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Research Paper

Learning styles, Technology Savviness, and Iranian EFL learners' Vocabulary Knowledge: The Mediating Role of Learners' Preferences and Needs during Agile App Development

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Abstract

Juxtaposing the ubiquitous facets of mobile technology as *everyware* (Greenfield, 2010) and vocabulary as one of the most axial aspects of language learning (Bowles & Cogo, 2016; Schmitt & Schmitt, 2020), besides the importance of considering learners' attributes and needs (Taghizadeh, 2019) while developing a mobile vocabulary application (app), necessitates analyzing the relationship and impact of all these elements in a single structural model. To tackle the issue, first, via a mixed-methods design, the researcher developed a bespoke mobile application using the task model and the principles of agile methodology. and then investigated the impact of using the app on a sample of 62 Iranian EFL university students' vocabulary recognition and recall, the results of which were published in two other articles. In this study, the researcher integrated the obtained data within a proposed structural model and assessed the model's fitness to investigate the interaction and interrelationship among the latent variables mentioned above. The results obtained from SEM-PLS analyses revealed that within the unified structural model, the learners' preferences and needs were favorably influenced by their learning style orientation and technology savviness. Similarly, the findings verified the positive impact of considering learners' preferences and needs during the agile

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app development lifecycle on the target participants' vocabulary knowledge, encompassing vocabulary recognition and recall. Finally, the fitness of the proposed structural model was verified based on the criteria for model assessment mentioned by Sparks and Alamer (2022). The SEM-PLS data analyses and the implications of the study are presented and discussed.

Keywords: Learning Styles, Technology Savviness, Needs Analysis, Custom-made Mobile Applications, Vocabulary Knowledge

English has been widely used in numerous aspects of human life, such as education, business, worldwide media, gaming, entertainment, and the internet. As Bowles and Cogo (2016) stated: "There has been a remarkable growth of interest in the phenomenon of English as a Lingua Franca (ELF) in recent years, and as a result, this has become a productive field of research, which has now found its place in applied linguistics and sociolinguistics discussions" (p. 1). Based on what was mentioned above, learning the English language can provide learners with more opportunities in today's life. Though mastering a language requires learning various facets, vocabulary is one of the most fundamental ones (Nation & Meara, 2002; Schmitt & Schmitt, 2020). According to Rashid et al. (2022), even though one may know the grammar of a language, he may not be able to communicate effectively, and the communication may be terminated if he does not know the appropriate words. Brooks et al. (2021) emphasized that a lack of proper vocabulary knowledge inhibits academic success; hence, vocabulary learning is central to mastering a language. Therefore, learning the English language as a universal medium of communication and vocabulary as its pivotal aspect is of utmost importance to succeed in various dimensions of today's life.

For a successful learning experience, many facets and dimensions should be taken into account. The participants' learning styles should be considered for effective teaching since they may affect their needs and preferences. In a pedagogical endeavor, learners may need different strategies and tools to overcome the barriers they may encounter during the learning process (Benitez-Correa et al., 2022). The pivotal role of fabricating teaching in accordance with the learners' needs was also emphasized by Dörnyei (2014), who highlighted the importance of adapting instruction to the learner's strengths, weaknesses, and preferences.

On the other hand, technology has penetrated numerous aspects of human life and integrated with it so tightly that the presence of technology per se seems blurred and unnoticed. In this respect, Greenfield (2010) coined the term everyware to highlight technology's ubiquitous and pervasive nature as dimensions of the same paradigm focusing on its presence in various aspects of daily life. In the late twentieth century, web technology emerged widely, followed by the emergence and worldwide spread of phablets and cellular phones at the beginning of the twenty-first century. Wearable computers and intelligent devices made it possible to penetrate farfetched situations; everyware itself disappeared from the scene, and technology turned into a natural phenomenon of human life. In fact, using technology in education is no longer a choice since it has already penetrated different realms of human life, and language teaching/learning is no exclusion.

Therefore, technology as a tool and the relevant background knowledge of the learners in this regard should be considered as one of the variables that may affect the learning process and outcome. In other words, technology background knowledge plays an important role in teaching/learning a language since learners' background knowledge may affect their needs and preferences. The axial impact of background knowledge on learning has been mentioned in the literature. Zhou and Wei (2018) stated that background knowledge of students' native language improves their online reading comprehension. The importance of background knowledge for recognizing phonemes and figuring out the meaning of foreign proper nouns was emphasized by Al-Jarf (2018). He stated that "results of questionnaire interviews with students showed that the source of difficulty was lack of prior knowledge and unfamiliarity with foreign proper names" (P. 3). According to Puebla et al. (2022), seniors who are self-assured, tech-savvy, and open to new ideas are more eager to study languages via an app than their less tech-savvy peers.

Technology, as everyware, has spread its presence by utilizing mobile affordances in various realms of human life. Mobile devices, especially smartphones and phablets, have enabled human beings to use technology affordances effectively (Alharbi, 2022). Many applications were developed and used for teaching the English language and its elements. Several studies were also done to find out how these applications affected the development of learners' English language abilities and subskills. However, according to Burston (2015), one of the most significant problems with Mobile Assisted Language Learning (MALL) studies was the absence of measurable, objective results. Though Taghizadeh (2019) emphasized the crucial role of needs analysis as the foundation of designing and developing a course, in another study, Burston and Athanasiou (2020) highlighted a lack of interpersonal communication to negotiate the real on-site learners' needs and preferences besides flaws in the design of the scrutinized MALL studies.

Besides the flaws and shortcomings pinpointed by the investigations mentioned above, the researcher of the current investigation did not find any study regarding the impacts of the latent variables of learning styles and technology savviness on the needs and preferences of the participants for developing a custom-made mobile app based on an agile approach to improve EFL learners' vocabulary knowledge. Furthermore, the observed studies have not investigated the interactions and interrelationships between the variables mentioned above. Hence, the researcher proposed a model to analyze the complex relationships between the relevant variables of the current study in a single structural model, as is pointed out in figure 1 below, to account for the gap mentioned above.

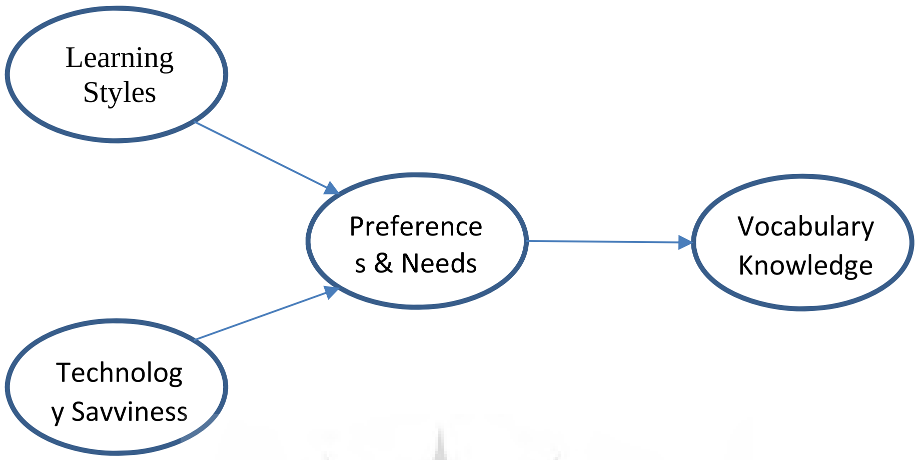

Figure 1. *The Proposed Structural Model*

The gap is manifest in the unique structural model of the study. The interrelationship of the latent variables and their mutual impacts on each other in a unified structural model has not been analyzed in the observed studies, a concept that makes the present paper a unique one in its own place. In fact, a new structural model with its own unique latent variables creates a complex system with many gaps not similar to any other complex system. Since a language system is a chaotic, complex system (Larsen Freeman, 2012), analyses of structural models can shed light on different dimensions of the complex interaction of the latent variables that cannot be revealed by any other known data analysis method.

The significance of this study dwells in the unique complex interactions of the variables in the unified structural model, which provides critical information for creating courses and developing apps. To account for all these complexities, more sophisticated multivariate data analysis methods are required to interpret such intricate structures and emerging subtleties (Hair Jr et al., 2021).

Structural Equation Modeling (SEM) is a multivariate analysis and a statistical method that simultaneously analyzes multiple variables in a unified model (Alamer & Marsh, 2022; Bowen & Guo, 2011). Accordingly, there are two types of SEM: Covariance-Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM). CB-SEM is confirmatory (Fathi & Savadi Rostami, 2018), and PLS-SEM is exploratory and requires fewer participants to deal with (Ravand et al., 2018). Due to the large number of participants and the objectives of the study, which included exploring the connections between the latent variables of learning style, technology savvy, learners' needs and preferences, and vocabulary knowledge as well as validating the fitness indices of the proposed structural model, the researcher employed PLS-SEM.

Bowen and Guo (2011) stated that for carrying out a PLS-SEM analysis, first, the structural (inner) model and the measurement (outer) model must be specified; in both processes, the theoretical framework should be based on the well-established theories that were previously worked on by the other authorities and proved to be acceptable. Therefore, in the next section, the variables of the proposed structural model and their individual relationships investigated by the other researchers were studied to provide the appropriate theoretical framework for justifying the proposed structural model depicted in figure 1 above, where all the variables are integrated within a single model to find out how well they function together, the aspect that was not studied in the previous investigations.

