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Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017

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ABSTRACT

In this study, the trends and developments of technology-enhanced adaptive/personalized learning have been studied by reviewing the related journal articles in the recent decade (i.e., from 2007 to 2017). To be specific, we investigated many research issues such as the parameters of adaptive/personalized learning, learning supports, learning outcomes, subjects, participants, hardware, and so on. Furthermore, this study reveals that personalized/adaptive learning has always been an attractive topic in this field, and personalized data sources, for example, students' preferences, learning achievements, profiles, and learning logs have become the main parameters for supporting personalized/adaptive learning. In addition, we found that the majority of the studies on personalized/adaptive learning still only supported traditional computers or devices, while only a few studies have been conducted on wearable devices, smartphones and tablet computers. In other words, personalized/adaptive learning has a significant number of potential applications on the above smart devices with the rapid development of artificial intelligence, virtual reality, cloud computing and wearable computing. Through the in-depth analysis of the trends and developments in the various dimensions of personalized/adaptive learning, the future research directions, issues and challenges are discussed in our paper.

1. Introduction

Learning is viewed as the mental processing of information (i.e., the construction, acquisition, organization, coding, rehearsal, storage in memory, and retrieval or non-retrieval from memory) from the perspective of cognitive theories (Schunk, 2012). From this point of view, the ability of learning can be considered as the mental ability of information processing. Constructivism claims that learning ability is mainly determined by learners' acquired knowledge and understanding, and that knowledge acquisition is a process of construction according to individual experience (Ormrod, 2011). It has been commonly acknowledged in various learning/psychological theories that learning experiences and acquired knowledge are uniquely individual. For example, according to Gestalt theory, humans can generate their own learning experiences and interpret information in the same or different ways as others, as each person has a unique perspective on the world (Boeree, 2000). The theory of transfer of learning advocates that features of the

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task, learner, organization and social context will have a unique impact on students' ability to use the transfer of learning (Cormier & Hagman, 2014; McKeough, Lupart & Marini, 2013).

In recent years, the personalization of learning has been achieved using various methods that have been made available by the rapid development of information communication technology (ICT) (Dawson, Heathcote, & Poole, 2010). Adaptive/personalized learning has become possible by implementing intelligent learning systems, integrating learners' preferences, analyzing individual learning data, and so on. According to the United States National Education Technology Plan 2017, personalized learning is defined as "instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner. Learning objectives, instructional approaches, and instructional content (and its sequencing) may all vary based on learner needs. In addition, learning activities are meaningful and relevant to learners, driven by their interests, and often self-initiated." (U.S. Department of Education, 2017, p. 9). Chen, Lee, and Chen (2005) proposed a personalized system which provides "learning paths that can be adapted to various levels of difficulty of course materials and various abilities of learners" (p. 239), while Klašnja-Milićević, Vesin, Ivanović, and Budimac (2011) stated that "personalized learning occurs when e-learning systems make deliberate efforts to design educational experiences that fit the needs, goals, talents, and interests of their learners" (p. 885).

Paramythis and Loidl-Reisinger (2003) defined that "a learning environment is considered adaptive if it is capable of: monitoring the activities of its users; interpreting these on the basis of domain-specific models; inferring user requirements and preferences out of the interpreted activities, appropriately representing these in associated models; and, finally, acting upon the available knowledge on its users and the subject matter at hand, to dynamically facilitate the learning process" (p. 239). Brusilovsky and Peylo (2003) argued that adaptive learning systems were built upon the development of adaptive media in the web, and defined adaptive learning as generally referring to how to use computer systems or tools to provide tailored learning materials or activities to cater to personalized learning needs. One important stream of such computer systems is the intelligent tutoring systems, which employ computational algorithms or models to deliver immediate feedback and learning instructions to learners without the intervention of human teachers (Psotka, Massey, & Mutter, 1988).

Although the terms "personalized learning" and "adaptive learning" are different, they are often used interchangeably in various studies (Aroyo et al., 2006; Göbel, Wendel, Ritter, & Steinmetz, 2010; Gómez, Zervas, Sampson, & Fabregat, 2014; Lin, Yeh, Hung, & Chang, 2013). According to the above definitions, the difference between the two is that they may cater to diverse learning needs via different approaches. Without adapting to the on-going progress of a learner's ability to perform tasks, personalized learning can be achieved by identifying individual learners' characteristics. Moreover, adaptive learning can be implemented according to a learner's performance without identifying relevant personalized information including individual characteristics and preferences that might further affect progress or performance. However, according to the above definitions, the similarity between "personalized learning" and "adaptive learning" is that the technology essentially aims to cater to the diverse learning needs of learners. In particular, the boundary between "personalized learning" and "adaptive learning" becomes vague if they are limited to the scope of "technology-enhanced learning" as they have been used as two interchangeable terms in many extant studies (Aroyo et al., 2006; Göbel et al., 2010; Gómez et al., 2014; Lin et al., 2013). Therefore, we review journal articles which fall within the scope of both "personalized learning" and "adaptive learning" in this article.

Technology-supported adaptive/personalized learning is a popular and important stream of research studies in the area of educational technologies. As shown in Fig. 1, there were totally 70 articles from six SSCI journals in the area of educational technologies from 2007 to 2017. Specifically, these journals were top-tier educational technology journals including *Computers & Education, Educational Technology Society, Interactive Learning Environments, the British Journal of Educational Technology, Educational*

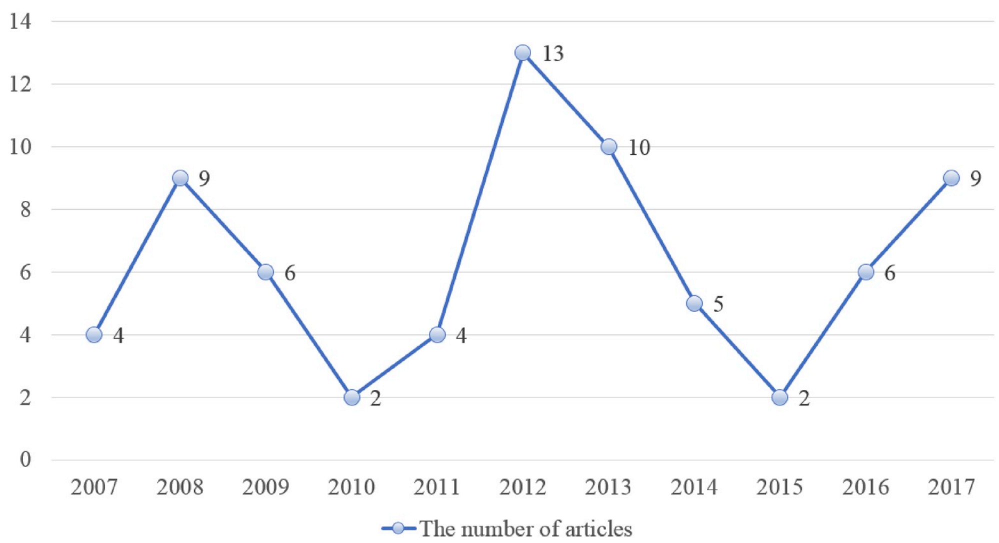

Fig. 1. The distribution of the number of articles on technology-supported adaptive/personalized learning in 6 SSCI journals in the area of educational technology from 2007 to 2017.

