Twenty Years of Personalized Language Learning: Topic Modeling and Knowledge Mapping

Xieling Chen[1], Di Zou[2*], Haoran Xie[3], and Gary Cheng[1]
[1]Department of Mathematics and Information Technology, The Education University of Hong Kong, Hong Kong SAR // [2]Department of English Language Education, The Education University of Hong Kong, Hong Kong SAR // [3]Department of Computing and Decision Sciences, Lingnan University, Hong Kong SAR // xielingchen0708@gmail.com // dizoudaisy@gmail.com // hrxie2@gmail.com // chengks@eduhk.hk
[*]Corresponding author

ABSTRACT: Personalized language learning (PLL), a popular approach to precision language education, plays an increasingly essential role in effective language education to meet diverse learner needs and expectations. Research on PLL has become an active sub-field of research on technology-enhanced language learning and artificial intelligence applications in education. Based on the PLL literature from the Web of Science and Scopus databases, this study identified trends and prominent research issues within the field from 2000 to 2019 using structural topic modeling and bibliometrics. Trend analysis of articles demonstrated increasing interest in PLL research. Journals such as *Educational Technology & Society* and *Computers & Education* had contributed much to PLL research. PLL associated closely with mobile learning, game-based learning, and online/web-based learning. Moreover, personalized feedback and recommendations were important issues in PLL. Additionally, there was an increasing interest in adopting learning analytics and artificial intelligence in PLL research. Results obtained could help practitioners and scholars better understand the trends and status of PLL research and become aware of the hot topics and future directions.

Keywords: Personalized language learning, Topic modeling, Knowledge mapping, Bibliometrics, Precision education

1. Introduction

Recent changes in curriculum design and pedagogical approaches emphasize the significance and effectiveness of personalized education in comparison to conventional cohort-based learning. Personalized education is one mode of precision education. They both consider individual differences to trigger the most effective intervention to meet the unique needs of individual learners and can identify at-risk students at early stages and provide timely intervention (Lu et al., 2018; Yang, 2019). Precision education involves the wide use of techniques of personalized learning, including learning analytics (LA) and adaptive learning software. It has been applied to various subjects and different education levels, with positive outcomes being reported. Connor et al. (2018) evaluated the efficacy of ISIMath, which tailored mathematics instruction for second-grade students. ISIMath significantly improved students' performance through individualized mathematics instruction based on assessment data. Chrysafiadi and Virvou (2013) presented ELaC, which provided adapted instructional materials based on the backgrounds, skills, and learning paces of individual learners. ELaC improved the adaptation efficiency of the instructional process and enhanced learning with personalized content and learning pace.

Personalized language learning (PLL) plays an important role in precision language education. It "heralds a new way of dealing with individual differences by effecting as precise a diagnosis as possible on each language learner, thus triggering specific interventions designed to target and respond to each person's specific language-learning problems" (Lian & Sangarun, 2017, p. 1). According to Lian and Sangarun (2017), personalization is the starting point to identify learner needs and provide precise solutions to satisfy their needs. Thus, personalization is "a subset of precision education", and precision education is "the ultimate objective" (p. 6). In other words, PLL is an important approach to precision language education.

Based on the definition of personalized learning by the US Department of Education (2017), this research defines PLL as an instruction that optimizes the pace, approaches, objectives, content, and activities of learning according to the interests and needs of individual language learners. Advances in analytic innovations and adaptive learning technologies have significantly facilitated the personalization of teaching and learning. Driven by the continuously growing requirement for the individualization of language learners' learning processes in a democratizing and globalizing world of exponential linguistic and cultural demands, PLL has become a prevailing focus of the educational technology industry, as well as a new challenge of the applications of artificial intelligence (AI), machine learning, and LA. Affordances of PLL have been highlighted. Wu et al. (2014) proposed a ubiquitous personalized English reading system based on RFID technology. The system

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recommended English articles with realistic scenarios to learners by analyzing their locations. Specifically, the system detected a learner's location and sent situation-related English articles for him/her to read and study. By considering the local context, the English content became more perceivable, thus supporting personalized and situational learning. Fang et al. (2018) proposed a content-driven method to recommend personalized grammar questions using a parse-key tree to detect grammatical structure and grammar question usage. The proposed approach effectively recommended grammar questions by considering both the conceptual and textual information of grammar questions.

A small number of review studies on personalized learning had been conducted. A representative one by Xie et al. (2019) discussed the status and tendencies of technology-assisted personalized/adaptive learning by reviewing 70 articles. Their study revealed that data sources such as students' profiles and learning logs were commonly used to support personalized/adaptive learning. Personalized/adaptive learning strategy had been integrated into many potential applications supported by smart devices and advances in AI, virtual reality, and wearable computing. Currently, few PLL reviews are available, with only one (Ismail et al., 2016) focusing on the classification, trends, and challenges of PLL systems. Their study suggested that PLL systems could be further improved by incorporating more complex adaptive learner models and contextualized learning tasks. Recognizing the significance of PLL research, a thorough analysis of the literature is needed to answer questions such as "what were the major issues in PLL" and "what is the future of PLL research." Such analysis can provide a state-of-the-art understanding of PLL research hotspots and useful implications for its future development.

Bibliometric analysis involves the application of mathematical/statistical techniques and quantitative measurements to evaluate academic literature (Chen et al., 2020a; Chen, et al., 2020d; Chen et al., 2018; Hao et al., 2018). Structural topic modeling (STM), a semi-automatic quantitative text mining approach with the basis of unsupervised machine learning, is receiving popularity among social science scholars "to discover topics from the data rather than assume them" (Roberts et al., 2014, p. 106). By combining STM with bibliometric analysis, this study analyzed PLL articles in terms of the trend of annual articles, top journals, countries/regions, institutions, essential research issues, and their evolutions to enable an in-depth understanding of the status and trends of PLL research. Findings obtained will enable scholars, educators, policymakers, and practitioners to better understand the latest PLL research and its developmental tendencies and to further facilitate its future development. Specifically, the following six major research questions were addressed:

(1) What was the trend of the annual number of PLL research articles?
(2) What were the top journals, countries/regions, and institutions ranked by Hirsch index (H-index)?
(3) What was the scientific co-authorship among major countries/regions and institutions?
(4) What were the major research foci?
(5) How did these research foci evolve?
(6) What were the research concerns of the major countries/regions and institutions?

2. Dataset and methods

The data collection and analysis flowchart (see Figure 1) includes data identification, data screening, and data analysis. The current study used bibliographic data collected from Web of Science (WoS) and Scopus databases using a search query as ((TS = ((personalization OR personalisation OR personalized OR personalised) AND (language) AND (learn*))) AND (Year of publication = 2000-2019) AND (Article type = journal articles)). In the query, "TS" (Topics) refers to the title, abstract, or keywords of a publication. The above search terms were decided with reference to previous work (e.g., "language" and "learning" in Zhang and Zou (2020) and "personalized learning" in Xie et al. (2019)) by considering both personalized learning and language learning. As indicated (Zhang et al., 2020), it was around 2004 that education systems worldwide were making efforts to personalize learning. To guarantee a full cover of PLL studies, we initially set the time span as recent two decades, i.e., from 2000 to 2019. We used journal articles because they usually undergo a meticulous peer-review process and are generally of high quality.

The following types of information were collected: titles, years of publication, authors and their institutions, and abstracts. With 650 initially retrieved articles, after excluding 159 duplicated articles, manual screening of the remaining 491 articles was conducted to ensure data relevance. The specific exclusion criteria for the screening are presented in Figure 1. When we decided whether a paper should be included, we started from the first criterion (i.e., relevant to language learning). If it was not, we excluded it directly without checking other criteria. In this first stage, a total of 314 articles were excluded, most of which were about the learning of programming languages. Moreover, many were about the use of machine learning methodology or natural language processing (NLP) that contain "learning" and "language" but were not about language learning by real learners. Subsequently, we read the article to check whether it was about personalized learning and included details concerning the PLL process. Some studies mentioned PLL as future research recommendations, while the main research per se was not about personalized learning. In this second stage, 40 articles were excluded. After confirming that the paper was related to PLL, we evaluated whether it was an original research article and excluded those that were reviews or survey papers. In this stage, 20 papers were excluded. Lastly, we evaluated whether the papers were on teacher education and excluded nine papers in this stage. The screening resulted in 108 relevant articles. The citation for each of them was provided by Google Scholar (see https://scholar.google.com/).