Review of Literature

In SEM investigations, it is crucial to highlight that the literature review creates the theoretical framework to generate research questions and relevant hypotheses (Acosta et al., 2018; Fathi & Savadi Rostami, 2018). Therefore, in the literature review, the variables of the proposed structural model and their probable relationships were highlighted.

Learners' preferences and needs

The importance of needs analysis as the foundation of course design and enhancing teaching/learning processes was emphasized and highlighted in the literature (Chostelidou, 2010; Seedhouse, 1995; Taghizadeh, 2019). Needs analysis is the fact-finding stage and a fundamental component of curriculum preparation, according to Huang (2019).

According to Ehrman (1996), a learning style can be anything from a mild taste to a vehement demand. As a result, learning styles are at the core of preferences and requirements. Similarly, strategies are drawn from the demands of the pedagogical environments. Dörnyei (2014), mentioned that both learning strategies and styles refer to specific methods by which students accomplish learning tasks, so they are conceptually related. This highlights the necessity to detect the needs and preferences of the participants of the study since they are rooted in the styles and affect the strategies they choose to eliminate the potential problems of their own unique path of learning.

Language learning is a multifaceted phenomenon that consists of many dimensions. Without considering learners' strengths, weaknesses, and preferences, the teaching process may not yield the expected results (Dörnyei, 2014). Students incorporate their unique experiences, learning preferences, and learning techniques into their coursework. (Benitez-Correa et al., 2022). In actuality, learning styles and tactics assist students in discovering their aptitudes and enhancing their academic experiences. Also, students can employ a range of learning styles, which are crucial components of effective learning settings. Given that each student learns in a unique way, the teaching and learning process must take into account each student's specific needs (Adnan & Marlina, 2017). Becker et al. (2007) stated that teachers should create an ideal environment that meets these needs and provide the learners with appropriate learning experiences by integrating the desired learning style pinpointed via ipsative assessment or considering personal preferences.

Hence, one of the cornerstones of an effective teaching process is considering learning styles which are discussed in the next section.

Learning Styles

Regardless of substantial investigations since the middle of the 1970s (Wong & Nunan, 2011), there is no universal definition for construct learning styles; Brown and Lee (2015) defined learning style as “cognitive, affective, and physiological traits that are relatively stable indicators of how learners perceive, interact with, and respond to the learning environment” (p. 651). According to the standard definition defined by Reid (1995), learning styles refer to “an individual’s natural, habitual, and preferred way(s) of absorbing, processing, and retaining new information and skills” (p. viii). Dörnyei (2014) mentioned that for educators, the idea of "learning styles" is appealing since, unlike abilities and talents, they do not indicate a natural aptitude that inevitably results in success. In other words, learning styles are not indicators that separate gifted learners from non-gifted learners; rather, they refer to individual preferences. Hence, learning style is a blueprint of an individual's preferred or habitual manner of perceiving, interacting with, and responding to the pedagogical context. It serves as a profile of that person's approach to learning. He highlighted that these preferences reflect a continuum from one extreme to the other, and that there is no value judgment about a learner's position on the continuum. In reality, one can be successful in each of these preferences by using various, unique working routes.

Dörnyei (2014) claimed that because they describe certain methods by which students complete learning tasks, learning style and strategies are two notions that are conceptually related. Style and strategy both tap the same issue but at different levels of breadth and stability. Snow et al. (1996) mentioned that a style is a “strategy used consistently across a class of tasks” (p. 281). Learners appeal to their learning styles unconsciously but choose their strategies intentionally; therefore, they can be trained to learn how to use better strategies; however, they cannot choose their own learning styles. Riding (2000) highlighted this issue and mentioned that in contrast to tactics, which can be learned and improved in order to deal with different situations and activities, styles are likely based on physiological factors and are largely fixed for the individual. Sternberg and Grigorenko (2014) stated that although strategies entail the deliberate choosing of many options, styles operate without the user being aware of them. They highlighted that “strategy is used for the task- or context-dependent situations, whereas style implies a higher degree of stability falling midway between ability and strategy” (p. 3).

According to what was mentioned above, unconsciously established learning styles make learners deliberately choose strategies and relevant tools to cope with their preferences or needs. Ehrman (1996) equated ‘preference’ with ‘comfort zones,’ offering a relatively lenient understanding of the term; hence, a preference is just something that makes us more comfortable for the vast majority of us, even though we are always free to choose another option. But, as she noted, learning styles are more firmly formed and extend beyond mere preferences for a minority of people. Because they are unable to modify their preferred style to fit the demands of the situation, learners may encounter difficulties. A learning style might therefore range from a small preference to a strong demand. Dörnyei (2014) mentioned that “the learning style dimension that most language teachers, and even many language students, would be familiar with is the categorization of sensory preferences into ‘visual,’ ‘auditory,’ ‘kinesthetic,’ and sometimes ‘tactile’ types” (p. 139). He continued that visual learners are most likely to remember information when it is presented visually. As a result, they favor reading-related tasks and frequently utilize colorful highlighting techniques to make specific material stand out visually. Accordingly, visual learners enjoy visual stimuli like movies and videos and are more willing to learn with pictures, graphs, charts, and other graphic forms. Auditory input, such as lectures or audiotapes, is used most efficiently by auditory learners. They benefit from reading out the written passages and reciting out loud whatever they have studied. So they prefer to practice orally without using their books (Ehrman, 1996). Dörnyei (2014) continued that since kinesthetic and tactile learners have similar but not identical preferences, they are often categorized as the ‘haptic’ style category. Whereas tactile learners prefer a hands-on, tactile learning style, kinesthetic learners prefer full-body experience (e.g., moving the entire body while learning). So, kinesthetic learners cannot sit motionless for a long time. They like to walk around and memorize something. Tactile learners like creating posters, collages, building models, and different forms of artwork.

As was highlighted above, various definitions exist for the learning styles construct. Wintergerst et al. (2002) and DeCapua and Wintergerst (2005) added two more dimensions and introduced six learning style preferences: visual, auditory, kinesthetic, tactile, group learning, and individual learning, which were the theoretical framework for designing and developing Perceptual Learning Style Preference Questionnaire (PLSPQ) (J. Reid, 1987); the definitions of all these preferences were adapted from the C.I.T.E. Learning Styles Instrument defined by Murdoch Teacher Center in Wichita, Kansas.

Ehrman (1996) highlighted the pivotal role of considering learning styles in a pedagogical setting by stating that “learning style mismatches are at the root of many learning difficulties” (p. 50). Accordingly, the consensus expressed by most devotees of learning style research is that considering learning styles enhances learning/teaching processes by reducing or removing many mismatches (Dörnyei, 2014).

Due to the crucial importance of learning styles and the fact that learning styles are theoretically positively associated with language outcomes, the researcher investigated the construct learning style's impact on the participants' preferences and needs. Therefore, the following research question was proposed in light of the previously provided theoretical and empirical justifications:

Research Question 1 (RQ1): Do learning styles affect the participants' preferences and needs meaningfully?

According to the structural model of this investigation, it is necessary to shed light on the latent variable of technology savviness as the background knowledge that may affect the study participants' preferences and needs.

Technology Savviness

Technology has penetrated into human lives and affected numerous critical facets as everyware (Atzori et al., 2010; Greenfield, 2010; Lu et al., 2005; NetMarketShare, 2019; Tewari & Gupta, 2020). This ubiquitous impact has altered thinking, language, and communication as Al-Sharqi and Abbasi (2020) stated that “the Internet has connected the world irrespective of time and space. Technology has influenced how we write, think, and communicate with others” (p. 5). Integrating technology with education shows substantial growth as Sartor (2020) emphasized that teachers who have only had experience teaching face-to-face may feel overwhelmed by the sudden evolution of teaching with technology from a gradual movement toward using digital resources into a roaring avalanche. Alexander (2020), continuously focusing on how technology is being used in education in current affairs, anticipated that many colleges and universities would close owing to financial losses. He also added that in order for teachers of all subject areas to remain effective, they must become adept at exploiting digital resources. The affordances technology may bring to a pedagogical setting have also been highlighted by him, as he mentioned that as a result of the development and distribution of digital content via the Internet, potential students now have more access to resources and professionals. The enquiring mind will find encyclopedia articles, videos, audio lectures, expert-written personal blogs, courses, textbooks, games, galleries, and complete libraries.

Heift et al. (2019) stated that the idea of utilizing technology affordances for language instruction was initially proposed in the 1960s by individual teachers and a small number of academic researchers at universities; this idea gave rise to the relatively new field of study known as technology-assisted language learning. He continued that Computer Assisted Language Learning (CALL), though a relatively new concept, has undergone numerous evolutionary cycles over the past 60 years, and our thoughts about teaching second languages using technology have been affected by linguistics, Second Language Acquisition (SLA), and psychological theories, among others, in addition to, of course, the ongoing developments and inventions of technology.

As Otto (2017) stated, it is now evident that effective pedagogies, technology training, and teacher attitudes toward technology positively affect teaching/learning procedures. Accordingly, the delivery of hybrid language courses, which combine in-person instruction containing internet elements and online courses, in which every part of the course is performed online, both depend heavily on technology. Higher education is under financial and practical pressure; thus, hybrid language classes that meet less frequently in person each week have been introduced as a way to reduce costs. She emphasized that computers offer an effective approach to handle the tutorial and activity aspects of the curriculum, allowing fewer staff members to supervise more students while freeing up more in-class time to be used only for communicative activities. Technology affordances can function independently or be integrated into the educational context to promote teaching/learning processes. According to Lord and Lomicka (2008), as educationalists exploiting the two delivery techniques (face-to-face and online), blended learning courses benefit from both in-person and online communities. Hence, various technical tools, including blogs, wikis, chat rooms, and discussion boards, can be used in blended learning environments to promote engagement and discussion. The development of the community and the promotion of learning and telecollaboration over distance depend on the consistent use of these technologies; rather than producing a cold and dehumanizing touch, such tools may promote a sense of community. They continued that "in spite of this growing interest in community development, only a limited number of studies have expanded this research to foreign language (FL) classes and FL teacher education courses" (p. 2).