Technology Research and Development, and the *Journal of Computer Assisted Learning*. On average, 6.4 articles related to adaptive/personalized learning were published in these journals each year. Furthermore, some studies have been commonly acknowledged and highly cited in the research communities. For example, Chen and Chung (2008) proposed a personalized mobile English vocabulary learning system based on item response theory and the learning memory cycle, which recommended suitable English vocabulary acquisition. This study is an influential work (receiving 365 citations in Google Scholar), which provides a personalized vocabulary learning framework taking Hermann Ebbinghaus' (1885) memory cycles theory and individual learner vocabulary ability into consideration. Hwang, Kuo, Yin, and Chuang (2010) proposed a heuristic algorithm for determining personalized learning paths in a context-aware ubiquitous learning environment by taking into account various factors including the object relevance, meaningfulness of the learning paths and numbers of simultaneous visitors. The citation count of this article was 183 according to Google Scholar. Yang, Hwang, and Yang (2013) took multiple dimensions of personalized features including eight dimensions of Felder-Silverman's learning style and the field dependent/independent cognitive style model into consideration when developing an adaptive learning system. Through the experiments in a networking course of two classes of undergraduate students, the results of their study (Yang et al., 2013) illustrated the effectiveness of the proposed adaptive learning framework. It has received 123 Google Scholar citations. More recently, Huang, Yang, Chiang, and Su (2016) developed a personalized mobile vocabulary learning system by employing the semantic similarity between target vocabulary and semantic contexts of the location. The experimental results of this study (Huang et al., 2016) revealed that the performance of both learning performance and motivation in the experimental group of students who used the proposed personalized mobile learning system improved significantly more than that of the control group which adopted the same learning strategy but using conventional learning materials. This study has also attracted attention in the research communities (with 38 citations within less than 2 years).

Motivated by the large volume of articles and many influential studies on technology-supported adaptive/personalized learning, it is necessary to have a systematic review of adaptive/personalized learning to identify the development, trends, challenges, and potential research directions. However, the recent review studies mainly focused on the learning technologies/subjects such as mobile learning (Fu & Hwang, 2018), language learning (Golonka, Bowles, Frank, Richardson, & Freynik, 2014), and nursing education (Chang, Lai, & Hwang, 2018). Adaptive/personalized learning is a learner-centered research topic which is worth investigating. To the best of our knowledge, this article is the first piece of work to conduct a systematic and comprehensive review of studies on technology-supported adaptive/personalized learning. More importantly, such a review of adaptive/personalized learning can facilitate the understanding of “how ICTs are exploited for implementing and supporting adaptive/personalized learning” (Dawson et al., 2010) and “what are the proper contexts for providing adaptive/personalized learning” (Butoianu, Vidal, Verbert, Duval, & Broisin, 2010), which are still open issues or even blanks in the research field. Furthermore, by examining the data distribution and trends in different categories, this review study can assist researchers in predicting the future development and trends of adaptive/personalized learning in terms of the potential new technologies, implementations, learning achievements and learning modes, which can provide a roadmap for establishing future learning models in various domains like technology-enhanced language learning (Zou, Xie, & Wang, 2018). Therefore, this review study is significant and indispensable to establish the linkage between extant adaptive/personalized studies and future trends such as future learning models and potential techniques to be employed for adaptive/personalized learning. In particular, the following research questions are investigated in this article:

(1) From 2007 to 2017, what are the parameters for implementing adaptive/personalized learning?
(2) From 2007 to 2017, what are the learning supports provided in adaptive/personalized learning?
(3) From 2007 to 2017, what are the learning outcomes to be achieved by adaptive/personalized learning? What are the distribution and amount in each category of learning outcomes?
(4) From 2007 to 2017, what are the subjects and participants of adaptive/personalized learning?
(5) From 2007 to 2017, what are the learning devices used for adaptive/personalized learning?

2. Research methods

2.1. Data collection and processing

As suggested by several review studies (Hsu et al., 2012; Hwang & Tsai, 2011), it is critical to review articles from high-quality data sources. To this end, the Web of Science database[1] was selected as the data source for this study as it is one of most reputable journal article collections. The Social Sciences Citation Index (SSCI) contains “over 3200 journals across 55 social science disciplines, as well as selected items from 3500 of the world's leading scientific and technical journals – 1900 to present[2]”. To be specific, the query (“adaptive learning” OR “personalized learning”) was issued to the Web of Science database. Furthermore, the search results were limited to the SSCI indexed journal articles by setting the query results from this database, as such articles are normally of high quality (Hsu et al., 2012; Hwang & Tsai, 2011). The publication period was set as a decade (i.e., from 2007 to 2017) to ensure that there were adequate data to observe research trends, and the publication type was set as “article” as recommended by other review studies (e.g., Hwang & Tsai, 2011; Lin & Lan, 2015). As “adaptive learning” is also a term in the machine learning area in computer science, we set the category as “education/educational research.” There were totally 161 articles in the query results. To ensure that

[1] https://apps.webofknowledge.com.
[2] https://clarivate.com/products/web-of-science/databases/.

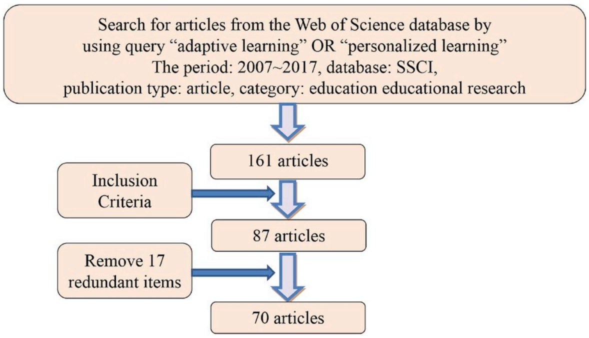

Fig. 2. The procedures of data collection and processing.

these articles were truly related to adaptive/personalized learning, they were carefully read and analyzed by using the following inclusion criteria. Each article must be relevant to technology-supported adaptive/personalized learning. To be specific, each article must be related to using e-learning systems to support adaptive/personalized functions such as adaptive/personalized interfaces, adaptive/personalized learning paths for implementing concrete adaptive/personalized teaching and learning activities. By adopting this criterion, 74 irrelevant articles were filtered out, leaving 87 articles relevant to adaptive/personalized learning. For example, Bingham, Pane, Steiner, and Hamilton (2018) discussed the school model for personalized learning for policy makers and practitioners engaged in implementing personalized learning models. However, their study is not related to "using e-learning systems to support adaptive/personalized functions like adaptive/personalized interfaces, adaptive/personalized learning paths for implementing concrete adaptive/personalized teaching and learning activities"; therefore, it was not included in this review. In addition, we double checked the 87 articles to remove duplicated articles, resulting in another 17 being eliminated. The remaining 70 articles formed the final dataset for analysis. Fig. 2 illustrates the overall procedures for the data collection and processing.

2.2. Coding scheme

To investigate and analyze the trends and developments of adaptive/personalized learning, the coding scheme of this study was developed as five main categories.

2.2.1. Codes for the learners

As suggested by Hwang and Tsai (2011), the codes of the participant types for the subjects aimed to categorize them according to their education levels, including elementary school students, junior and senior high school students, higher education students, teachers, working adults, others and none. The reason for separating teachers from working adults is that the teacher education and working adult learning are mainly two different research topics in the research communities (Darling-Hammond, 2006; Spaid & Duff, 2009).

2.2.2. Codes for the learning content

Codes for the learning content include various disciplines such as engineering or computers, science (e.g., physics, chemistry, biology, environmental science or natural science), health, medical or nursing, social science or social studies, arts or design, languages, mathematics, business and management, other and non-specified, as proposed by Fu and Hwang (2018).

2.2.3. Codes for the learning support/hardware

Both codes for learning support and hardware are system-oriented. The codes for learning support include personalized interfaces, personalized learning content, personalized learning paths, personalized diagnosis and suggestions, personalized recommendations, personalized prompts/feedback, personalized professional learning guidance, lower-order personalized interfaces, and other personalized functions. There are a total of nine categories of learning supports for the learning processes for the adaptive/personalized systems in this study.

The codes for hardware cover the different devices which run the adaptive/personalized learning systems. These codes were developed based on the previous review studies on mobile learning (Wu et al., 2012) and include wearable devices (e.g., Google glass, Apple watch, etc.), smartphones, tablet computers (e.g., iPad or Android pad), traditional computers/devices (e.g., personal computers, notebooks), and others.