We then analyzed the 108 PLL articles regarding the trend of articles, top journals and contributors, scientific collaborations, and major research topics. Analysis methods included descriptive statistics, bibliometric indicators such as the H-index, social network analysis, STM, and the Mann-Kendall trend test. The STM was conducted using software R with title and abstract information as input data.

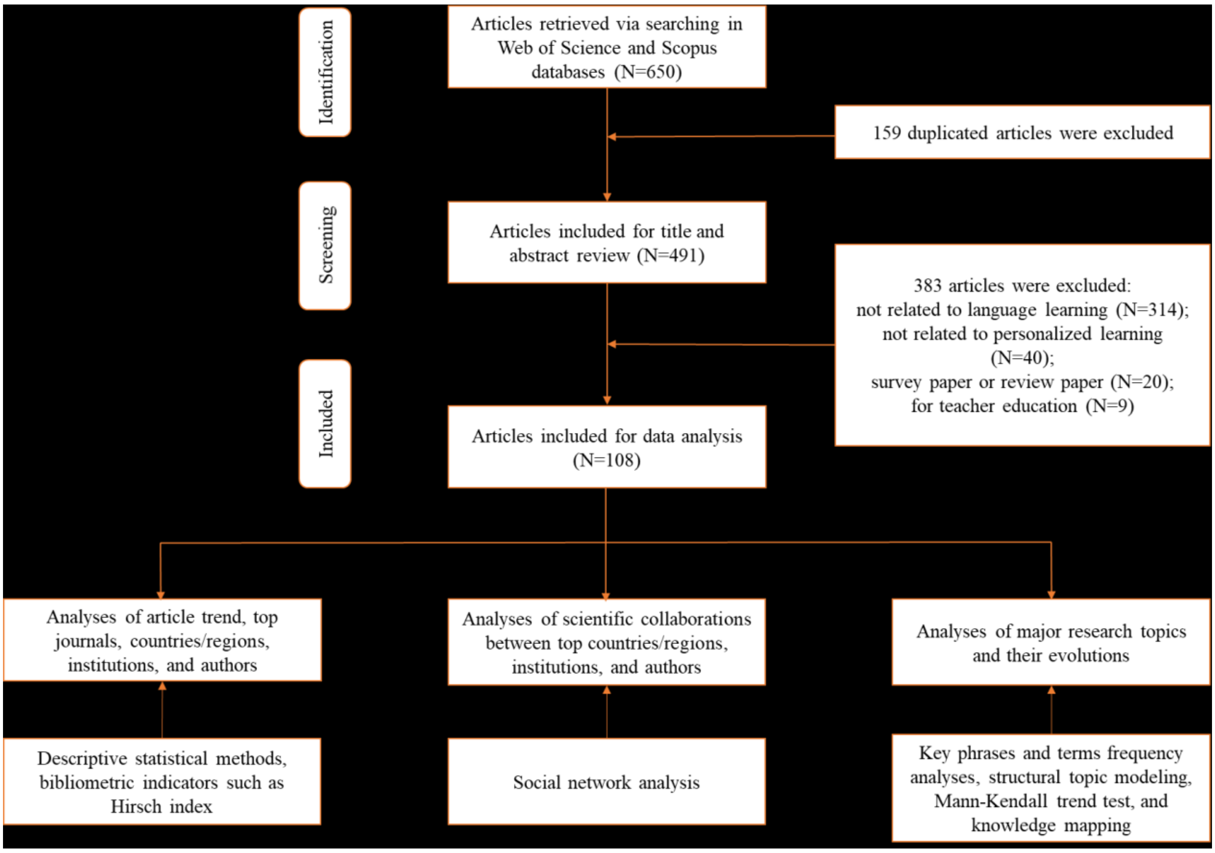

Figure 1. Flowchart of data collection and analyses

3. Results

3.1. Analysis of the trend of articles

Figure 2 shows the annual trend of PLL research. Overall, the annual number experienced an increasing trend from two in 2001 to 17 in 2019, demonstrating a constant increase in interest in PLL research, particularly since 2007. It is reasonable to anticipate that research enthusiasm in PLL will continue to increase in the future.

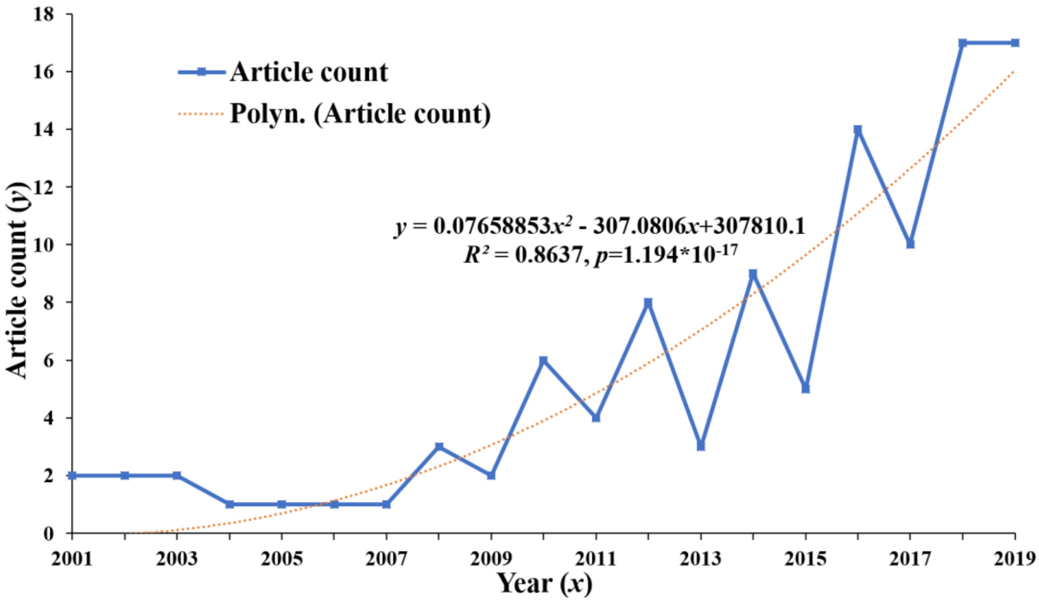

Figure 2. Year-by-year analysis of PLL studies

3.2. Top journals, countries/regions, and institutions

The 108 PLL articles were distributed in 77 journals. The top ones ranked by H-index (see Figure 3) accounted for 34.26% of the total articles. The top three were *Educational Technology & Society*, *Computers & Education*, and *Computer Assisted Language Learning*. The first two publish research about the application of technologies in education, and the last one specializes in applying technologies in language education. Among the listed journals, five are related to technology-enhanced language learning (i.e., *Computer Assisted Language Learning*, *Language Learning & Technology*, *Language Learning Journal*, *ReCALL*, and *System*). Meanwhile, over half of them are education-related, indicating a broad interest in PLL among education researchers, rather than limited to language researchers.