Due to the importance of technology in education and the crucial role of background knowledge and computer savviness, which have been highlighted in the literature (Al-Jarf, 2018; Puebla et al., 2022; Zhou & Wei, 2018), the following research question was proposed to account for the impact of computer savviness on the latent variable participants' preferences and needs:

Research Question 2 (RQ2): Does computer savviness affect learners' preferences and needs meaningfully?

The next section deals with the latent variable vocabulary knowledge and the concept of agile app development, respectively.

Vocabulary Knowledge

Alqahtani (2015) mentioned that vocabulary learning is essential in foreign language learning as the message is conveyed via words in different academic or social settings; therefore, vocabulary learning is paramount to teachers and language learners. Schmitt (2010) pinpointed lexical knowledge as a component of language use. He cited Wilkins (1972, p. 111), "without grammar, very little can be conveyed, without vocabulary, nothing can be conveyed" (p. 3). He continued that learning vocabulary is a crucial component of learning a second language, something that all parties involved in the learning process (students, teachers, material writers, and researchers) can agree on. In this regard, Schmitt (2010) emphasized that "… there is plenty of evidence pointing to the importance of vocabulary in language use. One strand of this evidence is the typically high correlations between vocabulary (usually measures of vocabulary size) and various measures of language proficiency" (p. 4).

The social aspect of learning vocabulary during acculturation was highlighted in the literature, too; Sari et al. (2020) stated that language usage and vocabulary are crucial for intercultural adjustment. The frequently made observation that students carry along dictionaries and not grammar books highlights the significance of vocabulary.

According to what was stated above, vocabulary learning is central to mastering a language; since the English language is a lingua franca that is used in different realms of human life worldwide, learning vocabulary as the pivotal aspect of the English language is of utmost importance to succeed in various dimensions of today's life.

Despite what was said earlier regarding the importance of needs analysis, none of the mobile apps studied during the literature review were tailored to meet the requirements and expectations of Iranian EFL learners following the principles of the agile approach. Therefore, in this study, the researcher conducted a semi-structured interview to define the participants' preferences and needs to consider during the agile development of a mobile app and to determine whether or not the integration of these aspects in the developed custom-made mobile application affects the participants' vocabulary knowledge. Hence, based on the concept mentioned above, the following research question was generated:

Research Question 3 (RQ3): Do the participants' preferences and needs affect their level of vocabulary knowledge meaningfully?

The following section sheds light on the proposed model and its inner and outer components defined based on the theoretical framework depicted in the literature review.

The Proposed Structural Model

The proposed research questions gave rise to an explanatory structural model of the effect of learning styles and technology savviness on Iranian EFL learners' vocabulary knowledge with the mediating role of needs analysis carried out during the agile development of a vocabulary application. The relationships between these latent variables and the proposed research questions are depicted in figure 2:

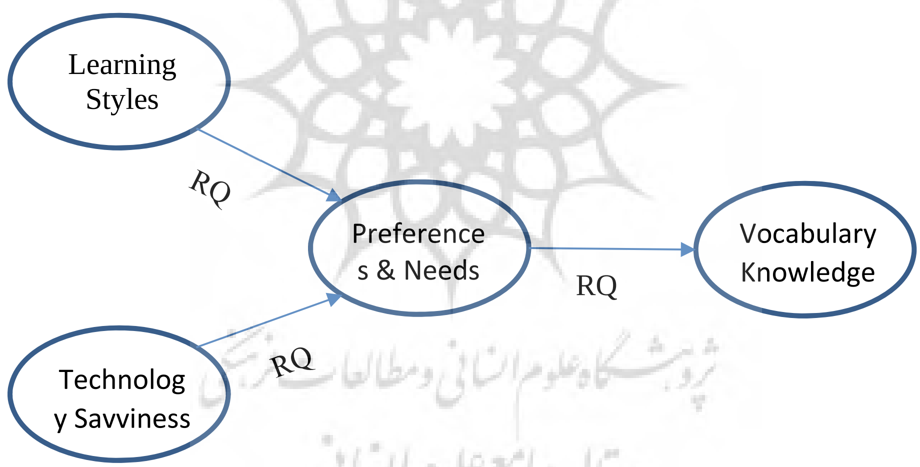

Figure 2. *The Hypothesized Relationships in the Structural Model*

Delving into the literature, the researcher defined the hierarchy and precedence of the constructs of the structural model. The relationship between these constructs and their relevant indicators followed the guidelines depicted in table 1, proposed by Hair Jr et al. (2021).

Table 1

Guidelines for Choosing the Measurement Model Mode Reprinted from Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Sage Publications.

Criterion	Decision	Reference
Causal priority between the indicator and the construct	• From the construct to the indicators: reflective • From the indicators to the construct: formative	Diamantopoulos and Winklhofer (2001)
Is the construct a trait explaining the indicators or rather a combination of the indicators?	• If trait: reflective • If combination: formative	Fornell and Bookstein (1982)
Do the indicators represent the consequences or causes of the construct?	• If consequences: reflective • If causes: formative	Rossiter (2002)
Is it necessarily true that if the assessment of the trait changes, all items will change in a similar manner (assuming they are equally coded)?	• If yes: reflective • If no: formative	Chin (1998)
Are the items mutually interchangeable?	• If yes: reflective • If no: formative	Jarvis, MacKenzie, and Podsakoff (2003)

Wintergerst et al. (2002) and DeCapua and Wintergerst (2005) defined six learning style preferences: visual, auditory, kinesthetic, tactile, group learning, and individual learning. Each indicator is addressed via five questions in the PLSPQ instrument. Based on the guidelines of table 1, the six learning style preferences were the formative indicators of learning styles. To reduce the complexity of the structural model, the researcher designed a higher-order model or Hierarchical Component Model (HCM); Hair Jr et al. (2021) emphasized that "higher-order modeling involves summarizing lower-order components. This modeling approach leads to more parsimony and reduces model complexity. Theoretically, this process can be extended to any number of multiple layers, but researchers usually restrict their modeling approach to two layers" (pp 43-44). According to Ringle et al. (2012), In most cases, testing second-order structures with two layers of components is part of higher-order models or hierarchical component models (HCMs). In this study, the construct learning styles is the second (higher) order component, connected with six first (lower) order components. Therefore, in the emerged structural model, the style preferences were defined as the latent variables forming the construct learning styles.

There are four measurement or outer models in the proposed model. The first measurement model includes six first (lower) order components of the construct learning styles. Each of these six components is connected to five questions of PLSPQ as their reflective indicators. The second measurement model consists of three indicators, including knowledge and expertise in using smartphones, mobile applications, and social media applications, forming the latent construct of technology savviness. These components were selected or emerged during the interviews as indicators of technology savviness since the participants were supposed to use a custom-made mobile application developed in the current study. The third measurement model is composed of the formative indicators of the construct learners' preferences and needs that emerged from the qualitative analysis of the interview data using MAXQDA software; they encompass the level of desire for dialectic problem solving, interaction, and telecollaboration among the app users. The fourth measurement model consists of vocabulary recall and recognition, defined as the reflective indicators of vocabulary knowledge based on the literature review. Figures 3 and 4 in the data analysis section depict the complete measurement and structural models.

Method

Participants

Selecting the participants of the current study was based on the convenient sampling method to follow the Iranian academic rules and regulations, which impose some limitations on research procedures. Therefore, 62 female students were chosen randomly from 141 students in six intact classes, which were the researcher's available classes at the university. As a result, the participants were 62 female Persian-speaking Iranian EFL learners from 18 to 35 years old, majoring in English language and literature at university. Moreover, they have all studied the English language for two successive years.

Instrumentation

The first latent variable which was addressed during the semi-structured interview was learning styles. Different instruments have been developed for defining native and non-native speakers' learning styles, but according to DeCapua and Wintergerst (2005), The earliest and most widely used instrument is PLSPQ. They emphasized that "only Reid's PLSPQ has been normed on non-native speakers of English, with reliability and validity established on high intermediate or advanced ESL classes" (J. M. Reid, 1987, p. 3). Accordingly, PLSPQ includes six learning style preferences: visual, auditory, kinesthetic, tactile, group learning, and individual learning. There are 30 statements, which participants rate on a five-point Likert scale. Since the study participants were all non-native EFL learners, the researcher selected PLSPQ as the quantitative learning styles instrument with established reliability and validity (DeCapua & Wintergerst, 2005; J. Reid, 1987; Reid, 1998).

