Review of Personalized Language Learning Systems

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Abstract*— *This study reviews published scientific literature on personalized language learning systems. The focus is threefold: 1) present a review and categorization framework that can be used to analyze and classify personalized language learning systems, 2) analyze recent work in personalized language learning systems and organize them under the proposed framework, 3) identify current trends, challenges and open research questions in the field. Our review led us to propose a review and classification scheme with two dimensions each with a few sub-elements: language learning dimension and technical dimension. The reviewed articles indicate that recent language personalization systems increasingly introduce Artificial Intelligence and focus on cognitive-based personalization. Findings also suggest that language personalization systems may improve by incorporating more complex adaptive learner's model and more complex contextual language learning tasks.

Keywords—Personalized Learning Systems; Computer Aided Language Learning; Personalized Language Learning

I. INTRODUCTION

Language allows us to express our ideas and thoughts, and facilitates our interactions with others. Thus, acquiring effective linguistic skills is crucial not only for communication, but also for knowledge acquisition and generation. To support and enhance language acquisition and learning, novel techniques, tools, and models have been devised to exploit the powerful multi-modal capabilities of smart devices. Specifically, computer-mediated communication, the Internet, and multimedia have been reshaping the use of computers for language learning [1]. Many foreign and native language resources, in addition to the traditional grammar books and dictionaries, have been developed under the rubric of "Computer aided language learning (CALL)" to facilitate language learning. According to Google Scholar's research metrics[1], CALL-related research articles had attracted lots of attention, between 2011 and 2015 [2] [3] .

Recent educational changes in methods, curriculum design, and pedagogical approaches stress the importance and effectiveness of personalized learning as opposed to traditional cohort-based learning [2]. Consequently, CALL efforts have emphasized a more learner-centric approach by targeting the integration of personalized language learning. Various efforts attempted to personalize language learning and embed it in various forms of software systems such as games, simulations, and online courses (e.g. [3], [4], and [5]).

The research contribution of this paper is threefold. We first present a review and categorization framework for personalized language learning systems. This framework identifies key elements of language learning dimension and technical dimension. The framework is used to elaborate an analysis of personalized language learning systems (i.e. game-based and context-aware). Based on the analysis we outline current challenges and directions of future research in this area.

II. LANGUAGE LEARNING DIMENSION

A considerable number of research work in the field of software-based learning emphasizes the importance of embedding good pedagogical design relevant to some learning theories to ensure effective learning [6], [7], [8]). Accordingly, it is important to recognize that designing a software for learning is more intricate than just embedding some learning content in a software application, simply because learning is a rather complex process. Some criteria related to the learning content as well as learning activities need to be considered to ensure that the learning software provides an actual learning experience. In the following sections, we present an overview of important language learning theories, methods and related concerns.

a. Language Learning Theories and Methods

In learning languages, a distinction is usually made between mother tongues, second languages, and foreign languages. A mother tongue is the first language or languages one learns (or acquires) as a child [9]. Considering research into first language acquisition, the mechanism that enables children to segment words out of the strings of sounds they hear, and to acquire grammar to understand and produce adult-like language is still quite a mystery [10]. One of the earliest scientific explanations of first language acquisition was provided by Skinner [11]. He accounted for language development by means of environmental influence. In contrast to Skinner's account, Chomsky proposed the theory of Universal Grammar: an idea of innate, biological grammatical categories, such as noun and verb categories that facilitate the entire language development in children and overall language processing in adults [12]. Subsequently, some psycho-linguists began to question the existence of Universal Grammar. They argued that categories like noun and verb are biologically, evolutionarily, and psychologically implausible and that the field called for an account that can explain for the acquisition process without innate categories. Consequently, the variety of language

1 Google Metrics - https://scholar.google.com/intl/en/scholar/metrics.html#coverage
2 Language Learning Metrics - https://scholar.google.com/citations?hl=en&view_op=search_venues&vq=+language+learning
3 Computer-Aided Language Learning Metrics - https://scholar.google.com/citations?hl=en&view_op=search_venues&vq=computer+aided+language+learning+

learning theories has inspired many approaches to the teaching of second and foreign languages. The study of these theories and how they influence language teaching methodology today is called applied linguistics.