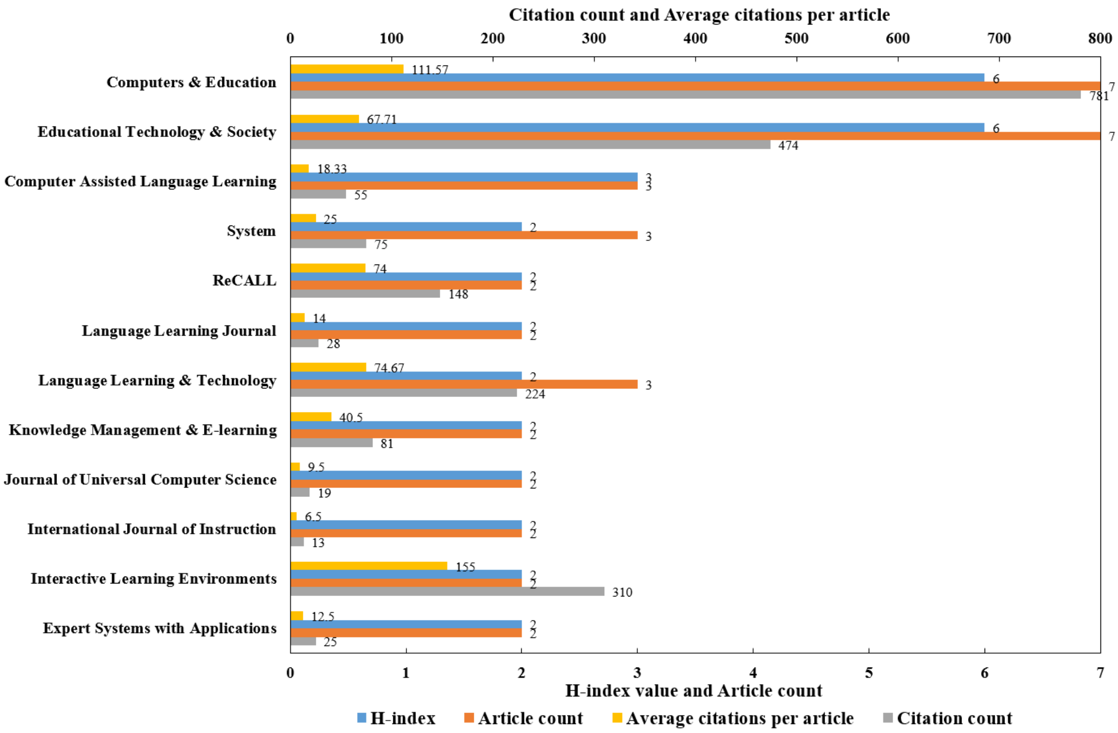

Figure 3. Top journals

There were 34 countries/regions and 147 institutions. Figure 4 presents the top 12 countries/regions ranked by H-index, indicating the important role of researchers in the Asia-Pacific region. Figure 5 presents the top institutions ranked by H-index. National Chengchi University was the most influential and prolific. Additionally, half of the top institutions are from Taiwan, indicating its dominance in PLL research.

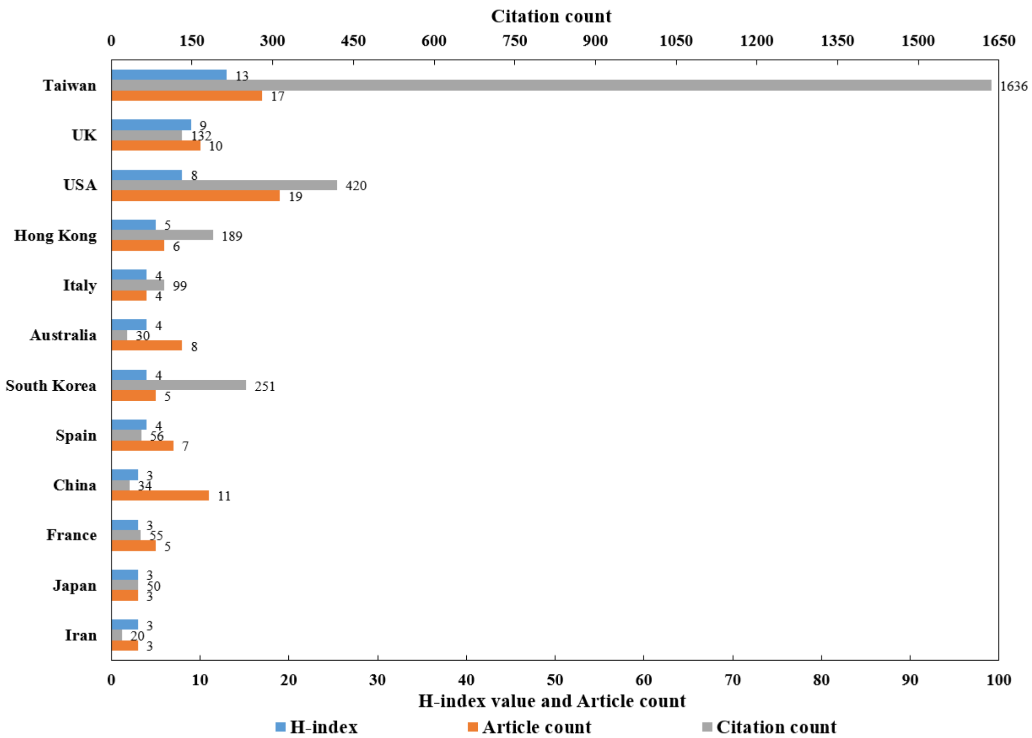

Figure 4. Top countries/regions

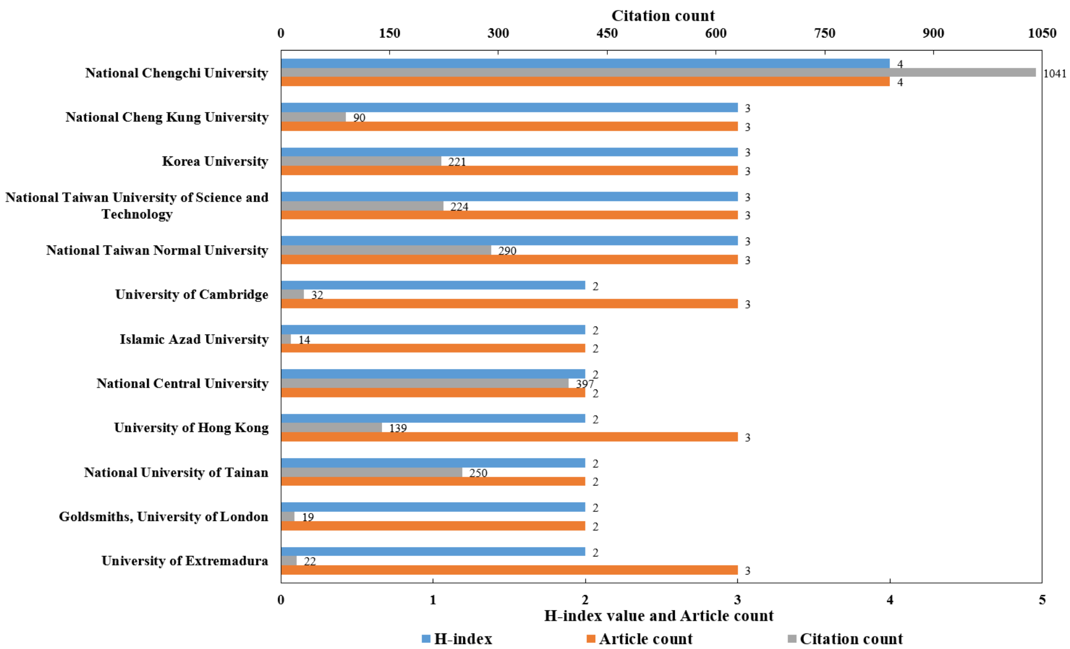

Figure 5. Top institutions

3.3. Analyses of scientific collaborations

The collaborations among the 34 countries/regions and the top 19 prolific institutions were visualized in Figures 6 and 7. Countries/regions and institutions were indicated using nodes with the size indicating the article count. Each node was colored based on its continental or national/regional information. Figure 6 shows that top collaborative partners included Belgium and the UK, Spain and the UK, as well as Hong Kong and China.

Collaborations among Asian and European regions were also close. From an institutional perspective, closest collaborative partners were also indicated in Figure 7, for example, East China Normal University and University of Hong Kong.