A semi-structured interview was the second instrument used during the second phase of this investigation. DeCapua and Wintergerst (2005) stated that using semi-structured interviews to gather data has many merits since they provide a rich data source for descriptive studies. Wintergerst et al. (2002) highlighted that:

> Open-ended questions allow the researcher to focus on a particular topic or topics while allowing for flexibility in providing opportunities for two-way communication. The semi-structured interview permits the researcher to ask more complex and involved questions, allows informants to expand and elaborate upon their answers, and allows the researcher and the informants to ask for clarification or explanation when they are unsure or require more detail. (p. 7)

Technology savviness was another latent variable of this investigation. According to Swilley (2019), a tech-savvy person goes beyond a perfunctory knowledge of technology; he highlighted that "tech-savvy individuals are not only ready for technology; tech-savvy individuals seek out knowledge and are ready to prove this knowledge to others" (p. 1). Since assessing these aspects requires discussion and dialogue with the participants, the appropriate instrument to gather data in this regard is semi-structured interviews (DeCapua & Wintergerst, 2005; Wintergerst et al., 2002)

Based on what was mentioned above, the semi-structured interview of the current study was conducted for three main reasons: to verify the participants' learning styles by discussing and delving into the results of their ipsative assessment via PLSPQ, second, to define the level of their computer savviness, and finally to find out their preferences and needs regarding using a custom-made vocabulary mobile app.

The researcher used MAXQDA software to delve into the needs analysis data from the semi-structured interviews to pinpoint the participants' preferences and needs. Marjaei et al. (2019) stated that MAXQDA "is a software designed for computer-assisted qualitative and mixed methods data, text, and multimedia analysis in academic, scientific, and business institutions" (p. 2). Therefore, MAXQDA was utilized to identify the underlying concepts and themes by analyzing the qualitative data from the semi-structured interviews to find the foundation for choosing the appropriate technology and tools to integrate within the app during its lifecycle. As a result, all the affordances and tools of the custom-made vocabulary application developed in the current study were to satisfy the participants' preferences and needs mentioned during the semi-structured interviews and the relevant themes extracted by MAXQDA.

In this investigation, vocabulary knowledge encompasses vocabulary recognition and vocabulary recall. The researcher developed two vocabulary recognition and recall tests to measure the participants' level of vocabulary knowledge. The degree of difficulty of a vocabulary is a measure of its use in various content areas, age of acquisition, and frequency of appearance in written language. (Hiebert et al., 2019); moreover, the impact of frequencies on the difficulty level of word recognition and recall tasks was emphasized. Hence, the frequency of vocabulary was the selection criterion. In this respect, the target words were chosen according to their frequencies in 120 million words of academic texts in the Corpus of Contemporary American English (COCA) Davies (2020), obtained from the query interface on the Academic Core Vocabulary (Davies & Gardner, 2019). The number of the selected vocabulary for each session was according to the memory model depicted by Miller (1956) and reaffirmed by Ozdemir (2017) and Baddeley et al. (2019); therefore, seven vocabulary items were selected for each session based on the criteria mentioned above. The battery of vocabulary recognition and recall tests included 12 fill-in-the-blank recognition and 12 fill-in-the-blank recall tests; the participants were required to choose from a list of words or use the appropriate words by heart, respectively. The test scores' reliabilities, estimated by the KR-21 formula, were 0.84 for the recognition and 0.87 for the recall test scores. Moreover, two TEFL experts confirmed the test's face and content validity.

Procedure

In the first phase of the study, during the first day of the academic course, the researcher elaborated on different types of learning styles and the benefits of knowing one's own learning style. Next, he administered the Perceptual Learning Style Preference Questionnaire (PLSPQ) provided by J. Reid (1987) to the participants to pinpoint their learning styles. In the second session, the researcher conducted a semi-structured interview for data triangulation to verify the participants' learning styles defined through their ipsative assessment during the previous session; furthermore, the interview was a means of detecting their levels of computer savviness. Also, during the interview phase, the preferences and needs of the participants were pinpointed and later analyzed by MAXQDA software to extract the underlying themes. Then, during the agile lifecycle of developing the app to account for the learners' needs and preferences, the necessary features and tools were selected to include in the custom-made mobile application. During the agile development of the app, which took 14 academic weeks, the participants were using it to learn the target vocabulary items. Next, two teacher-made vocabulary recognition and recall tests were administered to the participants to capture their vocabulary knowledge levels (the app's complete lifecycle and the quantitative data analyses and results were published in two other articles). Next, the current paper proposed a structural model to analyze the functionality and performance of all the involved latent variables. And finally, the researcher conducted SEM-PLS analyses via SmartPLS version 3.2.8 to assess the data and verify the model's fitness.

Data Analysis

This study investigates the fitness of the structural model of learning styles, technology savviness, and the mediatory role of needs analysis in developing the vocabulary knowledge of Iranian EFL learners. To analyze the data obtained from the Perceptual Learning Style Preference Questionnaire (PLSPQ), the semi-structured interviews, the tests of vocabulary recognition and recall, and the proposed measurement and structural models, the researcher used the Structural Equation Modeling (SEM) technique.

Hair and Alamer (2022) stated that "structural equation modeling (SEM) is a very useful technique for evaluating complex theoretical relationships between multiple variables, especially when conducting social science and second language (L2) research" (p. 1). There are two types of SEM: covariance-based (CB-SEM) on the basis of maximum likelihood estimation (MLE) and variance-based structural equation modeling (VB-SEM) or partial least square modeling (PLS-SEM). According to Shao et al. (2022), CB-SEM has been the most well-known and dominant statistical technique in the field of L2 and among the researchers utilizing SEM. Whereas PLS-SEM is an alternative that, under certain conditions, common in L2 quantitative analyses, is more suitable (Hair & Alamer, 2022; Razavipour et al., 2018; Ringle et al., 2015; Sarstedt & Cheah, 2019). Ringle et al. (2015) and Hair and Alamer (2022) mentioned that PLS-SEM is recommended with data that do not show a multivariate normal distribution, need more complex models, are formative models, have small samples, or are models with insufficient theoretical framework.

Therefore, due to the number of participants in the current study and the formative nature of the relationship among the constructs and their indicators, PLS-SEM analysis was conducted utilizing the SmartPLS software version 3.2.8 to test the proposed research questions. The sample size is in accordance with the often-cited ten times rule by Tompson et al. (1995), advising that the sample size be equal to the larger of either ten times the most formative indicators used to measure a single construct or ten times the most structural routes aimed at a specific construct in the structural model. Furthermore, sample size recommendations stated by Cohen (1992) in his statistical power analyses for multiple regression models were considered; simultaneously, the measurement models' outer loadings verified the acceptable quality of the relationships (i.e., loadings were above the common threshold of 0.70) (Hair Jr et al., 2021).

Chin (2010) stated that there are two stages for analyzing and interpreting a structural model via PLS-SEM: first, by considering the external or measurement model, and next, by the inner or structural model. Researchers ought to base their initial structural model assumptions on the body of existing knowledge. According to Hair and Alamer (2022), "solutions can then be obtained with PLS-SEM by performing two essential steps: (i) assessing the outer model's validity and reliability and (ii) assessing the inner model's predictive power" (p. 10).

Results

This section presents results from analyzing the structural models of this investigation and their components. To analyze and evaluate the model's fitness, first, the researcher of the current investigation assessed the validity and reliability of the learning styles model. Figure 3 sheds light on different components of the structural and measurement models of learning style latent variable and the result of running the PLS Algorithm via SmartPLS.

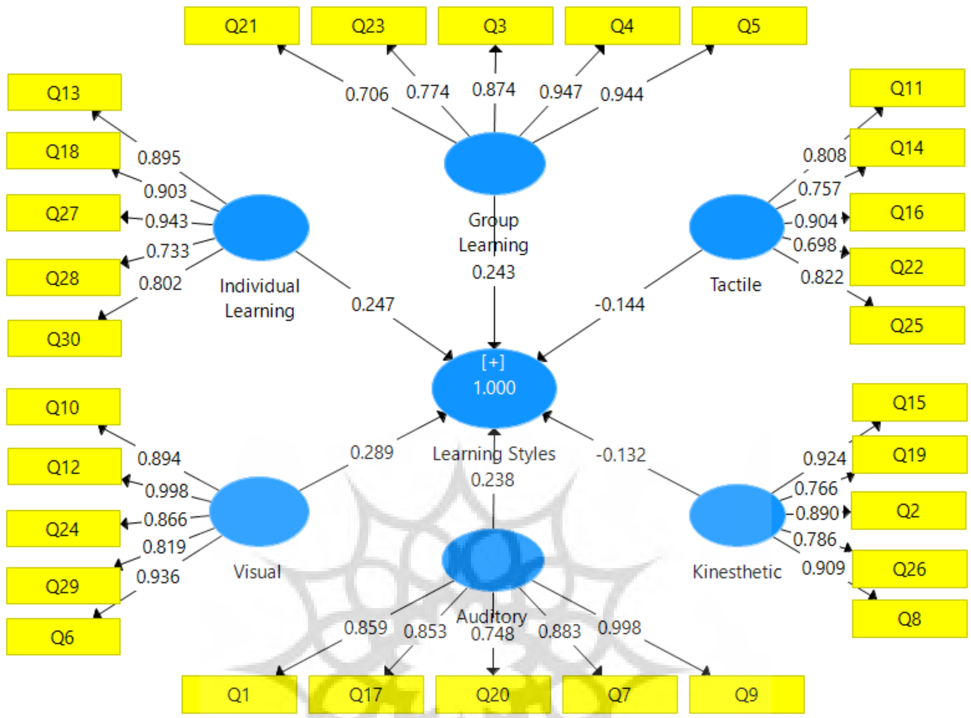

Figure 3. *The Results of Running PLS Algorithm for Learning Styles Models*

According to the information shown in figure 2 above and the results obtained from the measurement model estimations, the scales' reliability was acceptable since all Cronbach's Alpha and composite reliability coefficients were above or close to 0.7 (Bagozzi & Yi, 1988; Hair, 2009). Also, AVE coefficients were all above 0.50, which confirmed the convergent validity of the measuring instruments (Henseler et al., 2015). However, the path coefficients from constructs tactile and kinesthetic to the construct learning styles show negative values. Therefore, the researcher employed bootstrapping via SmartPLS to calculate the importance of the structural model route coefficients. All the obtained T Statistics values were above 1.98 (Ringle et al., 2015) except those of kinesthetic -> Learning Styles ($p = 0.151$) and tactile -> Learning Styles ($p = 108$). Since the mentioned path coefficients were negative and the relevant T Statistics were not significant enough, the kinesthetic and tactile components were excluded from the structural model to increase model efficacy (Hair Jr et al., 2021). Then for the second time, the researcher ran PLS Algorithm for the enhanced learning styles models to assess the learning styles model's validity and reliability. Table 2 depicts the results of running PLS Algorithm for learning styles measurement model.