The grammar-translation method [13] is an early method based on the assumptions that language is primarily graphic, that the main purpose of second language study is to build knowledge of the structure of the language. Such traditional methods as grammar translation assumed that students were aiming for mastery of the target language, and that students were able to study for years before actually using the language in real life. However, these assumptions were challenged by adult learners who were busy with work, and by pupils who were less academically capable. Educators realized that to meet the requirements of these adults and pupils an approach with more immediate results was necessary. These new views put greater emphasis on individualized instruction as well as a greater focus on the learner and on social interaction resulting in the Natural and Communicative approaches [14] [15] . These approaches favor learning of a wide range of vocabulary base over learning new grammatical structures. In addition, teachers using these approaches aim to create situations in the classroom that are intrinsically motivating for students to use new language and, hence, acquire new linguistic skills. A more recent approach of language learning, which is seen as a branch of communicative language learning, is task-based language learning in which teachers focus on the use of authentic language and on having students do meaningful tasks using the target language. These approaches are usually followed by teachers in the class. Accordingly, designing a personalized language learning software system requires integrating and modeling these approaches in order to allow learners develop language skills independently without teacher's direct help.

b. Content

As presented in the previous section, modern language teaching approaches focus mainly on vocabulary learning. Even though content may cover more complicated linguistic structures, in our review we focus on vocabulary learning as being the most commonly used technique in class rooms and in language learning software systems (e.g. [3] and [5]).

Acquiring a vocabulary sufficient to allow the learner to use the language for whatever purposes he/she desires is fundamental. It is obvious that without at least a basic knowledge of the vocabulary of a language no communication is possible except for such communication as can take place using non-linguistic devices such as gesture, mime, etc. [16].

Considerable research efforts (e.g. [17] and [16]) had focused on answering questions like: how much vocabulary a learner need to learn in order to be literate in a specific language? How much vocabulary need to be learned in a particular age? What vocabulary need to be learned? Even though we are not directly addressing these questions, we need to analyze the extent to which personalized language learning software systems follow any rational for the selection or organization of the used vocabulary. Any system that randomly uses any set of vocabulary may not be achieving language learning objectives.

c. Criteria

Based on the information presented in sections (a) and (b), we conclude with some important questions that can be used to analyze and evaluate a given personalized language learning software system based on language learning dimensions, such as: (1) does it focus on grammar rules or vocabulary? (2) Does it implement authentic communicative tasks/situations? (3) Does it focus on instructions? (4) How much vocabulary is used? (5) How difficult is the vocabulary? (6) How language learning is assessed?

Software systems that implement instructional learning tasks focusing mainly on grammar rules and language structure are more likely to develop language skills after long period of usage, whereas software systems that focus more on authentic and communicative learning tasks are more likely to help learners develop language skills quickly. On the other hand, software systems that consider suitable amount of vocabulary and consider criteria for selecting suitable vocabulary and suitable language assessment techniques are more capable to achieve the objectives of language learning.

III. TECHNICAL DIMENSION

According to The U.S. Department of Education learning personalization is defined as: "Instruction is paced to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners *[18]*." However, Interpretations and applications of learning personalization differ widely depending on the context *[19]*. In order to be more specific and relevant to the technological context. We present in the following sections definitions and explanations of learning personalization specific to the technical dimension.

a. Levels of Personalization

We will adapt Martinez's [20] categorization of learning personalization to define levels of personalization in language learning software systems. Martinez described personalization in technology with five levels with increasing sophistication; each level represents a specific personalization strategy. From the simplest to most complicated, the five levels are: (a) name-recognized; (b) self-described; (c) segmented; (d) cognitive-based; and (e) whole-person-based. Each type has a specific purpose, influence, and resulting impact. Given that the first level (i.e. name-recognized) is not specific to language learning and may not differ between a language learning software system and other personalized learning systems, we adapt the latter four levels.

1. ***Self-Described Personalization*** explicitly enables learners, using questionnaires, surveys, registration forms, and comments, to describe preferences and common attributes. In language learning, this level of personalization can be used to personalize the language of interest, language learning tasks or themes, and skill level of the learner as described by the learner.
2. ***Segmented Personalization*** uses demographics, common attributes, or cultural characteristics to group or segment learning populations into smaller, identifiable and manageable groups. For example, some language learning personalization systems are designed with learning tasks,

characters, and themes specific to a particular geographical area reflecting specific accent or dialect, and specific idioms commonly used in that area [21].

