J.W. (1988). Statistical power analysis for the behavioral sciences (2nd ed). Hillsdale, NJ: Lawrence Erlbaum Associates.
[40] Zafar, S., & Meenakshi, K. (2012). Individual learner differences and second language acquisition: A review. Journal of Language Teaching Research, 3, 639-646.
[41] Riding, R. J., & Buckle, C. F. (1990). Learning styles and training performance. Sheffield: Training Agency.
[42] Johnson, S. D., & Aragon. S. (2003). An instructional strategy framework for online learning environments. New Directions for Adult Continuing Education, 100, 31-43.
[43] Renzulli. J. S. (1994). Schools for talent development: A practical plan for total school improvement. Mansfield Center, CT: Creative Learning Press.
[44] Everton, W. J., Mastrangelo, P. M., & Jolton, J. F. (2005). Personality correlates of employees' personal use of work computers. CyberPsychology & Behavior, 8, 143-53.
[45] Hsieh. S. W. (2011). Effects of cognitive styles on an MSN virtual learning companion system as an adjunct to classroom instructions. Educational Technology & Society, 14, 161-174.
[46] Zarrinfard. S. (2020). The impact of a technology-enhanced flipped classroom versus computer assisted instruction on vocabulary learning and grammar achievement of language learners with different cognitive styles. [unpublished doctoral dissertation]. Tehran: Islamic Azad University. South Branch.
[47] Koehler, M. J, & Mishra, P. (2009). What is technological pedagogical content knowledge?. CITE, 9, 60-70.
[48] Cheung, A. C., & Slavin, R. E. (2012). How features of educational technology applications affect student reading outcomes: A meta-analysis. Educational Research Review, 7(3), 198-215.