J. Comput. Educ. (2021) 8(4):485–503
https://doi.org/10.1007/s40692-021-00188-7

A comprehensive analysis of personalized learning components

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Received: 30 September 2020 / Revised: 22 February 2021 / Accepted: 9 April 2021 /
Published online: 24 April 2021

Abstract Personalized learning is a learning approach that aims to personalize the learning experience according to the unique needs, goals, and skills of individuals which can be achieved by using current instructional technology that provides unique learning experiences in different learning environments. Technology is the main component that will enable and enrich personalized learning experience; however, even though technology is available to personalize the learning experience, there is still a lack of unified agreement on what components need to be considered for a dynamic personalized learning approach that is to be able to provide a unique and effective learning experience to each learner. To address this need, this study aims to analyze and synthesize different personalized learning approaches that consider different learning components, so that we have an evolving agreement on personalized learning models and approaches. The findings of this research identified the following main components: learner profiles and attitudes, previous knowledge and beliefs, personalized adaptive learning paths, and flexible self-paced learning environments that are generated by learning analytics. These prominent characteristics imply that a personalized learning environment (PLE) would need to be dynamic to maintain a current record of learner interests and attitudes, past experiences and performance, and activities and interactions likely to match a particular learner and learning goal.

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Keywords Personalized learning · Adaptive learning · Intelligent tutoring systems (ITSs) · Technology-enhanced learning (TEL) · Smart learning environments (SLEs) · Learning analytics

Peng et al. (2019) defined personalized adaptive learning as "a technology-empowered effective pedagogy which can adaptively adjust teaching strategies timely based on real-time monitored (enabled by smart technology) learners' differences and changes in individual characteristics, individual performance, and personal development." Learning involves activities shaped by personal experiences, awareness, personal bias and opinions, cultural background, and environment. This conception of learning implies a need to have a unique learning approach for individuals according to their unique situations. The typical learning situation is for a group of learners to be in the same learning environment and learning from the same source, regardless of their many differences and situations. The way one perceives and learns from resources and activities in a learning environment can vary significantly. However, a PLE's goal is to provide a unique and effective learning experience to each learner. This study analyzes and synthesizes different personalized learning approaches that consider different learning components. The goal is to develop general agreement on what is needed in an effective personalized learning environment in the form of a personalized learning model.

This study aims to review different personalized learning approaches and models used in research papers from 2010 to 2020 to compare the similarities and differences in components that have been used. Also, to analyze and synthesize the research done in the field, to use previous studies to analyze the problems and issues to allow further studies to build upon prior studies.

This paper presents a comprehensive review of personalized learning components based on published peer-reviewed research papers in the last ten years. The goal is to review different personalized learning approaches and models used in research papers published in primary databases and journals of learning technologies from 2010 to 2020 to compare the similarities and differences in components that have been used. The purpose is to thoroughly examine prior research and present an overview of findings to date.

Learning can be conceptualized as an experience or collection of experiences that expand knowledge, understanding, perspective, skills, thinking, interpretations, and perception. According to Spector (2012, 2013), learning generally involves a stable and persisting change in what one knows and can do. Moreover, different learning models and approaches have evolved over the years. Learning models and approaches evolve along with technology and our knowledge of human learning. According to Xie et al. (2019), personalized learning has become a critical learning paradigm in the research community of educational technologies.

A promising learning method, personalized learning (PAL), is a new personalized learning approach that is computerized and makes decisions based on data gathered by a programmed system that accommodates learning to learners' real-time learning conditions and adjust the learning content and activities to meet learners' characteristics and needs through SLEs (Peng et al., 2019). While personalized learning is still in the early stages of development and evolution, there are important lessons to be learned from reviewing the existing research literature in this area.

This research literature analysis suggests that it is much too early, and there is too little evidence to conclude that one model is the best. Moreover, different learning approaches will be appropriate depending on different circumstances, including course content, learner experiences, learner maturity, learner intelligence, instructor goals, learner skills, and preferences. There are many more choices and opportunities than were available to previous generations of learners and teachers. At least in principle, it is now possible, if not yet widely implemented, for teachers to facilitate personalized learning approaches according to individual learners' unique needs.