3. ***Cognitive-Based Personalization*** implicitly uses information about cognitive processes, strategies, and ability to deliver content specifically targeted to specific types of learners. This level of personalization is more advanced than self-described personalization as it attempts infer learner's cognitive characteristics that are not explicitly expressed. For example, personalizing the level of difficulty [4], the number of vocabulary used based on memory attributes [3], or display options (images vs. text, audio vs. plain text or images) based on learning style [22].
4. ***Whole-Person Personalization*** makes predictions about delivering content from a whole-person perspective. It does not only deliver content to help learners achieve learning objectives but it also attempts to improve overall learning ability. As the individual learns, the system also learns as it collects data, tracks progress, and compares responses and common patterns to improve responses (i.e., it becomes more precise over time). Key criteria of the system operating at this level is adaptability.

b. User Model

There exist a number of appraoches followed to model the learner in personalized learning systems. According to Abbey et.al. [23] learner profiling/modeling techniques in personalized learning software systems can be categorized into: (i) *Adaptive* that model the learner in an unsupervised mode (i.e. typically no reference framework is pre-defined in the system), or (ii) *Non-Adaptive* that model the learner in a supervised mode (i.e. using some pre-defined styles and types).

Profiling data input methods range between automatic/implicit and collaborative/explicit [23], [24]. In automatic profiling, learner's charecteristics are derived automatically either from historical data or by monitoring learner's interaction with the system such as: click logs, browse history, cache logs, mouse clicks, eye tracking, and cookies. Whereas in collaborative profiling, the learner is prompted to input profiling data either through questionnaire or other input mechanisms.

c. Techniques

Personalized learning systems in the literature follow different approaches and techniques to map learning resources to learner's model. We generally categorize available techniques into three main categories: (i) associations-based techniques that consider only the associations between learning resources and the learner, (e.g. [25]), (ii) attributes-based techniques that consider features and properties of learning resources and learners (e.g. [26] and [27]), and (iii) knowledge-based techniques that are based on comprehensive knowledge about the learning resource and the user (e.g. [5]). We adapt Burkes' [28] explanation of recommender systems to explain how different learning personalization systems work in general. In association-based techniques typically the system knows ratings or preferences of learners in ***L*** of Items in ***I,*** given input about a new learner ***l*** of items ***I,*** the system identifies learners in ***L*** that are similar to the new learner ***l*** and explores from their ratings of ***i***s. Distance measures and Matrix factorization algorithms are usually used in association-based systems [29]. In content-based techniques, the system knows features ***I*** of learning resources, given input about a new learner ***l*** mapped to these features ***I***, the system generates a classifier that fits the learner to a specific class ***C***. Finally, for knowledge-based systems, the system knows features of learning resources and how these learning resources meet specific learner's need, given a description of a new learner's needs or interests, the system infers a suitable match based on the rules or predicates defined in the knowledge-base.

IV. The Proposed Framework

Based on the main concepts stated above, we present a framework for analysis and categorization of personalized language learning research work as illustrated in Table1. The framework is composed of two main dimensions. Language learning dimension focuses on pedagogical and language specific elements. Whereas the technical dimension focuses on personalization level, user modeling and technical approaches. Each element has sub-elements that can fully characterize a personalized language learning system. In the following section, we review and categorize several recent research works under the proposed framework.

V. Analysis of Recent work

In this section we analyze some of the recent work in language learning personalization focusing on game-based and context-aware systems, summarized in Table 2.

Considering the interactive nature of games, many recent research works focus on imlplementing language learning tasks in game environment as it supports the modelling and implementation of authentic learning tasks, which is related to the communicative task-based language learning as explained earlier. For example, Nascimento et. al. [4], proposed a personalized Portuguese language learning game to assist students with difficulties in vocabulary aquisition. The proposed game implements a cognitive-based personalization in which the game continuously assesses the learner's skill level, match suitable learning tasks accordingly, and ends when the learner is considered by the game to be literate. The game implements advanced machine learning algorithms, based on logistic-regression, to generate predictions of students' level and match content accordingly. A communicative Match-to-Sample teaching tasks are used (i.e. match vocabulary to image, match sound to words … etc.). Even though the system assesses learner skill level continuosly and maps learning tasks accordingly, yet, the system is still restricted by the predefined learning levels, learning tasks and learnig objectives that need to be accomplished by all the students which reduces the adabtability of the system. Assessment is not personalized, rather same assessment is performed with all students. Jung & Graf [5], proposed a cognitive-based personalized web-based vocabulary learning framework through word association games. The proposed framework assists in learning English as a foreign language. The proposed framework is composed of four modules, an expert module responsible for presenting the vocabularies and their corresponding associations by means of semantic networks, a learner module reflecting the system's view of the learner that adapts to learner's lixical knowledge, a personalization engine responsible for tailoring suitable vocabulary associations to the current lexical level of the learner and an interface module responsible for rendering the learning material and inputting learner's data. The learner is assessed based on what vocabulary associations they seem to know and is presented with new associations accordingly. Vocabulary difficulty is measured based on word familiarity. A word with many associations is considered familiar, thus, easier that a word with less associations. Chen et. al. [3] proposed a cognitive-based personalized English vocabulary learning mobile game based on Item Response Theory [30] and learning memory cycle, which can appropriately recommend English vocabulary for learning according to the vocabulary ability of the individual learner and perform the review process based on various learning memory cycle of vocabularies to the individual learner. The proposed system overcomes a major weekness in previous work by using adaptive standardized assessment using Item Response Theory. Considering more complicated liguistic structures, Pei-hao et.al. [31] proposed a framework for personalized language learning as a pedagogical dialogue game. The game implements a tree-structured dialoguescript. The contents of the dialogue script are designed by language teachers to be phonetically balanced and prosodically rich with good coverage of commonly used words at the proper level. The script includes 9 short dialogues with a total of 176 turns. Dialogue manager adaptively selects sentences for each individual learner along with the progress of the dialogue based on the learning status of each pronunciation unit. Cognitive personalization is made primarly based on skill level identified by pronounciation ability. This objective is achieved using a Markov decision process (MDP) trained with reinforcement learning using simulated learners generated from real learner data. This work overcomes a major challenge related to modelling complex linguistic structures, but, it's very limited to few predefined sentences. Moreover, assessment is limited to pronounciation of words.