Table 2
Learning Styles Measurement Model

Construct	Item	Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Auditory	Q1	0.86	0.92	0.94	0.76
	Q7	0.88			
	Q9	0.99			
	Q17	0.85			
	Q20	0.75			
Visual	Q6	0.94	0.94	0.96	0.82
	Q10	0.89			
	Q12	0.99			
	Q24	0.87			
	Q29	0.82			
Individual Learning	Q13	0.90	0.91	0.93	0.74
	Q18	0.91			
	Q27	0.94			
	Q28	0.73			
	Q30	0.80			
Group Learning	Q3	0.87	0.91	0.93	0.73
	Q4	0.95			
	Q5	0.94			
	Q21	0.71			
	Q23	0.77			

Note. Construct reliability and validity indices generated by SmartPls

Table 2 above shows all factor loadings or Cronbach's Alpha, and composite reliability coefficients are above 0.7 (Bagozzi & Yi, 1988; Hair, 2009). Since the values of AVE coefficients are all above 0.50, the convergent validity of the instrument is also confirmed. Then, to estimate the significance of the path coefficients, the researcher ran bootstrapping via SmartPLS. All the estimated T Statistics values were above 1.98 (Ringle et al., 2015) and thus significant.

In the structural model of this investigation, the latent variables of the construct learning styles are all second-order latent variables; therefore, a two-step approach was used to define their values. De Souzabido and Silva (2019) suggested that:

> The summated rating scale is a method that consists of generating the score for each LV as the average of its indicators. A previous analysis of Cronbach's alpha or PCA's for each LV can help decide whether to maintain all indicators to obtain the scores or not. This procedure can also be related to the literature on item parcels (p. 491).

Accordingly, after modifying the components of the construct learning styles in the first step based on their factor loadings and their reliability and validity depicted in table

2 above, the average of each remaining latent variable of the construct learning styles was used as its indicator of the related measurement model during the second step analysis. It has been emphasized in the literature that “the relationships between the second-order LV and its dimensions (first-order LV) should be interpreted and used as factor loadings (not hypotheses)” (De Souzabido & Silva, 2019, p. 486). Furthermore, based on the criteria mentioned in table 1 above, the first-order LVs are the formative components of learning styles as the second-order LV. Therefore, there should not necessarily be a high correlation between them; the correlations can be positive, zero, or even negative (Hair Jr et al., 2021).

Based on what was mentioned above, after carrying out the required modifications to enhance model efficacy by deleting the latent variables with negative path coefficients and T Statistics less than 1.98, in the second step, the researcher analyzed the enhanced structural main model by running PLS-Algorithm shown in figure 4 below.

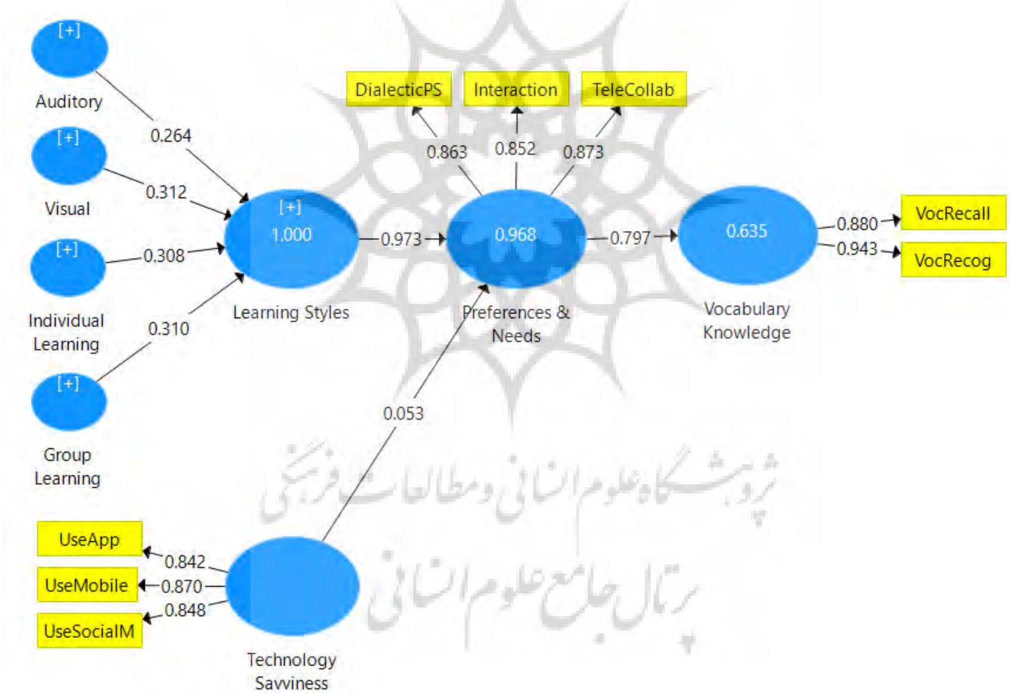

Figure 4. *The Results of Running the PLS Algorithm for the Main Model*

In accordance with the outcomes of the main structural model's PLS Algorithm, the scales' reliability was acceptable since all Cronbach’s Alpha and composite reliability coefficients were above or close to 0.7 (Bagozzi & Yi, 1988; Hair, 2009). Also, AVE coefficients were above 0.50, confirming the convergent validity of the measuring instruments (Henseler et al., 2015). Next, the researcher ran bootstrapping to estimate the significance of the structural model path coefficients. All the obtained T Statistics values were above 1.98 (Ringle et al., 2015). Table 3 depicts the results of running the PLS Algorithm for the main structural model.

Table 3
Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability	AVE
Auditory	0.919	0.94	0.76
Group Learning	0.904	0.93	0.73
Individual Learning	0.909	0.933	0.737
Learning Styles	0.85617	0.90275	0.6992
Preferences & Needs	0.83065	0.89729	0.84439
Technology Savviness	0.81825	0.88943	0.72841
Visual	0.943	0.957	0.818
Vocabulary Knowledge	0.80448	0.9084	0.83234

In the next phase, to assess the discriminant validity, the cross-loadings were examined to verify that the factor loadings for each item in the associated construct were, in every case greater than the loads on the other latent variables. Moreover, as shown in table 4, the square root of each AVE coefficient was larger than the correlations between constructs, according to the criterion suggested by Fornell and Larcker (1981) for assessing discriminant validity.

Table 4
Discriminant Validity: Fornell-Larcker Criterion

	Auditory	Group Learning	Individual Learning	Learning Styles	Preferences & Needs	Technology Savviness	Visual	Vocabulary Knowledge
Auditory	0.87177							
Group Learning	0.44069	0.85440						
Individual Learning	0.42474	0.77306	0.86023					
Learning Styles	0.78511	0.84196	0.83677	0.83618				
Preferences & Needs	0.67708	0.87316	0.8679	0.89249	0.91890			
Technology Savviness	-0.05218	0.13512	0.21847	0.17621	0.22407	0.85347		
Visual	0.81225	0.56977	0.56802	0.87823	0.85197	0.25903	0.90553	
Vocabulary Knowledge	0.70151	0.54183	0.57271	0.81734	0.79694	0.41574	0.92180	0.91233

According to Henseler et al. (2015), “for variance-based structural equation modelings, such as partial least squares, the Fornell-Larcker criterion and the examination of cross-loadings are the dominant approaches for evaluating discriminant validity” (p. 115). Hence, based on the Fornell-Larcker criterion and cross-loadings examination, the discriminant validity of the instruments of this study is acceptable.

The researcher examined multicollinearity values in this study to further evaluate the main structural model**.** Hair Jr et al. (2021) stated that items in formative constructs should not be highly correlated and hence are not interchangeable; accordingly, the variance inflation factor (VIF) is the measure of collinearity for formative constructs, and a VIF value of 5 or greater indicates serious collinearity issues among the predictor constructs. VIF values below 3 are signs of no collinearity; values between 3 to 5 can be acceptable if theoretical justifications are provided.

Hence, the researcher examined the multicollinearity of the items within and between the constructs to ensure that they are not highly correlated and, therefore, not interchangeable. Both outer and inner VIF values were below 3 except the collinearity value of the variable Visual (3.67021), which is also considered acceptable based on the theoretical background mentioned in the literature.

Then, the researcher analyzed the coefficient of determination (R^2) for the latent variables via running the PLS Algorithm, the predictive relevance (Q^2) via running blindfolding, and finally, the significance of the structural model path coefficients and effect size via running bootstrapping were analyzed (Hair Jr et al., 2021). Bootstrapping was utilized to generate standard errors and t values which were all above 1.98 (Chin, 1998; Vinzi et al., 2010). Furthermore, the sign and magnitude of path coefficients provided an estimation of the cause-and-effect relationship among the latent variables. Figure 5 sheds light on the results obtained from the structural model estimation.