Furthermore, Miliband (2006, as cited in Lee et al., 2018) discussed that the goal of personalized learning is to help and support everyone to reach their maximum potential by customizing instruction, including content, instruction delivery, and the pace at which it is learned, to meet unique needs, such as diverse learner characteristics and interests. The importance of personalized learning has been widely acknowledged by international organizations, governments, and education (Kinshuk et al., 2013). Also, there is growing evidence that the personalized, learner-centered paradigm can significantly enhance learning outcomes (Vandewaetere et al., 2012). In K-12 settings in the USA and other countries, it is already possible to create individual learning plans for students with disabilities that fit a student's capabilities with various learning goals and objectives. One way to characterize personalized learning in K-12 settings is to argue that every student should have an individualized learning plan.

For this review, Okoli's (2015) guidelines to conducting a systematic literature review for Information Systems Research were adapted due to a detailed framework for writing a systematic literature review with its information technology roots being provided. To analyze current literature, the researchers have selected the following well-known and reliable databases to structure this literature review: Scopus, Science Direct, EBSCOhost, IEEE Xplore, JSTOR, and Web of Science to ensure all related journals of the field (Shemshack & Spector, 2020) are included in this study. The most relevant journals for this study were chosen consistently from these databases. Furthermore, the Google Scholar h5-index for the category "Educational technology" was used as the starting point since it is a specific category for personalized learning studies. Peer-reviewed article papers from online journals were retrieved for this study because those online academic journals are reliable and authoritative. The researchers reviewed the primary databases for educational technology to ensure all related journals are included. This review is only focused on journals to keep the scope of the review manageable and provide reviewed data to create a resource for future studies (Shemshack & Spector, 2020). Relevant papers were initially determined through searches of online databases and journals. These papers were subsequently examined to determine their applicability to the study. The papers explained what components they considered for personalized learning systems were selected for further analysis.

The researchers believe that a comprehensive, personalized learning experience can improve the learning experience for all. As a result, this primarily descriptive study analyzed components used in different personalized learning systems and models to provide a comprehensive analysis of personalized learning components that provide unique learning experiences to all. To serve this study's purpose and address the gap suggested earlier, the following research question was addressed:

1. What components need to be included in a comprehensive, personalized learning approach? We also considered the following sub-questions:

1.1 What are the similarities and differences of used components of personalized learning approaches? This question narrowed the focus of the study on components and their impact on learning. The study focused on the differences and similarities of each component and how they impacted learning. This approach helped the researchers decide if the related component should be considered as a significant learning component. Researchers highlighted components in each system to look for patterns and similarities while paying attention to differences and their impact on learning outcomes.

    Furthermore, the following sub-question helped compare different personalized learning models, so any relationship between used systems/models and components could be identified.

1.2 What systems and models are available to personalize adaptive learning experience for all?

Sub-questions provided a more focused approach to the study. Moreover, researchers focused on analyzing and synthesizing different personalized learning approaches that consider various learning components, so an evolving cooperative agreement on a dynamic, personalized learning model can be created.

Researchers reviewed papers from primary databases and journals on learning technologies published between 2010 and 2020 years to analyze components of different systems and models of personalized learning. The articles were chosen to be reviewed, depending on the content of the papers' content and quality. Researchers thoroughly analyzed those components to provide a comprehensive analysis of personalized learning components that provide unique learning experiences to all. The researchers identified the study's purpose and intended goals to ensure the analysis is clear to readers.

Researchers presented previous work on personalized learning in the literature review section. The review results are explained in detail on different components used in different personalized learning environments in the current trends section under two subtitles: components of personalized learning models and systems and tools and systems.

The review's discussion is presented in the discussion section, followed by future research direction and conclusion.

Literature review

Boeree (2000) suggested that individuals can generate their own learning experiences and interpret information in the same or different ways as others, as each person has a unique interpretation and perspective on the world. Personalized learning (Chatti & Muslim, 2019; Peng et al., 2019; Yang et al., 2010) has been implemented by the support of intelligent learning systems that mostly consider integrating learners' preferences, analyzing individual learning data, creating learner profiles, etc. by dynamically facilitating the learning process.