On the other hand, personalized language learning has been considerably addressed in context-aware pervasive computing. In [32] a framework is proposed to support personalized knowledge mapping for language learning in pervasive computing environment. The psoposed framework models user context (i.e. including name, age, address, mood, experience, interest, habit, location, learning, etc), environment context, knowledge context and interactive context. Fu stresses on modelling the learner considering all relevant aspects. Knowledge Processing Engine (KPE), introduced in ref. [33], is used to deliver personalized learning service and knowledge to the learner. In the framework, the Knowledge Processing Engine is fed by three types of databases that are Context Objects Database, Knowledge Database and Log Database. Context Objects Database collects many kinds of context information from sensors or other servers. Knowledge database contains material related to the language such as videos, books, newspaper, etc. Log database records current learning or collaborating activities in the environment. There is no specific information provided on the pedagogical aspects of language learning. Petersen, S. A., & Markiewicz, J. K [34] proposed a context aware mobile system that supports personalized language learning based on context data as well as user entered data. It incorporates time and location dimensions to send automatic notifications to the learner when she/he is in the vicinity of a point of interest, such as a French art exhibition. In addition, related learning resources are recommended, such as resources related to a building. The authors implements context engine and adaptivity engines for personalization purposes, but, it's not mentioned what logic is used to achieve personalization. Also, no specific information is provided about assessment or pedagogical aspects.

VI. Discussion

Based on the information presented in this paper, we can see that most of the personalized language learning systems implements cognitive-based personalization in which, skill level or memory aspects are modelled most of the time. Context-Aware systems provide more comprehensive modelling of the learner, but, stress less on the pedagogical aspects. A whole-person personalization is not yet efficiently accomplished in which a comprehensive and adaptive learner model is created in the system that reflects learner progress as well as changes. Most of the reviewed work implement content-based personalization techniques that map learning resources to learners based on some pre-defined features.

A major weakness in existing learner's assessment approaches is subjectivity. In most of the cases, the learner's linguistic competency level is modelled and measured intuitively based on some formulas implemented in the learning personalization systems. Even though, the implemented logic is sometimes adaptive (i.e. considering the item response theory), and accomplishes some level of cognitive personalization, it is not standardized and doesn't align with an officially approved language learning measures. This in turn, may reduce the learner's confidence in the learning outputs assessed by the system.

The focus on English language might be a natural result for the richness of available electronic English linguistic sources (i.e. corpus, word association dictionaries, thesaurus … etc.) and natural language processing APIs. This in turn raises a need for such linguistic resources in other languages. On the other hand, commonly using vocabulary as the linguistic learning unit may be due that sentences are more complicated linguistic structures involving semantic, syntax and context elements which are not easily modelled in computer. However, learning language is not limited to vocabulary. Models of more complex linguistic structures are required.

The following points sum-up the current challenges and open areas of research in personalizing language learning: (1) dynamically and adaptively modelling the learner considering not only linguistic skill level but also preferences and interests as well as changes over time; (2) modelling language learning skill levels based on adaptive and standardized performance measures that are commonly approved; and (3) modelling more complex linguistic units such as sentences and account for context sensitive linguistic features.