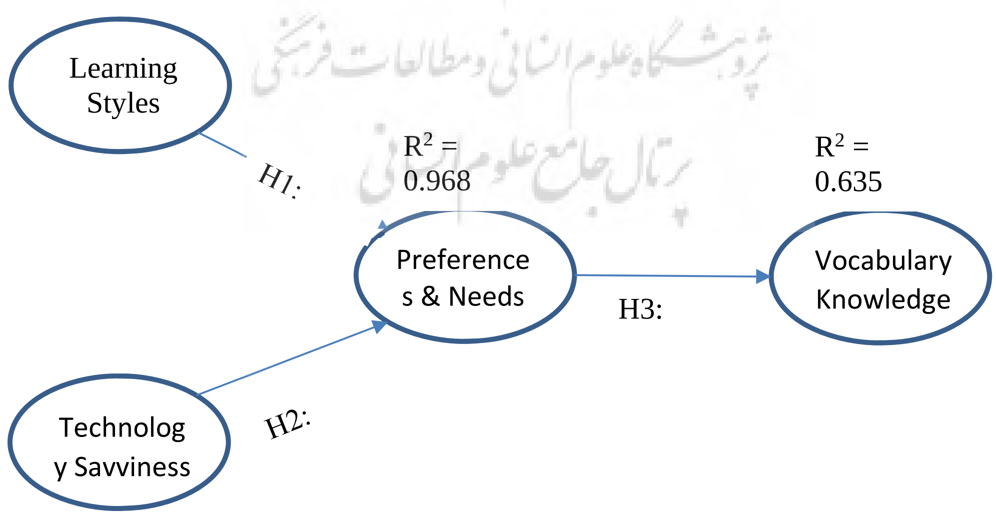

Figure 5. *Results Obtained from Analyzing the Main Structural Model*

Hair and Alamer (2022) highlighted that R^2 values are context dependent and should be interpreted based on the domain under investigation. For L2 research, they mentioned that "R^2 values between 0 to .10, .11 to .30, .30 to 50, and > .50 are indicative of weak, modest, moderate, and strong explanatory power, respectively" (p. 8). Hence, since all R^2 values are greater than 0.5, the strong explanatory power of the proposed model of this investigation is confirmed. Furthermore, the blindfolding process revealed that all Q^2 values are above zero and close to R^2 values, ensuring the model's predictive relevance considering the endogenous variables.

Finally, running bootstrapping procedure, the significance of the path coefficients of the structural model and the effect sizes were defined. Table 5 shows the path coefficient values, t values, and the relevant significance levels of the direct relationships between the latent variables, including first- and second-order constructs of the structural model:

Table 5
Direct Relationships between Constructs and the Coefficients, T Values, and P Values

Constructs	Coefficient	T Statistics	P Values
First-order latent variables			
Auditory -> Learning Styles	0.26418	16.39715	0.00000
Visual -> Learning Styles	0.31244	18.71821	0.00000
Individual Learning -> Learning Styles	0.30774	20.51386	0.00000
Group Learning -> Learning Styles	0.30962	21.11826	0.00000
Second-order latent variables			
Learning Styles -> Preferences & Needs	0.97323	128.58499	0.00000
Preferences & Needs -> Vocabulary Knowledge	0.79694	27.93895	0.00000
Technology Savviness -> Preferences & Needs	0.05258	2.23301	0.02599

To ascertain the significance of the inner paths of the structural model, the researcher verified that all Cohen's f square values are above 0.02, which is considered satisfactory indices, according to Henseler et al. (2009), for the endogenous latent variables and the relevant relationships.

To sum up, according to the results depicted and discussed above, all Cronbach's Alphas and composite reliability coefficients were above or close to 0.7. therefore, the reliability index of the measurement model was established. Furthermore, the convergent validity of the measuring instruments was confirmed since the magnitudes of AVE coefficients were all above 0.50. Besides, all the obtained T Statistics values were above 1.98, which highlighted the significance of the path coefficients. Regarding the discriminant validity of the instruments, it was verified that the factor loadings for each item in the associated construct were, in every case, more significant than the loads on the other latent variables; moreover, the square root of each AVE coefficient was larger than the correlations between constructs, which based on the Fornell-Larcker criterion, confirms the discriminant validity of the instruments of this investigation. Next, to avoid multicollinearity, the researcher verified that outer and inner VIF values were below 3.

Also, all R^2 values were more significant than 0.5, which showed the strong explanatory power of the proposed model. Moreover, the model's predictive relevance considering the endogenous variables was evident since all Q^2 values were above zero and close to R^2 values. Finally, the estimated Cohen's f-square values above 0.02 confirmed the significance of the inner paths of the structural model.

The findings mentioned above verified the affirmative answers to all the questions of this investigation. Therefore, the first-order constructs of the structural model, which are Visual, Auditory, Individual learning, and Group learning, are well-integrated into the model. According to the empirical evidence, learning styles positively and significantly affect learners' preferences and needs (RQ1). Technology savviness also positively and significantly impacts the construct learners' preferences and needs (RQ2). And finally, considering the participants' preferences and needs during agile app development positively and significantly affects learners' level of vocabulary knowledge (RQ3).

Regarding the fitness of the structural model, Hair and Alamer (2022) emphasized that comparative fit index (CFI), normed fit index (NFI), and Root Mean Square Error of Approximation (RMSEA), among the other indices, are not appropriate to verify the goodness of fit of PLS-SEM models which are variance-based models, since they are suitable for covariance-based SEM. Fundamentally, PLS-SEM was created as a multiple regression-style predictive method; hence, model fit indices were not developed for PLS-SEM; instead, the performance of a structural model, discussed above, provides the criteria for model assessment (Sparks & Alamer, 2022).

Discussion and Conclusion

This investigation assessed the predictive strength and performance of the proposed structural model (Hair & Alamer, 2022; Sparks & Alamer, 2022) of learning styles, technology savviness, vocabulary knowledge, and the mediatory role of needs analysis during the agile development of a mobile application. In other words, during this study, the researcher evaluated the impacts of learners' learning styles and technology savviness on their preferences and needs during the agile development of the mobile vocabulary application to improve their vocabulary knowledge.

It should be highlighted that the construct of learning styles at first had six formative components as their first-order constructs, including Auditory, Visual, Kinesthetic, Tactile, Individual Learning, and Group Learning based on PLSPQ classification (DeCapua & Wintergerst, 2005; J. Reid, 1987; Reid, 1998). However, due to the negative path coefficients and not significant T Statistics, the researcher eliminated the kinesthetic and tactile components to increase model efficacy (Hair Jr et al., 2021). These non-significant values may be due to the participants majoring in English language and literature, which is a philosophical and abstract subject in nature. And also since, as Dörnyei et al. (2014) highlighted that learning styles are personal preferences, the participants were not willing to be involved physically in classroom experiences or to do "hands-on" experiences with materials according to the explanation of learning styles by J. M. Reid (1987).

Regarding the first research question of this investigation, the results obtained from PLS-SEM analyses revealed the significant positive impact of the construct learning styles on the preferences and needs of the learners. These constructs were defined first via ipsative assessment and then negotiated with the participants during the semi-structured interview in the qualitative phase of the study. This is in line with the findings mentioned by Reid (1995) that learning styles are individuals’ personal preferences that should be considered for effective teaching since they are determinants for choosing the tools and tactics to overcome learning obstacles. Benitez-Correa et al. (2022) also confirmed the impact of learning styles on learners' strategies for enhancing their learning process. The findings of this investigation are also consistent with the study conducted by Kazu (2009), who, after elaborating on various learning styles and delving into the related literature, stated that considering learners’ differences, such as personality, perception, ability, and intelligence, is the best way to foster learning. Furthermore, the findings of the current research verify those of Liegle and Janicki (2006), who assessed the participants’ learning style preferences by using a version of the Kolb Learning Style Inventory Tool and found that learners’ styles affect their path of learning and the tools they use, which impact their test scores in a course. Though the instruments utilized in the current study to gather data differ (PLSPQ and semi-structured interviews), the findings are in line with the report of the above studies that learning styles have a significant positive effect on the learners’ preferences and needs.

The second research question of this study addressed the predictive significance and impact of technology savviness on learners’ preferences and needs. The findings confirmed the significant positive impact of technology savviness on the learners’ preferences and needs, a concept which is supported in the literature as Puebla et al. (2022) highlighted that tech-savvy learners are better language learners. Though the participants of their study were all above 60 years old and resistant to fully consuming the potentials of technology, their self-perceived digital literacy and openness to new advancements strongly helped them progress in language learning, an outcome that supports the findings of the present study. Eaton (2010) also emphasized the necessity and positive impact of technological background knowledge on learners’ achievement due to the positive findings during his study, which confirms the findings of the present research. Using apps, mobile devices, and social media are among the components of Web 2 technology (Kárpáti, 2009; O'Reilly, 2009) and also the reflective indicators of the construct technology savviness in this investigation. Malhiwsky (2010), via a mixed methods study (Creswell & Creswell, 2018), looked into how Web 2.0 technology affected students' performance in online language courses at a Midwestern community college. The tools consisted of an intermediate multiple-choice Spanish test, a Classroom Community Survey created by Rovai (2001), and online interviews. The outcomes showed that the accomplishments in the Web 2.0 enhanced courses, which made use of many technology resources, greatly improved.; therefore, the study conducted by Malhiwsky (2010) supports the findings of the present investigation.