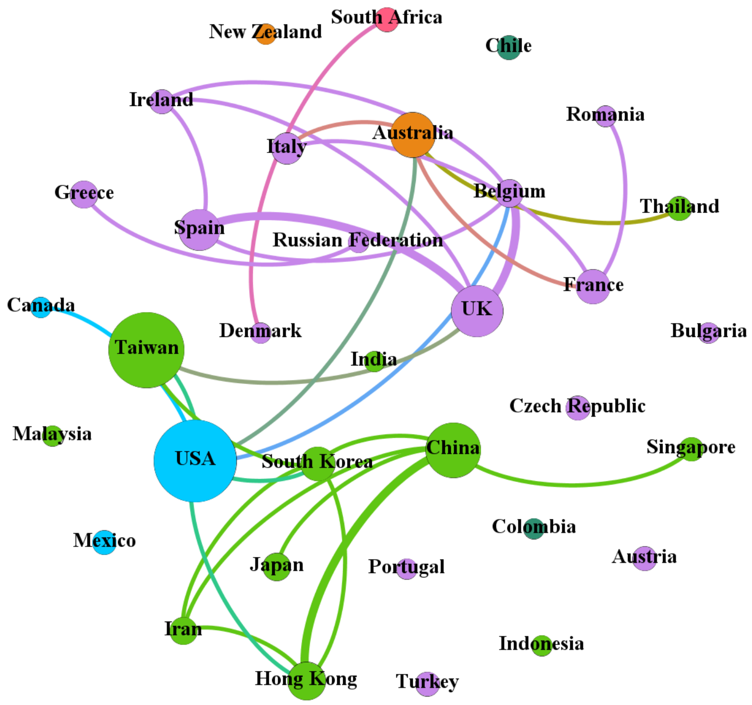

Figure 6. Collaborations among countries/regions

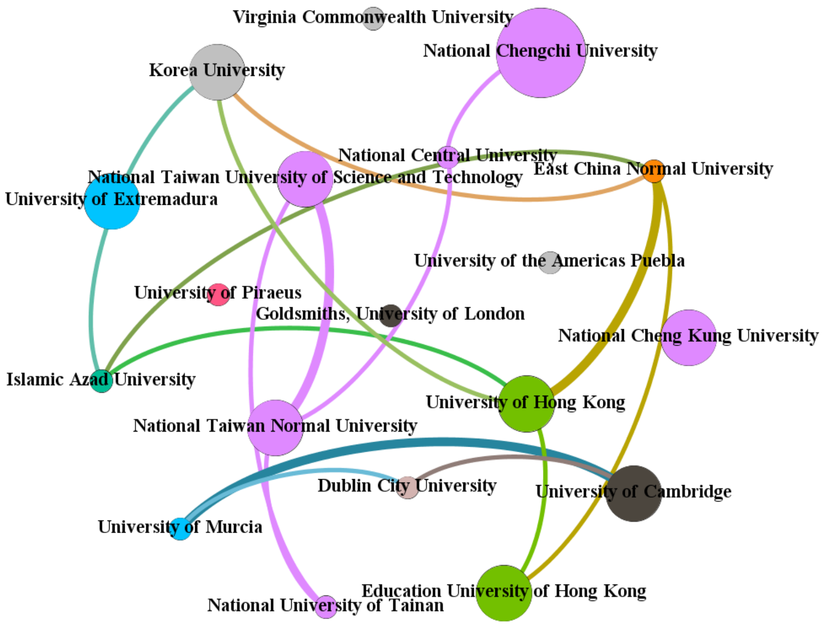

Figure 7. Collaborations among the top 19 prolific institutions

3.4. Results of STM

Figure 8 presents the STM results. The two most popular topics were Mobile-assisted PLL and Anxiety and PLL. According to the Mann-Kendall test results, Personalized grammar learning and Personalized recommendation system for language learning had received significantly increasing research interest.

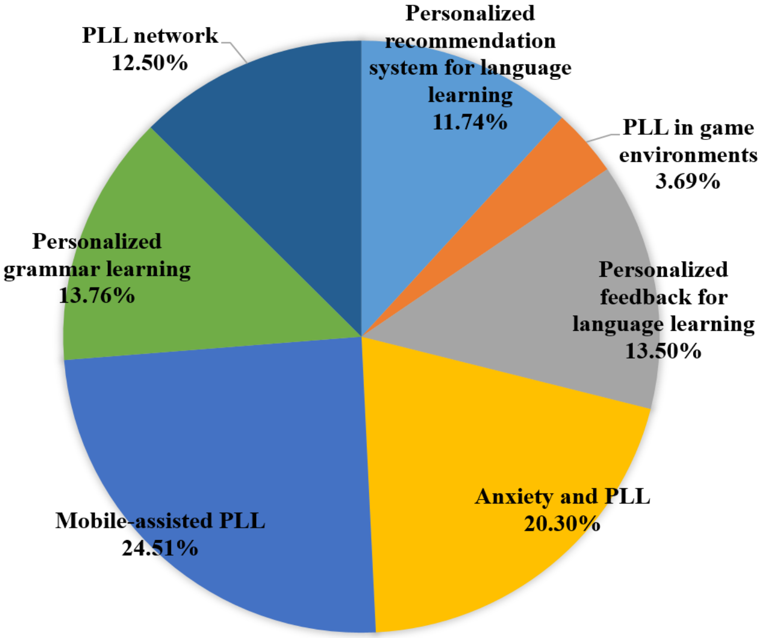

Figure 8. Identified topics with suggested labels and topic proportions

The topic distributions of the top countries/regions and institutions listed in Figures 4 and 5 are visualized in Figures 9 and 10, from which we could see to which research issues each contributor had devoted. For example, Hong Kong and South Korea were interested in Anxiety and PLL. Institutions from Taiwan (e.g., National Central University) devoted much to Mobile-assisted PLL. Such analyses can help countries/regions and institutions identify current and potential scientific strengths and collaborators in PLL research.