2.2.4. Codes for the learning outcomes

The codes for the learning outcomes consist of seven categories including affection, cognition, skills, behavior, correlations, others and no experimental results (e.g., review/conceptual articles). The first category "affection" can be further classified into technology acceptance/learning intention, learning attitudes/expectation of learning engagement, learning motivation, self-efficacy/confidence, interest/satisfaction, cognitive load, learning anxiety, and students' opinion/learning experiences (totally eight sub-categories). The second category "cognition" can be divided into learning achievements, high-order thinking/competence, and collaboration/

communication (totally three sub-categories). The remaining five categories are all self-contained and do not need to be further divided.

2.2.5. Codes for the adaptive/personalized parameters

The codes for adaptive/personalized parameters are user-oriented and are mainly relevant to the parameters such as learners' perceptions or experiences during the adaptive/personalized learning process. Specifically, they include the difficulty level of the learning materials, the sequence of the learning materials, the students' learning achievements, preferences, learning style, cognitive style, learning perceptions, and profiles, as well as portfolio or logs, and platform/technical support. There are totally 10 parameters in the learning systems to support adaptive/personalized learning. The students' learning perceptions can be further divided into the three parameters of learning attitudes/learning motivation/hard work and expectations, self-efficacy/confidence, and satisfaction/ interest.

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Based on the above coding scheme, three researchers (i.e., two coders and one supervisor) discussed the scheme in a meeting to guarantee that they fully understood it. During the coding process, two coders firstly read each paper and highlighted the necessary information source in the article for each dimension of the coding scheme. The coding process was independent, and then the two coders and the supervisor examined the inconsistent coding results. The agreement of the coding results reached 92% at this stage. They then discussed their own understanding of the inconsistent coding scores and provided the highlighted information sources in the article as evidence of their coding scores. Some inconsistencies were resolved during their discussion, but if no agreement could be reached, the supervisor made the final decision.

2.3. Theory framework

In this subsection, the theory framework which is based on a broad definition of constructivism is introduced and discussed. This framework can be viewed as theoretical support for the above proposed coding scheme.

Piaget (1960) formalized constructivism from the perspective of within-the-human, and pointed out that the internal models developed by learners are built upon the interaction between the individual and the external environment. Specifically, Piaget (1960) summarized that the key processes of interaction in constructing new knowledge from the experience of an individual are assimilation and accommodation. Assimilation is the process of the individual incorporating new information into his/her internal model for world representation, while accommodation means reframing the internal model to fit new information and experiences from the external environment (Piaget, 1960). In other words, from the perspective of constructivism, learning is an active process and highly individual. Bruner (1966) established three key principles of constructivism for instruction: readiness, spiral organization and generation. Readiness refers to the fact that "the instruction must be concerned with the experiences and contexts that make the student willing and able to learn"; spiral organization means "the content must be structured so that it can be grasped by the learner and material must be presented in the most effective sequences"; and generation denotes that "instruction should be designed to

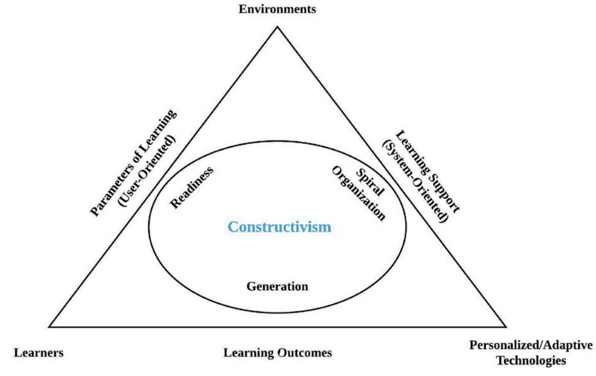

Fig. 3. The theoretical framework for the coding scheme based on constructivism.

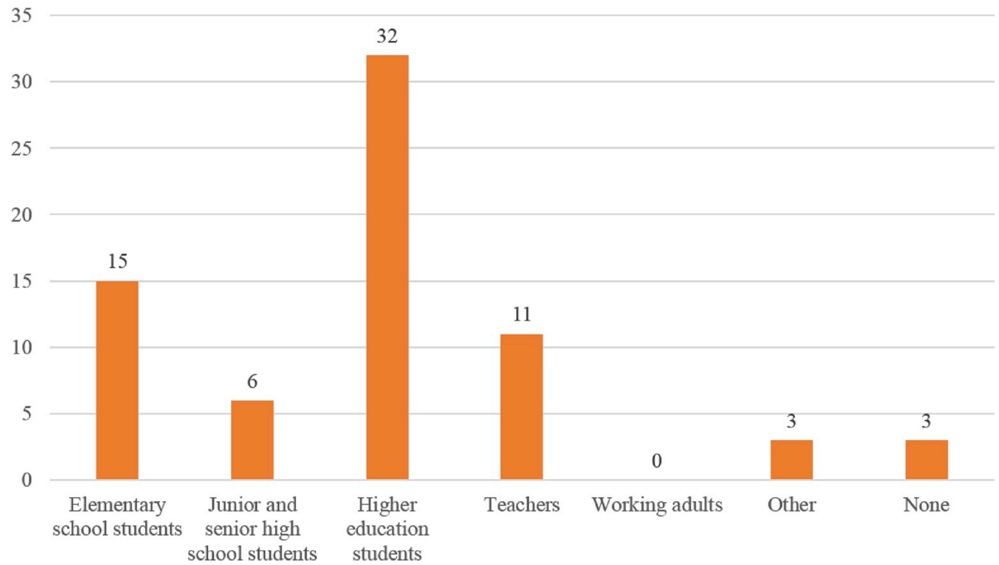

Fig. 4. The distribution of the learners in the research studies of adaptive/personalized learning.

facilitate extrapolation and or fill in the gaps" (Bruner, 1966, p. 225). As shown in Fig. 3, these three principles are externalized as three main aspects: (i) learning support; (ii) system parameters; and (iii) learning outcomes, by interacting with three fundamental elements (i.e., learners, environments, and technologies) as introduced in Fu and Hwang's (2018) research on technology-enhanced learning. "Learning support" is a system-oriented aspect which aims to cover the issues of how personalized/adaptive learning is implemented in their e-learning systems. For example, personalized learning content or personalized learning paths are common methods to achieve this goal. The linkage between the above coding schema and the fundamental elements/main aspects can be established by examining the context of adaptive/personalized learning.

It is worth pointing out that the reason for selecting constructivism is twofold. Firstly, both the selected theory and the review topic focus on personal learning processes. Constructivism argues that individual knowledge, which is constructed from experiences, beliefs, and interactions with the external environment, is highly personal (Wen & Tsai, 2003). As mentioned in Section 1, the learning process in personalized/adaptive learning is also personal to cater to the diverse needs of every individual. Secondly, constructivism can be used not only to implement the classroom teaching and learning (Alesandrini & Larson, 2002) but also to support technologies like mobile devices and the Internet for establishing learning environments (Tsai, 2008; Tsai, Tsai, & Hwang, 2012). However, as pointed out by Karagiorgi and Symeou (2005), the use of constructivism as the theoretical framework for technology-enhanced personalized/adaptive learning does not mean that the use of emergent technology tools is always required for constructivism teaching.

3. Research results

3.1. Distribution of learners

As shown in Fig. 4, higher education students were often selected as the research subjects (learners) in these studies. About 46% (32 out of 70) of the research studies chose this group of learners. The second group of learners recruited in the research is elementary school students. Meanwhile, we can find that the frequency of junior and senior high school students selected as research subjects is much less than the above two groups of learners. The distribution of learners in research studies of personalized learning is consistent with the distribution in other review studies like that on collaborative mobile learning (Fu & Hwang, 2018). In addition to the frequently selected research subjects in these studies, it is noted that there are no studies involving working adults. It is worth pointing out that teachers are also selected as research subjects, accounting for 16% of total studies, which indicates that teachers are also willing to provide or integrate adaptive/personalized learning in their classroom activities.