Considering the impact of integrating learners' preferences and needs within the agile life cycle of a mobile application on predicting their vocabulary knowledge improvement was the third research question of this investigation which was confirmed by the findings. Though Puebla et al. (2022) did not conduct any needs analysis in their study, they confirmed the necessity of needs analysis as they emphasized: "the need to consider the specific requirements of late-life learners in future implementations of language learning apps" (p. 169). Hence, the findings of the present study are confirmed by the results of their investigation. Moreover, many studies support the significant positive effect of using mobile applications on teaching/learning a language and its components; However, the current study's researcher was unable to locate any mobile applications created in accordance with the results of the analysis of the demands of the target users. Burston (2015) and Burston and Athanasiou (2020) analyzed 2000 MALL studies profoundly from 1994 to 2018; they reported the drastic design flaws, particularly in the outcome assessment, the small number of learners, short teaching sessions, and no support for interpersonal communication and the participants' preferences and needs. Shadiev et al. (2020) reviewed articles from journals published in the Social Science Citation Index between the years 2009 to 2018. Their review focused on the pedagogical approaches, data collection procedures, affordances of authentic environments, and the shortcomings of MALL research. They ascertained the same flows and pitfalls mentioned by Burston (2015) and Burston and Athanasiou (2020) above. Furthermore, no mobile app was developed based on the needs and preferences of the target learners, though in all studies, the positive effect of MALL on language learning was highlighted. Hence, the reviewed articles align with this investigation's findings. Basal et al. (2016) studied the effect of using a mobile application on teaching 40 figurative idioms from the Michigan Corpus of Academic Spoken English (MICASE) compared with traditional paper and pencil practices. According to the results, using the mobile application significantly impacted learning idioms. Though they did not account for learners' preferences and needs, their findings support the third research question of the current study. Furthermore, they recommended using mobile applications for teaching vocabulary. Therefore, the studies mentioned above were in line with the current studies regarding the significant positive impact of mobile apps on teaching/learning, but they did not conduct any needs analysis to tailor the app based on the needs and preferences of the participants.

In conclusion, the overall efficacy of the proposed structural model of this investigation was confirmed by considering the results obtained from conducting PLS Algorithm, Bootstrapping, and Blind folding analyses via SmartPLS software. As Sparks and Alamer (2022) pointed out, PLS-SEM is similar to a multiple regression procedure and is based on a predictive approach. Therefore, model fit indices were not developed for PLS-SEM; the criteria for model assessment in PLS-SEM is the performance of the structural model. Accordingly, it was found that learning styles and their formative components can significantly predict the participants' preferences and needs; this can be because different learners with different learning styles need tools and facilities which meet their way of learning (Dörnyei, 2014); besides, difficulties may derive from lack of considering different learning styles (Ehrman, 1996). Hence, considering different learning styles while designing and implementing a course should improve the outcome which is vocabulary knowledge in this study.

Though positive, the impact of technology savviness on the learners' preferences and needs was not as significant as the other latent variables. It can be rooted in the degree of user-friendliness of the developed app. If a task's difficulty level is low, the outcome cannot shed light on the various potentialities of the learners with different levels of background knowledge (Hunter & Schmidt, 1996). Hence, it can be concluded that since the mobile vocabulary application of the current study was developed based on needs analysis and constant agile negotiation with the participants, the final product was so user-friendly that learners' prior technology knowledge had less impact on their performance compared with the other exogenous variables of the structural model.

Overall, the results and findings of the present study revealed that analyzing the learning styles and considering the background technology knowledge of the participants while developing a mobile app with a continuous adjustment of the app features to meet learners' preferences and needs positively and significantly affects the learner's vocabulary knowledge encompassing vocabulary recognition and recall.

Regarding the limitations of the present study, the participants were selected based on the availability principle; therefore, care should be taken not to advocate the findings and generalize them to other settings. Due to the same limitation of subject selection, only female learners could contribute to this investigation; hence, gender was a control variable. Besides, there were only 62 female university students, which reduces the external validity of the scores obtained from the vocabulary recognition and recall tests, a point that also reduces the generalizability of the findings.

The findings of this research provide discerning implications for institutions, educators, and specialists interested in teaching language, particularly vocabulary, and those involved in the design and development of mobile applications. The educators who are willing to implement and actualize the post-method paradigm, framework, and pedagogic parameters, as discussed by Kumaravadivelu (2003, 2006); Kumaravadivelu (2008); Kumaravadivelu (2012), in their action research, may find practical implications in the current research report. Furthermore, this investigation brings about some insightful implications for test takers and those who develop language tests, especially language aptitude tests. Finally, some practical implications emerge from this study for language learners who are willing to elevate their learning strategies and pave their learning trajectories to become more successful language learners.

References

Acosta, A. S., Crespo, Á. H., & Agudo, J. C. (2018). Effect of market orientation, network capability and entrepreneurial orientation on international performance of small and medium enterprises (SMEs). *International Business Review*, *27*(6), 1128-1140.

Adnan, A., & Marlina, L. (2017). EFL students' learning style in English as a general course at Universitas Negeri Padang. Fifth International Seminar on English Language and Teaching (ISELT 2017),

Al-Jarf, R. (2018). Effect of background knowledge on auditory comprehension in interpreting courses. *Interpretation of Meaning Across Discourses, Brno*.

Al-Sharqi, L., & Abbasi, I. S. (2020). The Influence of technology on English language and literature. *English Language Teaching*, *13*(7), 1-7.

Alamer, A., & Marsh, H. (2022). Exploratory structural equation modeling in second language research: An applied example using the dualistic model of passion. *Studies in Second Language Acquisition*, 1-24.

Alexander, B. (2020). *Academia next: The futures of higher education*. Johns Hopkins University Press.

Alharbi, W. H. (2022). The affordances of augmented reality technology in the English for specific purposes classroom: Its impact on vocabulary learning and students motivation in a Saudi higher education institution. *Journal of Positive School Psychology*, *6*(3), 6588–6602-6588–6602.

Alqahtani, M. (2015). The importance of vocabulary in language learning and how to be taught. *International journal of teaching and education*, *3*(3), 21-34. https://doi.org/10.20472/TE.2015.3.3.002

Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: A survey. *Computer networks*, *54*(15), 2787-2805.

Baddeley, A. D., Hitch, G. J., & Allen, R. J. (2019). From short-term store to multicomponent working memory: The role of the modal model. *Memory & Cognition*, *47*(4), 575-588.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing science*, *16*(1), 74-94.

Basal, A., Yilmaz, S., Tanriverdi, A., & Sari, L. (2016). Effectiveness of mobile applications in vocabulary teaching. *Contemporary Educational Technology*, *7*(1), 47-59.

Becker, K., Kehoe, J., & Tennent, B. (2007). Impact of personalized learning styles on online delivery and assessment. *Campus-Wide Information Systems*.

Benitez-Correa, C., Vargas-saritama, A., Gonzalez-Torres, P., Quinonez-Beltran, A., & Ochoa-Cueva, C. (2022). Students' Preferences and Learning Styles in Relation to Reading and Writing Strategies at Distance Higher Education. *International Journal of Learning, Teaching and Educational Research*, *21*(4).

Bowen, N. K., & Guo, S. (2011). *Structural equation modeling*. Oxford University Press.

Bowles, H., & Cogo, A. (2016). *International perspectives on English as a lingua franca: Pedagogical insights*. Springer.

Brooks, G., Clenton, J., & Fraser, S. (2021). Exploring the Importance of vocabulary for English as an additional language learners' reading comprehension. *Studies in Second Language Learning and Teaching*, *11*(3), 351-376.

Brown, H. D., & Lee, H. (2015). *Teaching by principles: An interactive approach to language pedagogy* (4th ed.). Pearson Education.

Burston, J. (2015). Twenty years of MALL project implementation: A meta-analysis of learning outcomes. *ReCALL*, *27*(1), 4-20. https://doi.org/https://doi.org/10.1017/S0958344014000159

Burston, J., & Athanasiou, A. (2020). Twenty-five years of MALL experimental implementation studies: What do we know about it? In *Recent Tools for Computer-and Mobile-Assisted Foreign Language Learning* (pp. 35-59). IGI Global. https://doi.org/10.4018/978-1-7998-1097-1.ch002

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research*, *295*(2), 295-336.

Chin, W. W. (2010). How to write up and report PLS analyses. In *Handbook of partial least squares* (pp. 655-690). Springer.

Chostelidou, D. (2010). A needs analysis approach to ESP syllabus design in Greek tertiary education: a descriptive account of students' needs. *Procedia-Social Behavioral Sciences*, *2*(2), 4507-4512.

Cohen, J. (1992). Quantitative methods in psychology: A power primer. Psychological bulletin,

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (Fifth ed.). Sage publications.

Davies, M. (2020). *Corpus of Contemporary American English*. https://www.english-corpora.org/coca/

Davies, M., & Gardner, D. (2019). *Academic vocabulary lists*. https://www.academicvocabulary.info/

De Souzabido, D., & Silva, D. D. (2019). Smartpls 3: specification, estimation, evaluation and reporting [Report]. *Administração: Ensino e Pesquisa – RAEP*, *20*, 465+. https://link.gale.com/apps/doc/A600448544/IFME?u=anon~9befbcb7&sid=googleScholar&xid=349592ca

DeCapua, A., & Wintergerst, A. C. (2005). Assessing and validating a learning styles instrument. *System*, *33*(1), 1-16.