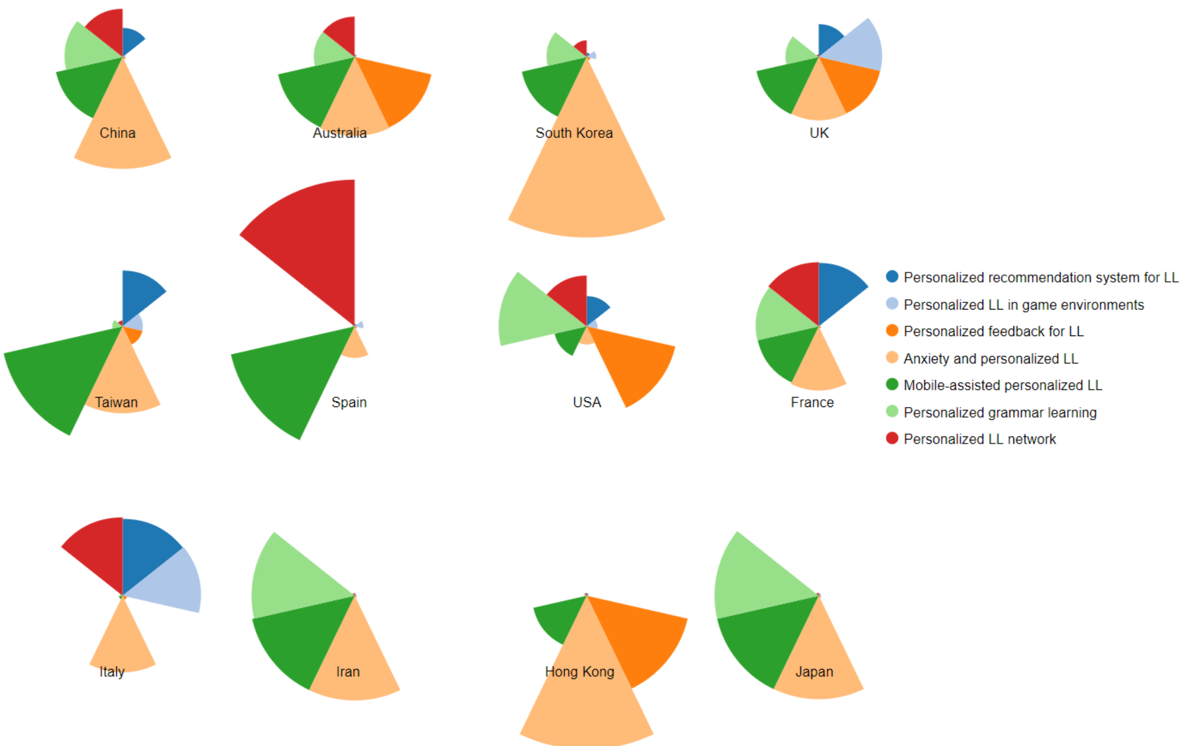

Figure 9. Topic distributions of top countries/regions

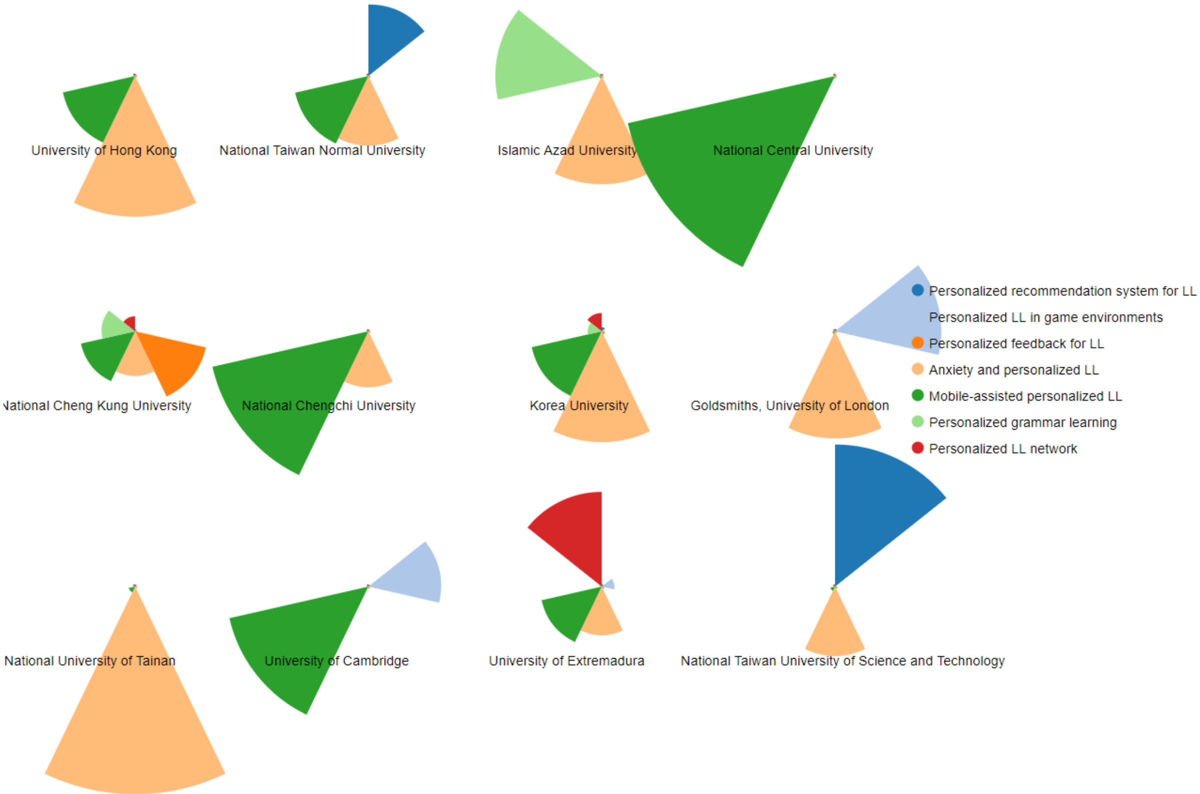

Figure 10. Topic distributions of top institutions

3.5. Results of evolution analysis

Figure 11 shows the evolution of the major phrases used in PLL studies. For a clear presentation, only phrases appearing in more than three studies were considered. Figure 12 shows the emerging phrases in the recent five years. From a technological perspective, very limited technologies (e.g., personal digital assistant) were adopted before 2010. However, due to technological advancement, both the types and applications of innovative technologies (e.g., social media, web 2.0, and computer games) had increased in recent years. For example, mobile devices have become popular since 2015. Intelligent tutoring systems (ITSs) and digital games appeared during 2010–2014 and gained increasing interest since then. There was also a trend in applying LA and AI techniques (e.g., NLP and support vector machines (SVM). From an educational perspective, research enthusiasm about providing personalized feedback increased. Moreover, the realization of PLL based on learner profiles gained increasing attention since the period 2010–2014. Additionally, issues concerning collaboration in PLL started to receive attention in the last few years.