3.2. Distribution of learning outcomes

As shown in Fig. 5, the most popular subject of the learning content is engineering/computer, numbering 17 studies. Another category of learning content, "Others," involved 18 studies. Strictly speaking, "Others" is not a single subject as this category involves various topics or a special topic which is not associated with a specific subject. For example, Lu, Chang, Huang, and Chen (2014) taught students the feeling of living in a game world, exploring the game world and completing quests via a context-aware mobile role-playing game. Fan, Wang, and Wang (2011) trained secondary in-school teachers about assessment literacy including the knowledge of how to develop a question bank, how to revise test items, and how to apply the theory of Bloom's taxonomy in

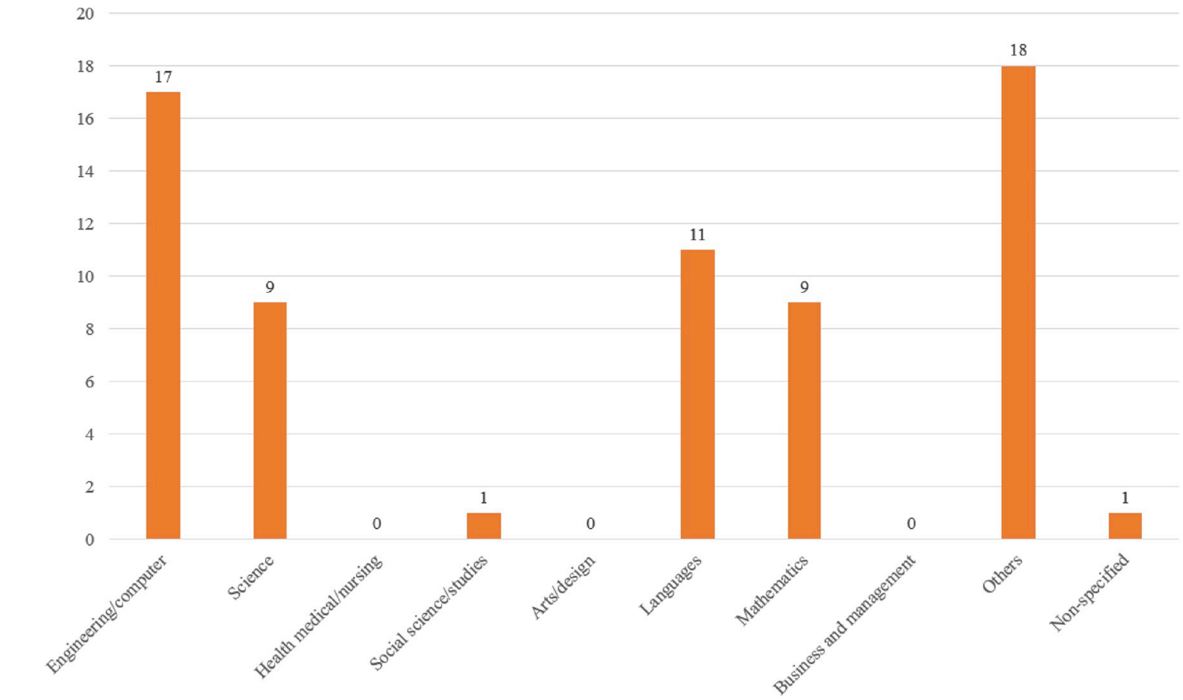

Fig. 5. The distribution of the learning content in the research studies of adaptive/personalized learning.

assessment by adopting a personalized web-based model. Besides engineering/computer and others, science, languages and mathematics were frequently selected as the learning content in these studies. In contrast, we can observe that other categories including health medical/nursing, social science/studies, art/design and business and management were rarely selected in the adaptive/personalized learning studies.

3.3. Distribution of system support/hardware

To understand how the adaptive/personalized learning processes are facilitated by systems in these studies, we focus on the various kinds of system supports. As mentioned, the codes for system support consisted of different types of learning supports, namely personalized interfaces, personalized learning content, personalized learning paths, personalized diagnosis and suggestions, personalized recommendations, personalized prompts/feedback, personalized professional learning guidance, lower order personalized interfaces and other personalized functions. The distribution of learning support types provided by adaptive/personalized systems to

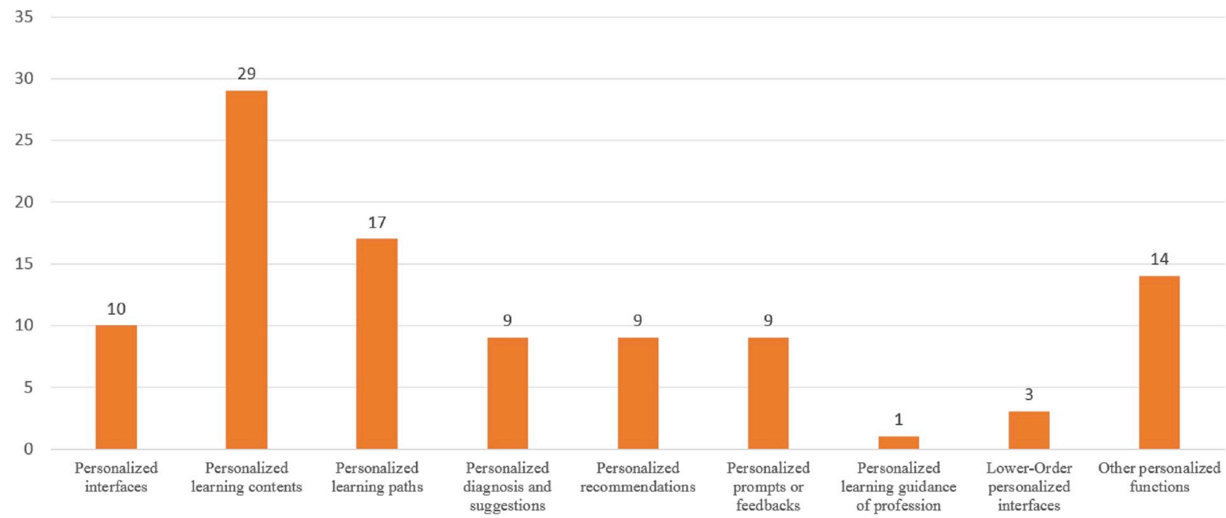

Fig. 6. The distribution of learning support types.

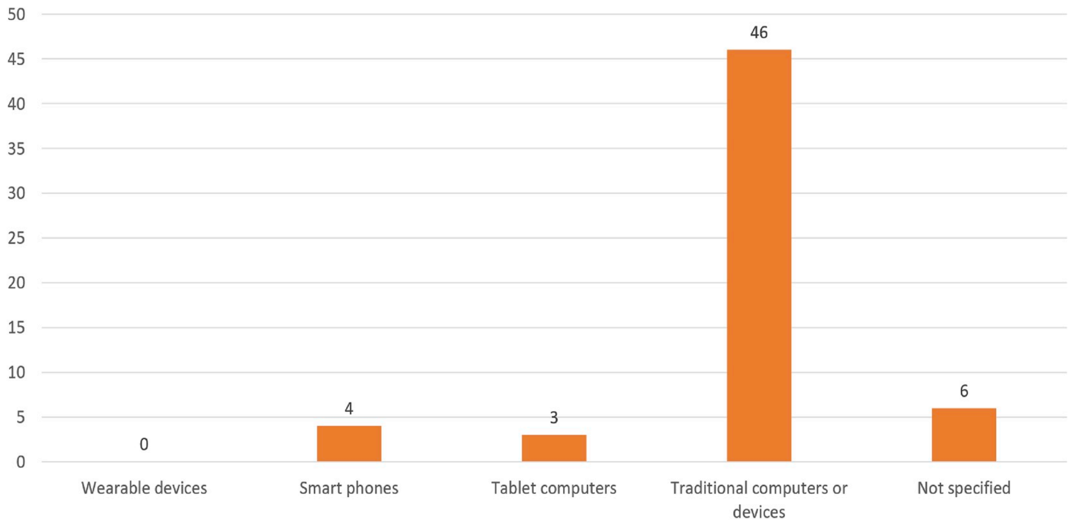

Fig. 7. The distribution of hardware used in the research studies of adaptive/personalized learning.

facilitate the learning processes is shown in Fig. 6. The most frequently adopted learning support type in these adaptive/personalized systems is personalized learning content, which was used in 29 out of the 70 studies. The second most frequent type of learning support is to provide each user of the system with personalized learning paths, the frequency of which is 17 out of 70. Another four types, personalized interfaces, personalized diagnosis and suggestions, personalized recommendations, and personalized prompts/feedback, have a similar frequency of about 10 out of 70. Meanwhile, the personalized learning guidance of profession and low-order personalized interfaces are infrequent types employed to facilitate the learning processes. In addition, there are 14 studies categorized as other personalized functions, an example of which is Chiu and Mok's (2017) study which used different order thinking skills such as remembering, understanding and analyzing to facilitate adaptive learning for algebra lessons in secondary schools.