The United States National Education Technology Plan 2017 defines personalized learning as instruction that allows adjusting the pacing of learning and the instructional approach to optimize each learner's needs (U.S. Department of Education, 2017). Indeed, pacing is one of the main components of the personalized learning but is not the only one for a holistic, personalized learning experience that provides a unique learning experience to all according to their needs, skills, interests, and goals. Furthermore, Peng et al. (2019) claimed that personalized learning has gradually become more complicated with technology development.

Peng et al. (2019) defined personalized learning as a technology-empowered effective pedagogy that can adaptively modify teaching strategies based on real-time monitoring, enabled by smart technology that considers learners' differences in individual characteristics, individual performance, and personal development.

The increased interest in personalized learning can result from the acceptance of learning as a unique experience, and acquired knowledge is unique to individuals. According to Xie et al. (2019), it has been commonly acknowledged in various learning/psychological theories that learning experiences and acquired knowledge are unique. To analyze the studies on personalized learning components, researchers thoroughly analyzed those components to provide a comprehensive analysis of personalized learning components that provide unique learning experiences.

Current trends

This study includes different components used for personalized learning models and systems, the systems and tools are available to personalize learning experience and the differences and similarities of each of those models and systems.

Components of personalized learning models and systems

Most personalized learning approaches focus on learner needs and previous knowledge and aim to provide content accordingly. Erumit and Cetin (2020) created a table to display design features of adaptive intelligent tutoring systems to list their features by the dates they were developed, and found that the last three systems are developed after 2015 focused on adapting content according to the learner responses, allows the learner to interact and to choose the content. These components seem to align with Peng et al.'s (2019) definition of personalized learning.

Learning styles

Tseng et al. (2008) believed that integrating two data sources of individual learning styles and learning behaviors such as learning effectiveness, concentration degree, and learning achievement can be used as the key parameters to determine the individual learners' personalized learning materials. However, Hwang et al. (2013) argued that even though learning styles are considered one of the most common factors that need to be considered in developing adaptive learning systems, few studies have been conducted to investigate if students can choose the best-fit learning systems or content presentation styles for themselves in terms of learning style perspective. Therefore, Hwang et al. (2013) investigated students' perceptions of the most beneficial educational systems from the perspective of learning styles. Their study findings showed that (a) Students learn better with the version designed for their learning style. This demonstrates the importance of adaptive learning systems, which are based on learning styles. (b) Students do not necessarily choose the version which has been designed for their learning style. This is very important because most adaptive systems create an initial user model based on individual students' answers to a questionnaire or choices of a set of parameters that are always assumed to be "reasonable." The experiment's results demonstrated that this might be untrue in some cases since user choices can be irrelevant to their learning performance. Hwang et al. (2013) claimed that this could significantly impact the design of adaptive learning systems that model needs to be refined and updated in an adaptive approach, which is inherently dynamic and subject to ongoing refinement.

Cognitive styles

On the other hand, the results of research on learning profiles that considered personality and cognitive styles (Triantafillou et al., 2003) to determine the correlation between learning profile and ability, academic performance or the atmosphere of teaching and learning in the classroom, (Ehrman, 2001; Ehrman & Oxford, 1995; Reiff, 1992) showed the importance of including personality and cognitive styles in personalized learning approaches. However, a robust learner profile is also likely to change with time as learner interests and competence change as they mature and have more experience.

Self-reflection and self-regulated learning

Furthermore, Chatti (2010) argued that progressive development learning is a complex activity that involves self-reflection and self-regulation. Panadero (2017) claimed that self-regulated learning (SRL) is one of the most critical research areas in education over the last two decades, including the cognitive, metacognitive, behavioral, motivational, and emotional/affective aspects of learning which increase the data available to researchers. Following the lead, a unified evolving personalized learning model can be generated to provide learners with a more satisfied and engaging learning experience that considers diverse needs and goals. With our current teacher–student ratio to provide instruction according to each student's needs seems not to be possible; Chatti and Muslim (2019) and Peng et al. (2019) suggested that SLEs are needed to support personalized learning by helping learners to achieve their learning goals by providing tools that promote awareness, recommendation, self-reflection, assessment, feedback, and motivation. There are indeed many personalized learning models and systems available to both researchers and educators; however, as in the example of SRL, there is no defined age or learner `preparation considered to ensure the learner is ready to self-regulate their learning experience.