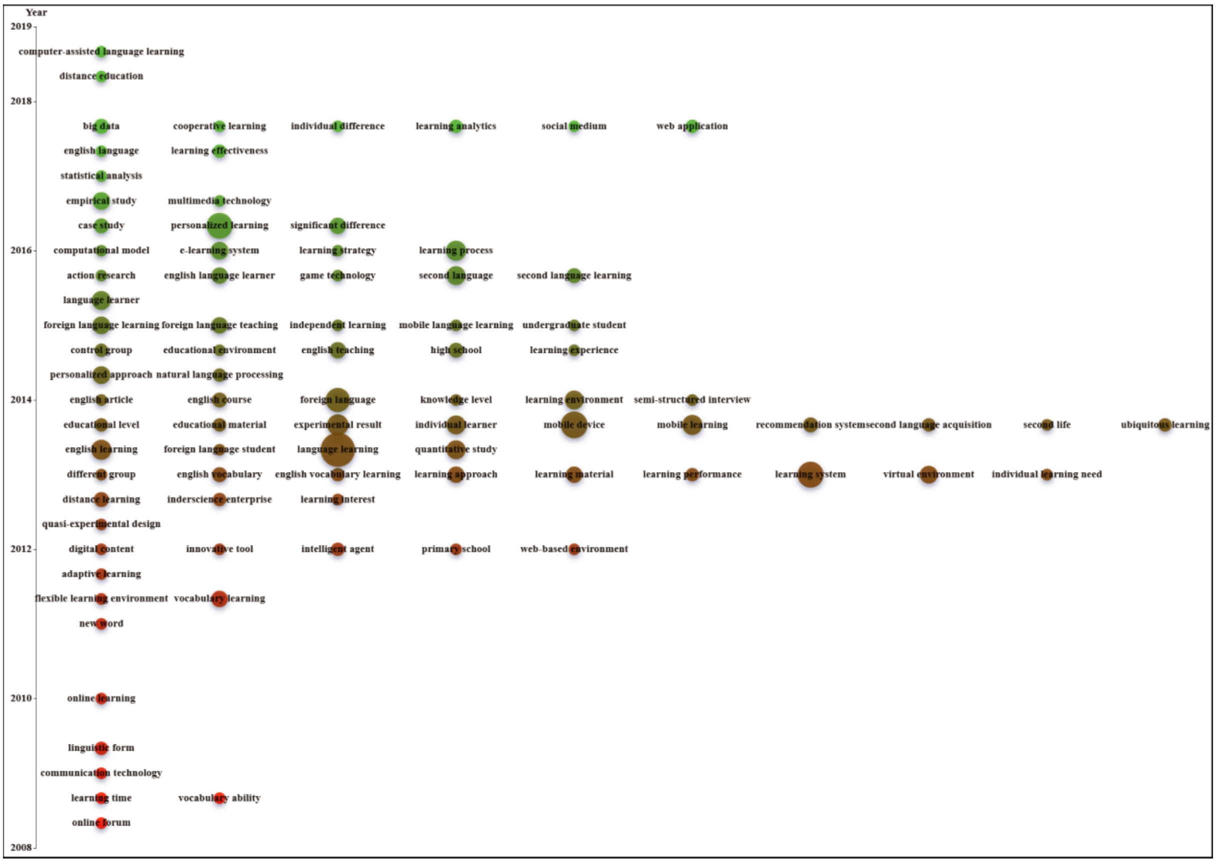

Figure 11. Evolution of major research issues

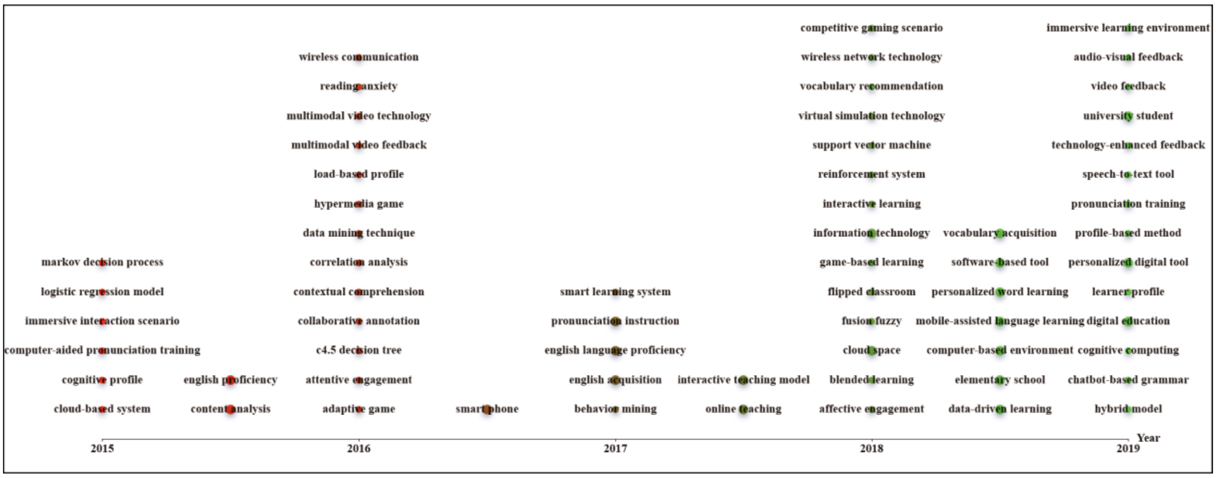

Figure 12. Emerging issues in recent five years

4. Discussions

This study presented a comprehensive overview of PLL research using topic modeling and bibliometrics. The overall increase in academic articles implies that PLL is an increasingly active field with a continuously expanding research community. PLL research enjoys great popularity among interdisciplinary journals that bridge education and technology. The close association between PLL and technology use is also demonstrated by topic and phrase analyses. Countries/regions and institutions (e.g., Taiwan, the USA, and the UK) with large numbers of international collaborations showed better performance and fast development, indicating that international collaboration plays an important role in PLL research to embrace the affordances and face the challenges. Furthermore, the close regional/institutional collaborations are noteworthy, whereas the cross-regional/institutional collaborations should be enhanced. Additionally, institutions with close collaborations tended to show more similarities in research foci. Findings regarding phrase and topic analyses provide insights into future directions for PLL research, as elaborated in the following sub-sections.

4.1. Personalized recommendations in ITSs

The popularity of personalized recommendations in ITSs is associated with its data-driven feature and its ability to reduce the burden of information overload. A data-driven recommendation strategy in ITSs can automatically and dynamically schedule the learning sequences during the learning processes based on learners' performance to further recommend appropriate materials and activities to optimize learning outcomes. In Xie et al. (2015), a recommendation strategy was conducted based on task diversity, word coverage, and context familiarity criteria to determine the subsequent task types, target words, and learning contexts. If a user had completed two reading comprehension tasks that focused on the same target knowledge, then based on task diversity criteria, a cloze task related to the knowledge would be recommended. The system could also rearrange the types and sequence of learning tasks automatically and dynamically based on the learner profiles and learning performance during the learning process. Moreover, a data-driven recommendation strategy in ITSs can balance the suitable recommendations to current knowledge and new learning trajectory exploration. However, optimal recommendations based on dynamic programming is computationally intensive and sometimes infeasible in personalized learning systems. To resolve this, Tang et al. (2019) optimized recommendation systems for adaptive learning through reinforcement learning by iteratively alternating between collecting learners' data using a strategy to choose potential learning materials and improving the strategy using the collected data. Specifically, such a strategy worked by dynamically utilizing current information, for example, knowledge about learning model based on previous students' learning trajectories and the learner information through assessment.

Furthermore, a personalized recommendation strategy in ITSs can reduce the information overload burden through appropriate learning material recommendations to learners based on their interest to provide the "right" information at the "right" time and in the "right" way (Xie et al., 2019). Faced with tasks of different types and varying difficulty levels, few learners know how to make appropriate learning plans due to information overload. According to constructivism and the input hypothesis (Krashen, 1989), it is necessary to recommend tasks with suitable difficulty levels according to learners' prior knowledge levels. Understanding learners' prior knowledge plays a crucial role in optimizing instructional approaches and paces and providing personalized material recommendations that meet learner needs. Such a task could be resolved by analyzing learner profiles or learning portfolios (Xie et al., 2015). In a personalized vocabulary learning system proposed by Xie et al. (2015), load-based learner profiles were constructed to examine and evaluate the involvement load of various tasks and words based on learning logs. The profiles could help effectively optimize recommendations of task types and target words for individual learners.

Our research found that most extant studies concerning personalized recommendations in ITSs are related to reading and vocabulary learning, whereas little research is conducted on personalized grammar learning recommendations. Current grammar learning applications primarily recommend learning materials and exercises according to grammar topics. However, learners are more interested in exercises with similar grammatical structures and usage, particularly those that they have not fully mastered. Thus, future research may consider investigating personalized grammar question recommendations based on learner preferences and needs.

4.2. Personalized feedback and assessment

Technology-driven methods (e.g., automatically analyzing learners' answers, understanding their progress, and adjusting tasks) can enhance learning with the provision of formative assessment and personalized feedback. Our results showed that there is an increase in affective engagement in feedback provided by personalized screencasts and multimodal videos. According to Harper et al. (2018), personalized screencasts for written assignment feedback enhanced students' sense of instructor presence and promoted communication. This might be because hearing the instructor's voice explaining solutions or recommendations for improvement onscreen enabled an increase in students' affective engagement. In line with multimedia learning theory, personalized audio-visual feedback with multimodal formats, conversational tone, and verbal explanations promotes successful engagement with feedback, especially for those with lower language proficiency. Video technologies could significantly enhance computer-mediated communication for language learners by allowing personal appearance and individual language variations, thus promoting interaction and fostering personalized learning and attentive engagement. From the perspective of interaction, personalized video feedback helps build connections with the unconscious mind and emotions, thus creating a platform for socialization between instructors and students and among peers (Hung, 2016). Such socialization benefits learners in providing ideas for peer feedback and learning from their peers' feedback. According to the sociocultural theory, such a scaffolding process enables language knowledge and skill extension. Moreover, according to communities of practice, because videos enable language learners to visualize contexts, body languages, and facial expressions and artifacts, they understand better about their learning and attach more attention to the feedback provision process. Additionally, the contribution of the personalized videos to the sense of personalization can be enhanced by incorporating more extensive use of personal pronouns, hedges, and praise to create a less-distant discourse stance and stronger interpersonal feel.

4.3. Personalized context-aware ubiquitous language learning

Personalized context-aware ubiquitous language learning involves providing personalized and adaptive language learning activities based on learner locations, learning/leisure time, and personal abilities. In Chen et al. (2019), an interactive geographic map (iMap) system was developed to provide learners with a personalized learning environment to facilitate their context-aware ubiquitous learning through detecting locations, considering realistic scenarios, and recommending learning materials accordingly. Learners could navigate within iMap to learn theme-related topics without physical attendance. Also, with iMap, learners could learn about situational dialogues through contextualized dialogue video watching, grasp important vocabularies and phrases, and practice applying knowledge in context to gain mastery. Chen and Li (2010) also developed a personalized context-aware ubiquitous learning system based on learner location as detected by wireless positioning technologies to facilitate situational English vocabulary learning. In such situational learning, social, cultural, and life contexts are used to promote learning in meaningful situations. With the rapid development of location intelligence and wireless technologies, particularly WLAN, which can provide precise location information, personalized context-aware ubiquitous learning can be realized through recommendation mechanism to select language learning materials that associate with learner location from database, so that students experience active interactions with the real world and apply authentic and social knowledge to their surroundings.

4.4. Mobile chatbots for PLL

Mobile chatbots for PLL can be interpreted as integrating chatbots into mobile applications to scale up personalization in language learning by providing services at the learners' convenience with unique learning and human-like interactive learning experiences. Haristiani and Danuwijaya (2019) developed a chatbot-based grammar dictionary application, Gengobot, and integrated it into LINE. When a user sent a grammar item in his/her second language in the Gengobot-integrated LINE, the app would automatically interpret the message, process its intent, and respond with text to provide the meaning of the grammar item, usage patterns, examples, and translations of the examples in the user's first language. In this way, Gengobot enabled users to adjust their learning pace, meet personal needs and preferences, thus supporting PLL. Also, when users communicated with foreign speakers and needed grammar information, they could directly access Gengobot without leaving the chat or exiting LINE. This is different from using a separate application where she or he would need to leave the chat, open the dictionary application, and then return to chat, which is comparatively inconvenient. Moreover, Pham et al. (2018) proposed a mobile English learning application with an integrated chatbot as a virtual personal assistant that automatically responded to casual conversations (e.g., greetings, courtesy, and emotions), recommended personalized learning content (e.g., quizzes, vocabulary or grammar lessons) according to user requests, provided personalized scaffolding or explanations for problem-solving (e.g., helping users to show the term for a definition in a flashcard), and reminded target users to review the previously learned content. This interaction between human beings and chatbots provides a personalized experience for foreign language learning. The social connectivity of mobiles also benefits learners in terms of interactive and personalized learning, particularly when it is combined with chatbots and social media. Nevertheless, our results indicated a lack of critical attention on the development of chatbots as personal assistants to support PLL. Thus, we recommend that more studies focusing on this direction should be conducted.