From the perspective of the hardware used in these studies, the distribution of the five categories of devices is shown in Fig. 7. Wearable devices refer to smart electronic devices (e.g., Google glasses, Apple watch) which can be worn by users. Smartphones are the mobile phones with smart operating systems like Android, iOS, or Windows mobile. Tablet computers include Android pads and iPads. Traditional computers/devices refer to personal computers, notebooks and PDAs. The category "not specified" means that those studies did not limit their adaptive/personalized systems to a specific category of devices. Some studies which did not include any information about the hardware were not counted in this distribution. From the above distribution, we can find that the majority of studies adopted traditional computers or devices for running their adaptive/personalized systems.

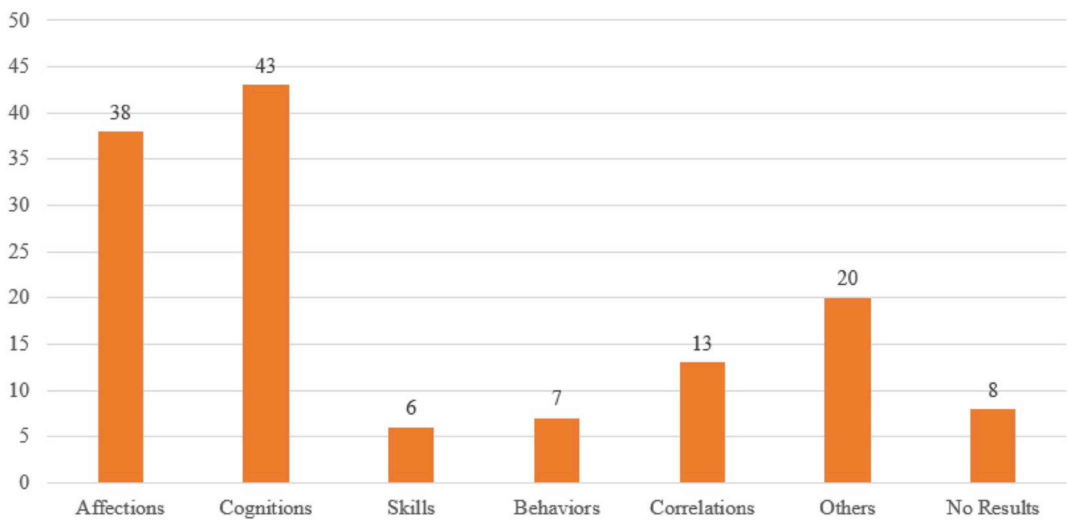

Fig. 8. The distribution of learning outcomes measured in adaptive/personalized learning studies.

3.4. Distribution of learning outcomes

There are seven main categories, namely affection, cognition, skills, behavior, correlations, others and no experimental results for coding the learning outcomes. As shown in Fig. 8, the distribution of learning outcomes measured in the adaptive/personalized learning studies indicates that affection and cognition are the most frequent learning outcomes to be achieved in these studies. Among the 70 studies, 54.2% involved measuring affection during the learning, while 61.4% involved measuring cognition.[3] For example, Gamrat, Zimmerman, Dudek, and Peck (2014) used digital badges for personalization in workplace learning, which was found to improve the technology acceptance of the personalized learning system for professional development. Rau, Bowman, and Moore (2017) verified two hypotheses: (i) problem-solving activities involve visual representation and (ii) visual representations involve collaboration, by examining the learning achievements of students in an adaptive collaborative scripting system for chemistry courses. Besides, the percentage of studies involving skills, behavior, correlations and others are approximately in the range of 8.6%–28.6%. In addition, about 11.4% of the studies had no explicit experimental results, as they were mainly review or conceptual modeling studies.

As the categories of affection and cognition are the primary measured learning outcomes among all categories, it is important that the sub-categories of these two dimensions be investigated. The category of affection can be further classified into eight sub-categories as follows: technology acceptance/learning intention, learning attitudes/expectation of learning engagement, learning motivation, self-efficacy/confidence, interest/satisfaction, cognitive load, learning anxiety, and opinion/learning experiences of students. The distribution of these eight sub-categories is illustrated in Fig. 9. Among them, technology acceptance/learning intention, interest/satisfaction and opinion/learning experiences of students were measured in about 20 of the 40 studies involving affection. In contrast, learning anxiety (one study) and cognitive loads (four studies) were infrequently measured in these studies.

The category of cognition can be further classified into three sub-categories: learning achievements, high-order thinking/competence, and collaboration/communication. The distribution of these three sub-categories is shown in Fig. 10. Learning achievements are the most frequently measured learning outcomes among these three sub-categories of cognition. There are 37 studies which measured the learning achievements in all 43 studies involving cognition. The remaining two sub-categories, high-order thinking/competence and collaboration/communication, are involved in seven and four studies respectively.

To understand the polarity of the learning outcomes, we have further labeled each experimental result into three types (i.e., positive, negative and mixed). The distribution of positive, negative and mixed results across the five categories of learning outcomes is shown in Fig. 11. The remaining two categories "Others" and "No results" were not included as only some descriptive statistical results were discussed in these studies. Note that a single study may involve different subcategories of affection/cognition, so the total number of results is larger than the total number involving affection/cognition as shown in Fig. 8.

As the number of results in each category is largely dependent on the number of sub-categories (e.g., 85 positive results in affection due to seven sub-categories), 100% stacked bars are adopted in Fig. 11. From these statistical results, most personalized/adaptive learning studies in the categories of affection (95.5%), cognition (89.6%), skills (66.7%) and behavior (100%) report positive results in learning outcomes. The studies about correlations reported both positive and mixed results in a close ratio (i.e., 53.8% positive results vs. 46.2% mixed results). In addition, there is only one negative result identified in all studies. To be specific, Liu, McKelroy, Corliss, and Carrigan (2017) studied the effects of an adaptive learning intervention on students' learning in the four content areas of Biology, Chemistry, Math and Information Literacy and found that there was a negative result in the technology acceptance if the learning intervention was not well designed.

Furthermore, the breakdown of positive, negative and mixed results in the sub-categories of affection and cognition is shown in Figs. 12 and 13 respectively. As there are no further divisions of the two sub-categories of affection and cognition, stack bars of absolute values are used to illustrate the distributions of positive, negative and mixed results in these two figures.

3.5. Distribution of parameters of adaptive/personalized learning

The learning tools (i.e., the adaptive/personalized systems) were examined according to two dimensions: parameters of systems to support adaptive/personalized learning and the hardware used in these studies. As mentioned in the coding scheme, the parameters for these systems to support adaptive/personalized learning include the difficulty level of the learning materials, the sequence of the learning materials, the students' learning achievements, preferences, learning styles, learning perceptions, cognitive styles, and profiles, as well as portfolio or logs, and platform/technical support. Fig. 14 illustrates the distributions of the parameters of adaptive/personalized learning systems adopted in these studies. As revealed in Fig. 14, the most prevalent parameters employed to facilitate adaptive/personalized learning are students' learning achievement and platform/technical support, the frequencies of which are each 28 times. As an example of platform/technical support, Huang and Yang (2009) used the semantic web technology ontology to aid adaptive learning by re-organizing the resources and content from wikis and blogs. An example of selecting students' learning achievement as the parameters of adaptive/personalized learning is a location-aware mobile system which not only supported learning from real contexts but also facilitated personalized learning guidance for natural science courses based on a two-tier test approach (Huang & Chiu, 2015). The least frequent parameter of adaptive/personalized learning is the students' cognitive styles, the frequency of which is 5. Except for the second least adopted parameter, the sequence of learning materials with a frequency of 9 times, the other six parameters–the difficulty level of the learning materials, students' preferences, students' learning styles, students'

[3] Note that a single study may involve two or more categories of learning outcomes.