Dörnyei, Z. (2014). *The psychology of the language learner: Individual differences in second language acquisition*. Routledge.

Dörnyei, Z., Henry, A., & MacIntyre, P. D. (2014). *Motivational dynamics in language learning* (Vol. 81). Multilingual Matters.

Eaton, S. E. (2010). *Global trends in language learning in the 21st century*. ERIC.

Ehrman, M. E. (1996). *Understanding second language learning difficulties*. Sage. https://www.google.com/books/edition/Understanding_Second_Language_Learning_D/ig05DQAAQBAJ?hl=en&gbpv=0

Fathi, J., & Savadi Rostami, E. (2018). Collective teacher efficacy, teacher self-efficacy, and job satisfaction among Iranian EFL Teachers: The mediating role of teaching commitment. *Teaching English as a Second Language (Formerly Journal of Teaching Language Skills)*, *37*(2), 33-64.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Greenfield, A. (2010). *Everyware: The dawning age of ubiquitous computing*. New Riders.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), 100027.

Hair, J. F. (2009). *Multivariate data analysis* (7th ed.). Pearson.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Heift, T., Mackey, A., & Smith, B. (2019). History, pedagogy, data and new directions: An introduction to the educational technology issue. *Annual Review of Applied Linguistics*, *39*, 1-7.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*(1), 115-135.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *New challenges to international marketing*. Emerald Group Publishing Limited.

Hiebert, E., Scott, J., Castaneda, R., & Spichtig, A. (2019). An analysis of the features of words that influence vocabulary difficulty. *Education Sciences*, *9*(1), 8.

Huang, W. (2019). A needs analysis approach to the design of college English elective courses: A descriptive account of Chinese college students' needs. 2018 6th International Education, Economics, Social Science, Arts, Sports, and Management Engineering Conference (IEESASM 2018),

Hunter, J. E., & Schmidt, F. L. (1996). Intelligence and job performance: Economic and social implications. *Psychology, Public Policy, and Law*, *2*(3-4), 447.

Kárpáti, A. (2009). Web 2 technologies for Net Native language learners: A "social CALL". *ReCALL*, *21*(2), 139-156.

Kazu, I. Y. (2009). The effect of learning styles on education and the teaching process. *Journal of Social Sciences*, *5*(2), 85-94.

Kumaravadivelu, B. (2003). *Beyond methods: Macrostrategies for language teaching*. Yale University Press.

Kumaravadivelu, B. (2006). *Understanding language teaching: From method to post-method*. Routledge.

Kumaravadivelu, B. (2008). *Cultural globalization and language education*. Yale University Press.

Kumaravadivelu, B. (2012). *Language teacher education for a global society: A modular model for knowing, analyzing, recognizing, doing, and seeing*. Routledge.

Larsen Freeman, D. (2012). Chaos/complexity theory for second language acquisition. *The encyclopedia of applied linguistics*, 710-717. https://doi.org/DOI: 10.1002/9781405198431

Liegle, J. O., & Janicki, T. N. (2006). The effect of learning styles on the navigation needs of Web-based learners. *Computers in Human Behavior*, *22*(5), 885-898.

Lord, G., & Lomicka, L. (2008). Blended learning in teacher education: an investigation across media. *Contemporary Issues in Technology and Teacher Education*, *8*(2), 158-174.

Lu, J., Yao, J. E., & Yu, C.-S. (2005). Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. *The Journal of Strategic Information Systems*, *14*(3), 245-268.

Malhiwsky, D. R. (2010). Student achievement using web 2.0 technologies: A mixed methods study. *Open access theses and dissertations from the College of Education and Human Sciences*, 58.

Marjaei, S., Yazdi, F. A., & Chandrashekara, M. (2019). MAXQDA and its application to LIS Research. *Library Philosophy and Practice*, 1-9.

Miller, G. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *The Psychological Review*, *63*(2), 81.

Nation, I., & Meara, P. (2002). Vocabulary. In N. Schmitt (Ed.), *An introduction to applied linguistics* (pp. 35-54). Arnold.

NetMarketShare. (2019). *Market share statistics for internet technologies*. https://netmarketshare.com/operating-system-market-share.aspx

O'Reilly, T. (2009). *What is web 2.0*. " O'Reilly Media, Inc.".

Otto, S. E. (2017). From past to present: A hundred years of technology for L2 learning. *The handbook of technology and second language teaching and learning*, 10-25.

Ozdemir, M. S. (2017). Seven. *International Journal of the Analytic Hierarchy Process, 9*(3), 1. https://doi.org/https://doi.org/10.13033/ijahp.v9i3.552

Puebla, C., Fievet, T., Tsopanidi, M., & Clahsen, H. (2022). Mobile-assisted language learning in older adults: Chances and challenges. *ReCALL*, *34*(2), 169-184.

Rashid, M. H., Lan, Y., & Hui, W. (2022). The importance of vocabulary in teaching and learning in applied linguistics. *Linguistics and Culture Review*, *6*, 541-550.

Ravand, H., Rohani, G., & Faryabi, F. (2018). On The Factor Structure (Invariance) of the PhD UEE Using Multigroup Structural Equation Modeling. *Journal of Teaching Language Skills*, *36*(4), 141-170.

Razavipour, K., Gooniband Shoushtari, Z., & Mansoori, M. (2018). The structural invariance of a model of washback to test takers' perceptions and preparation: The moderating role of institutions. *Teaching English as a Second Language (Formerly Journal of Teaching Language Skills)*, *36*(4), 171-201.

[Record #384 is using a reference type undefined in this output style.]

Reid, J. M. (1987). The learning style preferences of ESL students. *TESOL Quarterly*, *21*(1), 87-111.

Reid, J. M. (1995). *Learning styles in the ESL/EFL classroom*. ERIC. https://eric.ed.gov/?id=ED396587

Reid, J. M. (1998). *Understanding learning styles in the second language classroom*. Prentice Hall Regents.

Riding, R. (2000). Cognitive style: A review. *Interpersonal perspectives on individual differences*, *1*, 315-344.

Ringle, C., Da Silva, D., & Bido, D. (2015). Structural equation modeling with the SmartPLS. *Brazilian Journal Of Marketing*, *13*(2).

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). Editor's comments: A critical look at the use of PLS-SEM in" MIS Quarterly". *MIS quarterly*, iii-xiv.

Rovai, A. P. (2001). Building classroom community at a distance: A case study. *Educational technology research and development*, *49*(4), 33-48.

Sari, B. T., Chasiotis, A., van de Vijver, F. J., & Bender, M. (2020). The importance of language vocabulary and language usage for sociocultural adjustment among Indonesian adolescents from three bilingual ethnic groups. *Journal of Multilingual and Multicultural Development*, *41*(6), 531-546. https://doi.org/10.1080/01434632.2019.1630417

[Record #390 is using a reference type undefined in this output style.]

Sartor, V. (2020). Digital age pedagogy: Easily enhance your teaching practice with technology. English teaching forum,

Schmitt, N. (2010). *Researching vocabulary: A vocabulary research manual*. Springer.

Schmitt, N., & Schmitt, D. (2020). *Vocabulary in language teaching* (2nd ed.). Cambridge University Press.

Seedhouse, P. (1995). Needs analysis and the general English classroom. *ELT Journal*, *49*(1), 59-65. https://doi.org/10.1093/elt/49.1.59

Shadiev, R., Liu, T., & Hwang, W. Y. (2020). Review of research on mobile-assisted language learning in familiar, authentic environments. *British Journal of Educational Technology*, *51*(3), 709-720.

Shao, K., Elahi Shirvan, M., & Alamer, A. (2022). How accurate is your correlation? Different methods derive different results and different interpretations. *Frontiers in Psychology*, 2791.

Snow, R. E., Corno, L., & Jackson III, D. (1996). Individual differences in affective and conative functions. https://psycnet.apa.org/record/1996-98614-008

Sparks, R. L., & Alamer, A. (2022). Long-term impacts of L1 language skills on L2 anxiety: The mediating role of language aptitude and L2 achievement. *Language Teaching Research*, 13621688221104392.

Sternberg, R. J., & Grigorenko, E. L. (2014). A capsule history of theory and research on styles. In *Perspectives on thinking, learning, and cognitive styles* (pp. 1-22). Routledge.

Swilley, E. (2019, 2019//). Investigating the Tech-Savvy Consumer: An Abstract. Finding New Ways to Engage and Satisfy Global Customers, Cham.

Taghizadeh, M. (2019). The effect of needs analysis on designing ESP courses in Iranian context: A case study. *English Language Teaching Letters*, *1*(1), 46-50.

Tewari, A., & Gupta, B. (2020). Security, privacy and trust of different layers in the Internet-of-Things (IoTs) framework. *Future generation computer systems*, *108*, 909-920.

Tompson, R., Barclay, D., & Higgins, C. (1995). The partial least squares (PLS)approach to causal modeling: Personal computer adoption and uses as an illustration. *Technology Studies: Special Issue on Research Methodology*, *2*(2), 284-324.

Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of partial least squares: Concepts, methods and applications* (Vol. 201). Springer.

Wintergerst, A. C., DeCapua, A., & Verna, M. A. (2002). An analysis of one learning styles instrument for language students. *TESL Canada Journal*, *20*(1), 16-37.

Wong, L. L., & Nunan, D. (2011). The learning styles and strategies of effective language learners. *System*, *39*(2), 144-163.

Zhou, Y., & Wei, M. (2018). Strategies in technology-enhanced language learning. *Studies in Second Language Learning and Teaching*, *8*(2), 471-495.