4.5. Personalized content generation for game-based language learning

Personalized digital game-based language learning can enhance individual learners' professionalism development and command of various language skills via personalized recommendations and tailored advices that are in accordance with their learning needs, preferences, and styles (Hooshyar et al., 2018). Hooshyar et al. (2018) also argued that a data-driven procedural content generation (PCG) method could automatically generate adaptive contents that are tailored to individual learners' language proficiency levels in a game, DLLgame, for children's early reading skill development. In DLLgame, the PCG approach first generated the total of domain-specific contents like learning objectives, materials, and instances. Then, SVM was trained based on data collected from DLLgame to be further added to a genetic algorithm-based content generator to assess content fitness. Subsequently, contents targeting the intended learning outcomes and suiting the players' capabilities were generated and relayed to DLLgame. One specific application of the proposed PCG in DLLgame was to automatically enhance letter recognition through gameplay by identifying and selecting the correct grapheme from various floating letters on the screen. Though given graphemes were presented alphabetically for all players, object pictures for each grapheme were generated by the data-driven PCG strategy in accordance with an individual player's knowledge strengths or deficiencies, thus facilitating the personalized learning experience and enhancing learning performance. In a personalized Portuguese language learning game (Pereira et al., 2012) for vocabulary acquisition, cognitive-based personalization was implemented to continuously assess learners' skill levels and match suitable learning tasks accordingly. The personalization and adaptability of the game could be improved by automatically defining learning levels, tasks, and objectives rather than being predefined by players. Moreover, collaborative game-based learning with interaction and communication features could support social interactivity during gameplay and allow learners to learn along with and from one another, thus enhancing their foreign language learning. Additionally, in collaborative PLL games, instructions, dialogues, and interfaces are presented in a second language, and learners are encouraged to speak or write in a second language to communicate with their collaborators, thus providing intense and meaningful practices of listening and reading.

4.6. AI for personalized diagnosis and adaptation

Moving towards the next generation of PLL environments requires intelligent approaches powered by LA based on powerful AI algorithms that can adapt to individual learning needs for personalized diagnosis and trace of their learning progress (Pérez-Paredes et al., 2018). The rising pervasiveness of AI applications with the ability to predict and adapt based on massive language learner data indicates a promising future of personalized language education. For example, three-dimensional (3D) face recognition techniques are commonly combined with automatic speech recognition (ASR) to provide PLL experience based on individual characteristics. Ming et al. (2013) developed a Mandarin edutainment application for learning Mandarin in an immersive and interactive virtual environment. Specifically, 3D face recognition was used for learner detection, based on which learning materials were adjusted in accordance with the learner's preference and emotional states. Speech recognition interface identified and assessed the spoken content of foreign learners and presented the recognition results onscreen. The proposed system with open, shared, and interactive properties significantly enhanced learner communication ability and created a real-life social community responding to the learners' speech, intent, gesture, and behaviors. Moreover, fuzzy fusion algorithms have demonstrated effectiveness in refining different native speakers' pronunciation characteristics, optimizing personalized evaluation, and improving user feedback adoption rates.

An individual learner's pronunciation error patterns can be detected in an unsupervised manner by using deep learning technologies such as convolutional neural networks (Lee, 2016) which analyzes the acoustic similarity between speech segments from the learner and accommodates variations in pronunciation patterns across students to provide personalized diagnosis and feedback. To diagnose language learning anxiety, Chen et al. (2016) showed the effectiveness of the C4.5 decision tree in facilitating the diagnosis, prediction, and reduction of reading anxiety based on reading annotation behaviors to provide adaptive reading assistance to learners with different levels of learning anxiety. Specifically, the personalized reading anxiety prediction model instantly predicted the reading anxiety of individual learners according to their reading annotation behaviors and interactions with their peers during collaborative reading annotation activities and meanwhile identified the likely reasons for the anxiety using the fired prediction rules determined by a decision tree. The prediction results were displayed on the online tutors' interface, with which the tutors could provide personalized assistance to reduce learners' reading anxiety. Additionally, in a system for automated tracking of learner responses to instructor feedback in draft revision (Cheng et al., 2017), NLP was used to match teacher feedback against syntactic rules and semantic words extracted from annotated data. Specifically, on the syntactic side, every sentence was processed with a part-of-speech tagger to assign parts of speech to each word, while on the semantic side, a word-by-type matrix was constructed based on latent semantic analysis. As the system highlighted gaps between what learners should revise and what they actually revised, students found that it helped them engage in the cognitive process of revisions and reflect critically on gap-bridging, thus promoting effective revisions and high-quality writings. The personalization of the system can be further enhanced by providing personalized suggestions/links to relevant learning resources using collaborative filtering. Based on our results, there is still a lack of critical attention paid to AI techniques, particularly deep learning algorithms.

We thus suggest that scholars keep up with the latest trends in AI by exploring its potential and effectiveness for PLL.

4.7. Personalized LA dashboards

Personalized LA dashboard is a visualized and intuitive display of data to support improvements in personalized learning and performance. In Gelan et al. (2018), learning dashboards were implemented in a Business French course to intuitively visualize online learning behavior to learners and their tutors, provide recommendations inspired by former successful learners, and share the feedback with learners and tutors. Based on the insights obtained from learning visualization through personalized dashboards, learners are provided with personalized recommendations of effective learning strategies, suitable learning resources, and personalized learning pathways to improve learning performance. The connection between personalized learning and LA is significant. Specifically, personalized learning aims at building a profile of each learner's strengths, weaknesses, and learning pace, similar to LA-driven monitoring of learner performance, finding patterns to predict their performance, and customizing instructional support accordingly. Although LA is still in its infancy in implementation and experimentation, it does show great room in its potential use to facilitate PLL, with affordances emerging in data collection and processing, data analysis and interpretation, pattern detection, and learning visualization. LA contributes to PLL research and practices in many ways, for example, allowing for more significant insights into self-directed learning, collecting and analyzing sizable learner data, and promoting personalizing learning through learning dashboards.

4.8. Personalized practice in data-driven learning

Personalized practice in data-driven learning (DDL) is a corpus- and concordance-driven approach for language learning where students use retrieval software to discover rules and draw conclusions by observing and analyzing sizable real corpus and to grasp a grammatical structure or word usage through real-time practice. Particularly, the combination of DDL and mobile devices allows learners to obtain personalized and instant feedback on their own production for practice. For example, a DDL-based mobile app (Pérez-Paredes et al., 2018), TELL-OP, with personalized access features to various corpus-based open educational resources, could effectively support on-the-go PLL due to the instant and personalized assessment via multiple NLP tools and personalized feedback for learners to improve their texts with convenient access to context-sensitive information from various monolingual and collocation dictionaries. DDL emphasizes the active role of learners and their self-directed learning ability to explore language knowledge in accordance with their needs to constantly introspect and induce language rules, which adapts well to the individualization and personalization trends in computer-assisted language learning. Through DDL, the authentic data with various inductive and deductive language learning chances helps individuals get familiar with target language communication and deepen their acquisition of the target knowledge.

4.9. Challenges of PLL

4.9.1. Data policy

While it is common that educational institutions need to store student data to provide an optimal personalized learning experience since such data are critical for automation and personalization, it is important to pay attention to data privacy. Specifically, clear declarations about who can access student learning data, what data they can access, how the data is protected, and what laws protect student data should be provided. Institutions should be transparent about student data privacy practices to dispel misperceptions about student data use and allay concerns (see https://ies.ed.gov/pubsearch/pubsinfo.asp?pubid=NFES2019160).

4.9.2. AI model training

How to choose suitable algorithms is important as each algorithm has advantages and disadvantages. For example, SVM algorithms might show poor performance for sizable data mining since the training of SVMs depends highly on data size. Comparatively, although deep learning algorithms generally show higher performance, their comparatively higher complexity and requirement of expensive computational devices like high-ended GPUs are potential issues regarding their utilization.