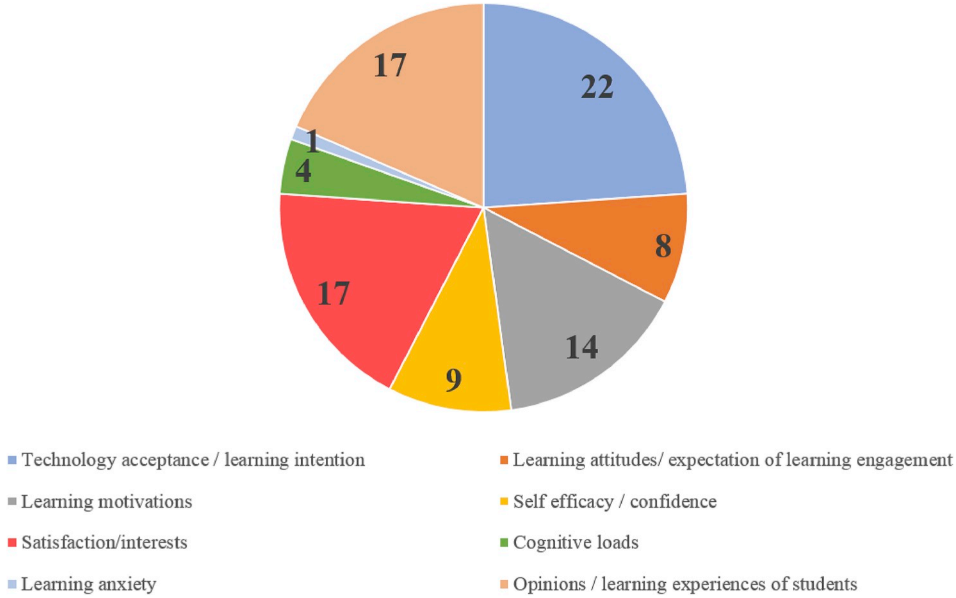

Fig. 9. The distribution of the eight sub-categories of affection.

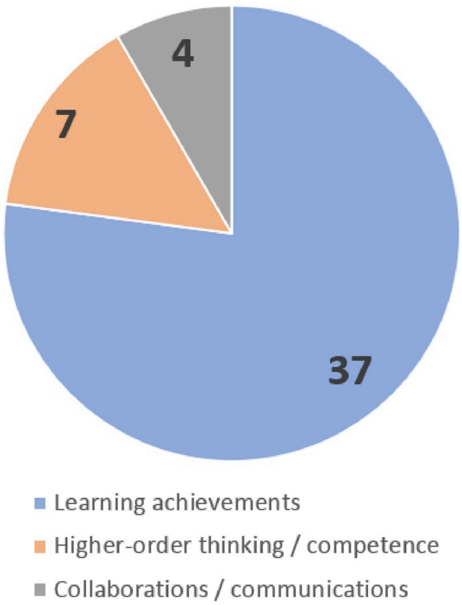

Fig. 10. The distribution of the three sub-categories of cognition.

learning perceptions, students' profiles and portfolio or logs–are not far from the average frequency of 17.2 for all parameters.

The parameter of students' learning perceptions can be further divided into three sub-categories: (i) learning attitudes, learning motivation or hard work and high expectations; (ii) self-efficacy or self-confidence; and (iii) satisfaction or interest. The distribution of these three sub-categories of the 14 studies related to students' learning perceptions is shown in Fig. 15. There are seven, three and four studies in these three dimensions, respectively. The sub-category of learning attitudes occupies 50% of all studies using learning perceptions as the parameter for adaptive/personalized learning.

4. Discussion

4.1. Research issues related to learners

As mentioned in Section 3.1, no research studies involved working adults as the research subjects. One possible reason is that

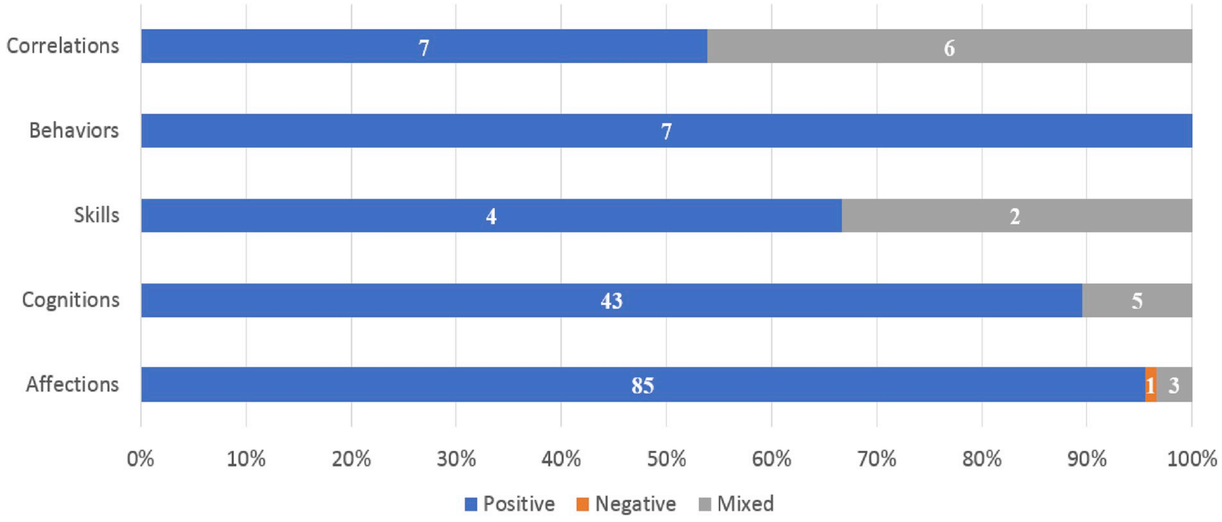

Fig. 11. The distribution of positive, negative and mixed results in learning outcomes.

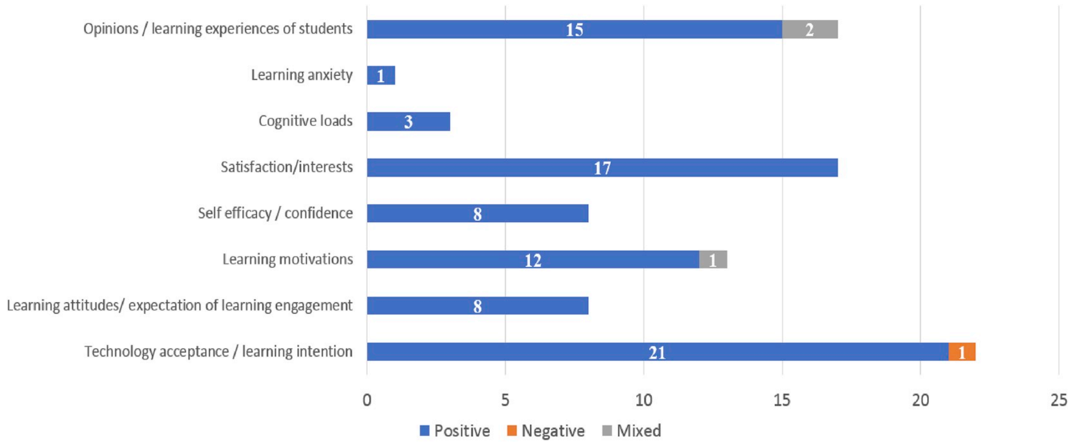

Fig. 12. The distribution of positive, negative and mixed results in affection.