Table 1-Framework for Characterization and Comparison of Personalized Language Learning Software Systems

Dimension	Elements	Sub-Elements	Description
Technical Dimension	Personalization Level	Self-Described	Tailor content or learning tasks based on preferences and attributes explicitly inputted by the learner
		Segmented	Based on location, culture or other types of segments
		Cognitive-Based	Mapping learning resource to the learner's model identifying skill level, learning style or memory aspects
		Whole-Person	Adaptive personalization technique, changes as the learner change in terms of skills and preferences
	User Model	Type	Adaptive vs. Non- Adaptive
		Input Method	Automatic/Implicit vs. Collaborative/Explicit
	Technique	Association-Based	Mapping a new learner to similar learners based on associations
		Attribute-Based	Mapping a new learner to a class based on learner's features
		Knowledge-Based	Infer suitable learning tasks based on knowledge about the learner
Language Learning Dimensions	Language	English, Arabic, French … etc.	Any natural language
	Focus	Grammar vs. Vocabulary	Grammar-based approaches focus on grammatical categories such as nouns, verbs … etc. Vocabulary-based approaches focus on presenting large vocabulary set
	Tasks	Authentic Communicative tasks vs. Instructional	Associating words, matching to sample, word to image, image to word .. etc. Choosing the right verb tense, choosing between verb or noun
	Size of Vocabulary	Number	Number of different words used if specified or size of corpus
	Difficulty Level	Yes/No	Grade-Level Criteria or any word difficulty/familiarity measure used
	Assessment	Yes/No	Specify whether assessment used is based on assessment framework or just random assessment tasks are used.

Table 2 - Analysis of Recent Work in Language Learning Personalization

Research Work	***Technical Dimension***									***Language Dimension***					
	Level				***User Model***		***Technique***								
	Self-Described	*Segmented*	*Cognitive*	*Whole-Person*	*Adaptability*	*Input*	*Association-Based*	*Attributes Based*	*Knowledge-Based*	***Language***	***Focus***	***Tasks***	***Size of Vocabulary***	***Difficulty Level***	***Assessment***
Nascimento Et. Al. **[4]**	-	-	Skill Level	-	**Not-Adaptive** (user is mapped to some pre-defined levels)	Automatic/Implicit (calculated task score and click-logs)	-	Logistic – regression used to classify learners based on pre-defined features	-	Portuguese	Vocabulary	Communicative – Match to Sample	Not Specified	Reading & Writing Difficulty	Formulas calculate level based on task score and other aspects
Jung & Graf **[5]**	-	-	Skill Level	-	**Adaptive** (no pre-defined levels rather every learner's lexical knowledge is different, represented in semantic	Automatic/Implicit (game interactions)	-	Graph clustering algorithm used to cluster semantic networks	-	English	Vocabulary & associations	Communicative – word association	Not Specified	Based on number of associations a word has with other words, more associations imply familiarity & easiness	Assess lexical level based on user input
Chen et. al. **[3]**	-	-	Skill Level & Memory Cycles	-	**Adaptive** (vocabulary ability levels and memory cycles are adapted for each learner)	Automatic/Implicit (game interactions)	-	Maximum info. strategy recommends the vocabulary with the max. information function value among all vocabularies to learner's	-	English	Vocabulary	Fill in the blanc & Select from Sample	Not specified	Vocabulary difficulty parameter	Item Response Theory & memory cycle schemes
Pei-hao et.al. **[31]**	-	-	Pronunciation	-	**Adaptive** (each learner has different level)	Explicit	-	This problem is considered as an optimization problem of a sequential stochastic decision, solved by reinforcement learning based on an MDP model.	-	Chinese - Mandarin	Dialogue	Speaking in specific contexts	176 turns	Not specified	Assess poorly-pronounced units
Fu, T. **[32]**	Personal info.	Location, time	Skill level and previous knowledge	-	**Adaptive**	Explicit and implicit	-	-	Knowledge Processing Engine	English	words, expressions, composition, listening, reading, and talking	Virtual class	Not specified	Not specified	Not specified
Petersen, S. A., & Markiewicz, J. K **[34]**	Personal info.	Location, time	Skill level and previous knowledge	-	**Adaptive**	Explicit and implicit	-	Context engine and adaptivity engine (no specific information about the algorithm used)	-	English	Not specified	Not specified	Not specified	Not specified	Not specified

VII. CONCLUSION

Following recent educational changes in methods and curriculum design, CALL has become more sophisticated and has moved toward personalized language learning, giving learners more voice and choice. The process of personalizing language learning involves a number of technical complexities, such as: (a) modelling the learner, (b) collecting and organizing the language learning resources, and (c) modeling a personalization mechanism. Current challenges in personalizing language learning can be summarized in the following points: (1) adaptively modelling the learner as a whole; (2) modelling language learning skill levels based on adaptive and standard performance measures; and (3) modelling more complex linguistic structures.

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