4.9.3. Challenges for PLL instructors

Given the learner variability, instructors are challenged to differentiate lessons and to individualize learning for each student while simultaneously keeping the overall level of expectation and rigor in classrooms high. This can be extremely hard since there may be many differences (e.g., personalities, lifestyles, and backgrounds) among students that do not directly impact academic learning. Moreover, since most instructors are not taught about personalized instruction or how to incorporate it into their teaching practice, they usually find it challenging to shift from knowledge imparters to facilitators of learning. Technologies can help instructors overcome obstacles to implementing differentiated or personalized instruction by enabling them to address students' needs in numerous ways (e.g., through content input, learning activities, and opportunities to demonstrate comprehension) (Schmid & Petko, 2019) and to bridge the relationships with students who generally have a predisposition for using tech seamlessly.

4.10. Pedagogical implications for the application of technologies to facilitate PLL

Our findings provide implications for instructors conducting precision language education or are thinking of doing so. To personalize students' learning of pronunciation, listening, and speaking, instructors can take advantage of chatbots, online chat rooms, and VR-based dialogue games. User-friendly mobile phones and chatbot-based applications are effective supplementary tools for regular language curricula to realize language learners' personalized listening and pronunciation practice with voice messages. In an online chat room, students convert their input into the intake in situations where language serves as a communication tool instead of the focus of such interaction. Moreover, VR games can be integrated into pronunciation recognition and assessment systems embedded with ASR to construct a real-life social community responding to the learners' speech, intent, gestures, and behaviors. Additionally, collaborative game-based learning with interaction and communication features can support social interactivity during gameplay and allow students to communicate and interact with one another, thus enhancing their communication and speaking skills.

To recommend personalized materials, we highlight the effectiveness of cluster-specific recommendations, data-driven PCG, similarity-based approach, fuzzy inference mechanisms, context-aware recommendations, and recommendations based on learner emotion. Cluster-specific recommendations help deliver suitable and personalized content to students based on their preferences, learning styles, and learning patterns detected by cluster analysis, sequence analysis, and association rule mining. A data-driven PCG method improves individuals' performance-based gains by providing adaptive content suited to various proficiencies, capabilities, and performance targets of individual learners. Similarity-based recommendation computes the similarity between question query and database questions to generate suitable questions for individual learners. The use of fuzzy inferences and personal memory cycle updates has the potential to find materials best suited for both a learner's ability and her/his need by implicitly modifying memory cycles of content learned before. Moreover, back-propagation neural networks estimate learner location to further recommend appropriate language learning tasks based on context-awareness information to individual learners. Additionally, the personalization of learning material and instructional strategy recommendations can be optimized and adjusted according to individual learners' emotional states identified by face recognition, decision trees, and sentiment analysis techniques. To determine the PLL materials for individual language learners, the integration of students' domain knowledge, working memory capacity, learner profiles, and learning behaviors are key parameters. Nevertheless, comprehensive theoretical frameworks are essential for the optimal design of intelligent PLL systems (Zou & Xie, 2018). For example, in Xie et al. (2015), the involvement load hypothesis was used for incidental word learning task evaluation.

To personalize feedback provision for language learners, instructors are advised to transform feedback from uni-modality to multi-modality and to move the traditional written feedback to video-driven feedback to promote learner engagement. Furthermore, DDL enables learners to receive personalized and immediate feedback right after the completion of learning tasks. Additionally, fuzzy logic supports misconception detection and feedback provision to promote adaptive educational experience by automatically modeling students' learning and forgetting processes using personalized fuzzy inference.

4.11. Future directions for PLL research

Based on our investigation, PLL studies have shown increased use of innovative technologies, particularly in recent years, including multimodal videos, digital games, mobile devices, ITSs, and chatbot, which are effective in providing PLL experience. Additionally, virtual/augmented reality, with advantages in supporting collaborative and immersive learning, can be incorporated in PLL systems to cultivate higher-order thinking skills and communication.

Concerning personalized recommendations, PLL studies focused mainly on providing personalized learning materials. However, research on how to provide the optimal or most suitable recommended materials that match individual needs is lacking, particularly by using ranking-based algorithms to calculate the matching and suitability of each material to target learners. Another potential direction is to involve user decision/opinion to help optimize recommendations by integrating content authoring tools for learners and educators to adaptively add, edit, rate, and evaluate recommended materials, and to make annotations to customize their own recommendation criteria, thus generating more adaptive recommended materials and bringing more personalized learning experience. Additionally, most PLL recommendations were generated based on the learner portfolio and behavioral data analysis. As online learning community activities increase exponentially, social interactions and social connectivity can be considered by incorporating social influence and interactive information (e.g., social media data) between individuals and groups of learners to enhance PLL recommendations.

Concerning emotion recognition, only one study focused on reading anxiety prediction. To further this topic, the development of a merged decision tree considering different types of reading materials to automatically predict the reading anxiety levels of individual learners can be considered. In addition to anxiety, the automatic recognition of learners' overall sentiment in a dynamic and real-time mode can be proposed to further adjust the intelligent learning environments based on learners' emotional states.

In terms of personalized feedback, multimodal videos and screencasting have demonstrated effective for a particular research population. Further study may consider comparing these technologies' affordances in personalized instruction and feedback at different levels of proficiency, or with different languages, learning styles, or skill areas such as the teaching of pronunciation or grammar.

Additionally, we highlight the necessity to keep up with the latest trend in AI (Chen et al., 2020b; Chen et al., 2020c), particularly deep learning (e.g., long short-term memory and generative adversarial network) that have been proven effective in many fields but are currently seldom considered in PLL research. For example, a generative adversarial network has the potential to recommend reading/writing materials of different styles and transform the materials from one style to another based on learners' requirements and needs. Long short-term memory can facilitate PLL in terms of auto-completion and grammar checking, automatic essay scoring, and automatic speech grading when combined with ASR techniques. AI, coupled with deep learning and NLP, has the potential to realize a higher level of personalization by integrating more sophisticated applications that are able to adapt, learn, and predict with ultimate autonomy. In sum, attention should reach beyond computer-related technologies to the latest AI technological trends and their applications in language education to construct language knowledge and develop critical thinking, thus promoting language learning achievement in a personalized way. Particularly, inter-department collaboration among system developers, language experts, and practitioners should be enhanced to provide more effective and easier-to-use PLL systems representing true integration of language pedagogy, language practice, and technology.

4.12. Limitations

There are several limitations in this study. Firstly, our analysis was based on records retrieved from WoS and Scopus. Although WoS and Scopus are multidisciplinary databases of academic output and are commonly adopted for literature reviews, there might still be PLL articles that were not included in the two databases. Furthermore, this study used merely English language research articles. However, as PLL is being explored worldwide, publications written in other languages should also be considered in future research. Additionally, as mentioned in section 2, in data screening, most of the articles were excluded due to irrelevance to personalized learning (N = 40) or language learning (N = 314). However, they were retrieved initially due to the share of search strings by studies from different research fields. Future studies may consider optimizing the search strategy by using a more context-specific search query.

5. Conclusions and significance

Our study was the first-in-depth to track current advances in PLL research using STM and knowledge mapping. Such timely work is needed with PLL attracting increasing attention from academia, although the total number of studies is small at the current stage. A large proportion of PLL studies focused on providing personalized recommendations on learning materials and tasks and personalized feedback, while issues such as emotion detection, cognitive loads, and higher order thinking skills, receiving relatively less attention. Technologies play an important role in facilitating PLL, with various applications (e.g., mobile devices, digital games, ITSs, multimodal videos, and wireless technologies), analytical techniques (e.g., LA, PCG, and AI), and learning strategy (e.g., DDL) being increasingly adopted with positive effectiveness being reported. Language learners experiencing personalized learning generally showed improvement in learning gains and engagement, satisfaction with the personalized learning experience, and an increase in self-efficacy and confidence. Personalized language learners were also viewed as having higher learning motivation and a positive attitude toward language learning, together with higher acceptance toward technologies involved in the learning process. In sum, our study indicates that (1) multimodal videos promote effective personalized feedback; (2) personalized context-aware ubiquitous language learning enables active interaction with the real world by applying authentic and social knowledge to their surroundings; (3) mobile chatbots with ASR provide human-like interactive learning experiences to practice speaking and pronunciation; (4) collaborative game-based learning with customized gameplay path and interaction and communication features supports social interactivity and learning of various language skills; (5) AI promotes effective outcome prediction and instruction adaptation for individuals based on massive learner data; (6) LA dashboards facilitate personalized recommendations through learning data visualization; and (7) DDL allows personalized and immediate feedback in real-time practice.

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