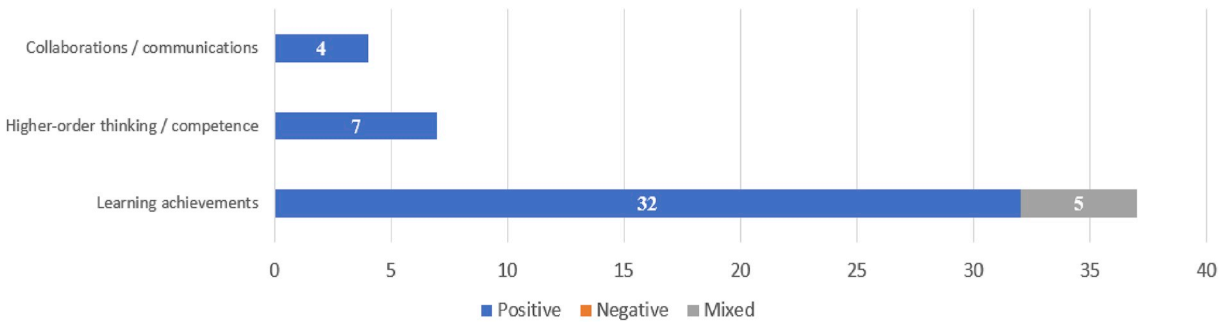

Fig. 13. The distribution of positive, negative and mixed results in cognition.

adaptive/personalized learning usually requires a relatively longer study duration (i.e., understanding the individual characteristics of learners, learning process with adaptive/personalized features, and/or evaluation of learning outcomes) than other kinds of educational studies. Therefore, it is challenging for researchers to involve working adults in the whole learning process and to ensure their equality of prior knowledge levels in a control/experimental setting.

Another possible reason is related to the types of hardware employed in these studies to support adaptive/personalized learning. Specifically, the majority of studies adopted traditional computers as the main hardware to run the adaptive/personalized systems. Such a deployment may have potential compatibility problems for working adults who may prefer to use portable devices such as

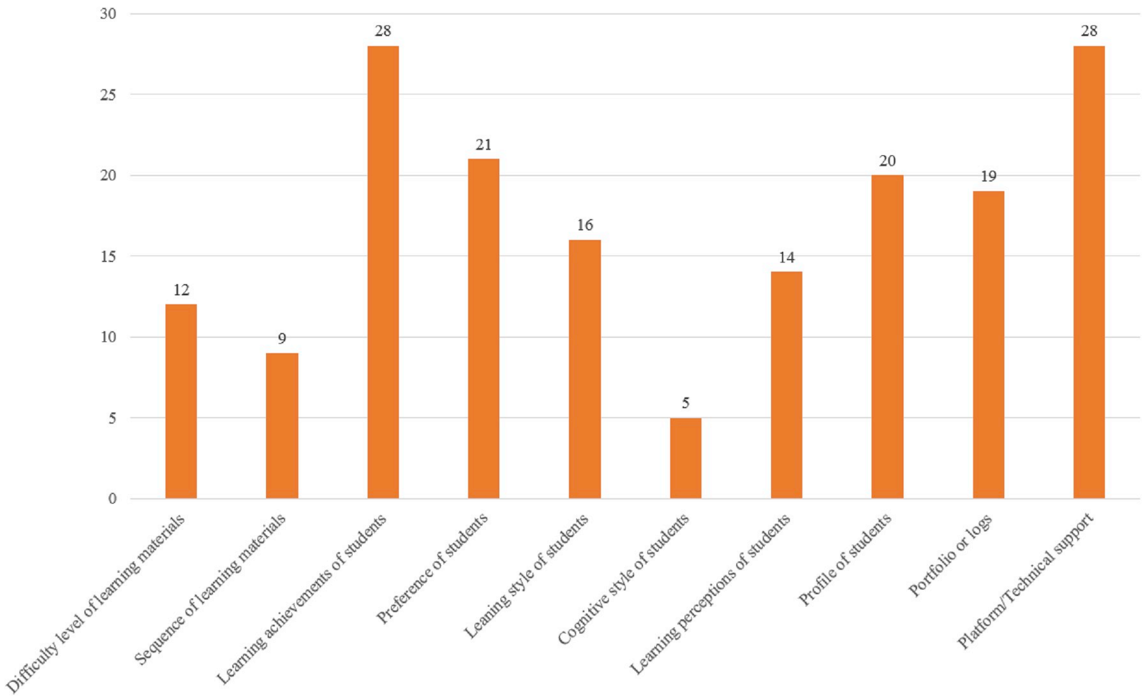

Fig. 14. The distribution of parameters of adaptive/personalized learning.

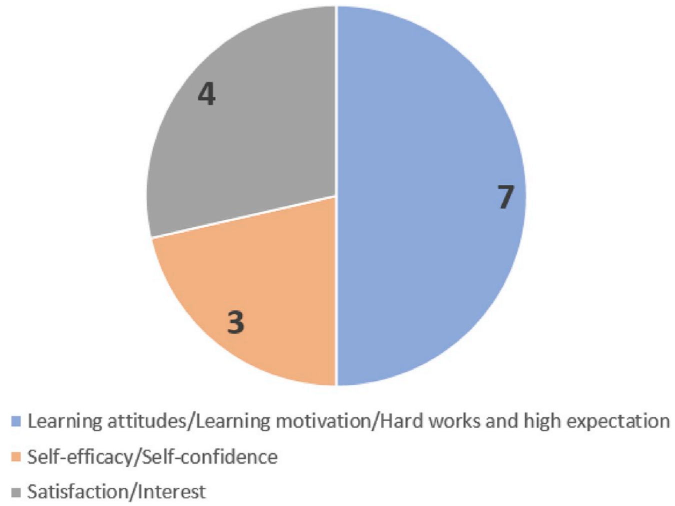

Fig. 15. The distribution of the three sub-categories of the parameter of students' learning perceptions.

smart phones. For example, the system interface may not be displayed correctly on smart phones or tablets if the responsive design is not adopted in the interface (Smutný, 2012). In addition, the involvement of working adults during the whole learning process is more difficult to administer compared with the other categories of learners such as university students or teachers who may be able to meet more frequently with the research team members. Therefore, if working adults are the target participants in future research studies, it would be more feasible to build web-based adaptive/personalized systems that are compatible with portable devices like smartphones or wearable devices to facilitate their participation throughout the whole learning process. For example, Huang et al. (2016) developed a context-aware personalized language learning system for mobile devices, which would be easy for working adults to use. In the future, we argue that working adults will be more likely to be selected as research subjects with the cost of adaptive/personalized systems for mobile or wearable devices largely reduced (Ranck, 2012).

4.2. Research issues related to learning content

As noted in Section 3.2, engineering/computer and others, science, languages and mathematics are more frequently used in these studies, while health medical/nursing, social science/studies, art/design and business and management are rarely selected. One possible explanation is that science, language, and mathematics are commonly taught in primary/secondary schools, and researchers normally have domain knowledge and expertise to understand the contexts. On the other hand, they are less likely to have domain knowledge in health medical/nursing, social science/studies, art/design or business and management if their higher education majors are not in these disciplines (Alexander, Rose, & Woodhead, 1992; Lee, Croninger, & Smith, 1997). Without domain knowledge, it is quite difficult to support adaptive/personalized learning experience in these categories. It is important to have adaptive/personalized learning in various disciplines. One possible direction is to adopt some existing learning systems in these disciplines to be personalized/adaptive. For example, Lin and Lin (2016) proposed a mobile interactive learning and diagnosis system to support problem-based learning, which can easily support adaptive learning if the learning processes are recorded for each nurse. Another trend is to automatically extract the knowledge structure of these disciplines by employing deep neural networks for establishing the knowledge graphs (Shi & Weninger, 2017) so that researchers can understand the structure of the domain knowledge in these disciplines and then organize the learning content of the adaptive/personalized systems.

4.3. Research issues related to hardware

As discussed in Section 3.3, the most frequently used hardware type for adaptive/personalized learning systems is the traditional computer. The reason is that the most adaptive/personalized systems were established based on the development packages and extant systems for traditional computers/devices to save the human power and/or time costs of the development processes (Patterson & Erturk, 2015). In addition, there are no personalized/adaptive systems using wearable devices, as these systems not only have to be built from scratch but also require up-to-date IT skills and knowledge from educational researchers.

With the development of information technologies for applications in mobile or wearable devices, there will be a large number of adaptive/personalized learning systems deployed in these devices. For example, Borthwick, Anderson, Finsness, and Foulger (2015) proposed the definition of “wearable personal learning technologies,” which can gather data from the person wearing the device or from the surrounding environment to enhance differentiation of instruction and student engagement. We believe that the popularity of wearable learning technologies with personalized data will be a new trend in adaptive/personalized learning.

4.4. Research issues related to learning outcomes and system support

As mentioned in Section 3.4, higher order thinking skills and communications attract less attention than learning achievements. The reason is that the higher-order thinking skills and communication are more difficult to measure than learning achievements in the classroom (Brookhart, 2010; White, 1993). For example, Mavroudi, Hadzilacos, Kalles, and Gregoriades (2016) developed a set of the critical success factors to assess the higher order thinking skills in a teacher-led designed adaptive learning environment by employing qualitative comparative analysis (QCA). Specifically, both fuzzy set (a value between 0 and 1 denoting the degree of membership) and crisp set (i.e., 0 denotes non-membership and 1 denotes membership) QCA were adopted in this study. However, the assessment method adopted cannot be conducted on a larger scale due to the complexity of the calculation and data collection process, which require a long process of manual data input from users and research team members (Mavroudi et al., 2016).

Another possible reason is related to the system support types as investigated in Section 3.3. We can find that the personalized learning content is the most popular learning support type in the adaptive/personalized systems. The higher order thinking skills and communications are not likely to be supported in this learning support type as such support focuses on facilitating learning achievements. We believe that there will be more studies to investigate the higher order thinking skills and communication in the adaptive/personalized learning systems with the increasing popularity of collaborative and immersive learning environments supported by virtual reality techniques (Greenwald, Corning, & Mae, 2017).

4.5. Research gaps and theoretical analysis

According to the theoretical framework proposed in Section 2.3 and the statistical results in Section 3, we can identify the following research gaps.

The first is related to spiral organization, which refers to two aspects. The first one is *structure,* meaning that “the content must be structured so that it can be grasped by the learner” (Bruner, 1966, p. 225). The second aspect is the *sequence*, which means that “the material must be presented in the most effective sequences” (Bruner, 1966, p. 225). As shown in Fig. 3, spiral organization is implemented through system parameters and support types in adaptive/personalized systems. There are many research studies related to *structure* or *sequence* as shown in Fig. 15. For example, 29 studies are related to personalized learning content, which is directly linked to the definition of *structure*, while 17 studies about personalized paths are relevant to the definition of *sequence.* However, there is only one study (Chen, Huang, Shih, & Chang, 2016) which integrates both personalized learning content and personalized learning paths into one adaptive/personalized system. In other words, either *structure* or *sequence* is taken into account independently in extant studies and there are only a limited number of studies which consider spiral organization as a whole in the extant research.

The second research gap is related to readiness, which means that “instruction must be concerned with the experiences and contexts that make the student willing and able to learn" (Bruner, 1966, p. 225). The readiness is externalized as the parameters of adaptive/personalized learning like learning perceptions. Although many studies have attempted to enhance the learning experience with parameter data from user input or system records, data sources for supporting adaptation or personalization in these systems are limited. For example, Wang and Liao (2011) proposed an adaptive learning system and the data sources for adaptive learning are the student input data like profiles, learning styles and so on. Although Lin et al. (2013) developed a personalized creativity learning system for providing personalized learning paths by exploiting more fruitful data sources including profile data input from users and questionnaire answers during the learning, the required user efforts are intrusive. It is worth pointing out that techniques for context-aware user data collection in an implicit way for personalized services have been widely adopted (Hong, Suh, Kim, & Kim, 2009; Woerndl, Schueller, & Wojtech, 2007). Therefore, it is necessary to integrate these techniques in technology-enhanced learning for context-aware adaptive/personalized learning in a real-time fashion. From the perspective of our theoretical framework, the gap of adopting data collection techniques in the technology-enhanced learning becomes a bottleneck for providing instructions closely and truly concerned with the experiences and contexts of the learners.

5. Conclusion

Adaptive/personalized learning has become a key learning paradigm in the research community of educational technologies. In this review study, we have answered some important research questions including the parameters for implementation, the learning supports, the learning outcomes to be achieved, participants, and the hardware devices for the adaptive/personalized learning systems in the selected studies from 2007 to 2017. To code each selected article, a systematic coding scheme is supported by constructivism. The statistical results of each category of the coding scheme are discussed and analyzed.

Furthermore, from the viewpoints of various human factors of personalized learning, Chen et al. (2016) identified that the learners' gender differences, cognitive styles, and prior knowledge would lead to different reactions to the personalized or non-personalized systems during the learning process. For example, female learners achieved better performance than male learners in the personalized scenario, whereas male learners outperformed females in the non-personalized learning scenario (Chen et al., 2016). From the perspective of critical data sources for facilitating adaptive/personalized learning, Tseng et al. (2008) believed that the integration of two data sources of individual learning styles (i.e., sequential processing skill, discrimination skill, analytic skill, and spatial skill) and learning behaviors (i.e., learning effectiveness, concentration degree, and learning achievement) can be used as the key parameters to determine the personalized learning materials for the individual learners. Nevertheless, understanding domain-specific learning theories is a critical issue to facilitate adaptive/personalized learning in a specific subject/area. For instance, Chen and Chung (2008) adopted the item-response theories and learning memory cycles to recommend the proper English vocabulary according to individual learning capability and memory curves for facilitating personalized vocabulary learning. A follow-up study on the personalized vocabulary learning made use of the situational learning theory to assist learners to acquire the vocabulary from their contexts by collecting the context-aware data from the mobile devices (Chen & Li, 2010).

In addition, some research issues and potential future development directions are discussed. According to the discussions and results, it was found that adaptive/personalized learning systems may give more attention to working adults in the future. Their participation during the whole learning process will be facilitated by adaptive/personalized systems built on smartphones or wearable devices. On the other side of the coin, wearable personal learning (Borthwick et al., 2015), which aims to collect data from the person wearing the device or from the surrounding environment to enhance differentiation of instruction and student engagement, will become a new trend with the development of information technologies for learning applications deployed on mobile and wearable devices. For the learning content in adaptive/personalized systems, disciplines such as health medical/nursing, social science/studies and so on, which need a great deal of domain-specific knowledge and skills, will be boosted by knowledge graph techniques in artificial intelligence (Shi & Weninger, 2017) and the acquisition of individual learning data. The higher order thinking skills and communication have attracted little attention in terms of both learning outcomes and the process of adaptive/personalized learning due to the difficulty of measurement and the limited learning support types. Recently, virtual reality techniques have started to be able to support collaborative and immersive learning environments, which will give more possibility to cultivating higher order thinking skills and communication in adaptive/personalized systems in the near future.

To sum up, this study discusses the trends and issues in the area of technology-enhanced adaptive/personalized learning by reviewing research studies in the recent decade. More important, it reveals that there will be a spectrum of potential applications such as wearable personal learning technologies, collaborative and immersive personalized learning and so on with the recent development of information technology in the areas of artificial intelligence, virtual reality, cloud computing and wearable computing.

As the present study mainly adopted a quantitative approach to analyzing the trends and developments in technology-enhanced adaptive/personalized learning, it would benefit the researchers in this field more if a follow-up review study can be conducted using a critical approach.

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