Flexible pacing

One of the components that most educators and researchers agreed upon is allowing students to learn at their own pace is a strength and advantage that personalized learning provides. Sturgis and Patrick (2010, as cited in Lee et al., 2018) explained that well-designed technology systems allow personalized learning to be operational by monitoring individual progress, suggest personalized learning paths, and allow students to move at their paces.

Also, Wang and Liao (2011) used four components: gender (Chen et al., 2016), learning motivation, cognitive type (Triantafillou et al., 2003), and learning style as different learning characteristics. Wang and Liao (2011) aimed to propose an algorithm to determine optimal adaptive learning sequences for instruction that accommodate a variety of individual differences by using a survey of the literature as a basis; four factors were derived and selected as the variables to be used for the learners' characteristics in the experiment that included 295 first-year students in Taiwan. Wang and Liao (2011) defined learning profiles as a preference for specific ways of learning to suggest optimal way to support learning, as Curry; Shaughnessy (1991, 1998, as cited in Wang & Liao, 2011) explained that a combination of one's motivation, engagement, and cognitive processing habits shows distinctive and habitual ways in which people proceed to concentrate on and interact with instructional content presented in a learning environment. Besides, Scanlon et al. (2012, as cited in FitzGerald et al., 2018) explained that issues that affect learners' lives, in the classroom, on field trips, and in their homes could support learning; as a result, they identified three aspects of personalization: personal relevance, choice, and learner responsibility. Scanlon et al. (2012, as cited in FitzGerald et al., 2018) also mentioned that systems could capture learner data and model their emotions via facial recognition, processing voice recorded data, sentiment analysis of student comments, heart rate detection using video cameras, and so forth (see, e.g., Calvo & D'Mello, 2010). This would be exemplified by the "whole person" personalization element and have a high level of sophistication, considering many learning characteristics.

Furthermore, Lee et al. (2018) pointed out that to take advantage of technology, it is essential to have a technological system that collects learners' data and seamlessly feeds the data into each function. Learners' data collected in the assessment function should flow into the recordkeeping function, where the data are analyzed with the previous history of each student's data. The learning analytics (LA) should flow into the planning function to prepare personalized learning plans. Based on these LA data, artificial intelligence can suggest a project that may be interesting to the student and meet their learning needs in the instruction function and guide it. The assessment function should be fully integrated with the instructional function through just-in-time tutorials that entail each student practicing each competency until the criterion for mastery has been reached.

Chen et al. (2016) suggested considering the gender (Wang & Liao, 2011) component for personalized learning. Chen et al. (2016) identified that the learners' gender differences, cognitive styles, and prior knowledge would lead to different reactions to 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. Furthermore, Atkinson (2006) found a significant difference in learning achievement between male and female students and students who used different learning styles.

Liu and Yu (2011) added mood to personalized learning components and defined personalized learning as a service that provides learning content to fit learners' differences. Learning achievements are influenced by cognitive and non-cognitive factors such as mood, motivation, interest, and personal styles. Liu and Yu (2011) also suggested that teachers and educational designers need to understand the variations in students' attitudes, motivation, and style and their ability using Item Response Theory (IRT) model to understand the learners' abilities.

Li et al. (2013) pointed out the importance of knowing the learning habits. They developed a SCROLL system (System for Capturing and Reminding of Learning Log) that allows learners to log their learning experiences with photos, audios, videos, location, and share and reuse them with others. The goals of SCROLL are lying in helping users efficiently record their learning experiences and recall them via the context, recommending other learners' learning experiences for them, finding out individuals' learning habits, and supporting their learning per personal learning habits.

Tools and systems

There are many tools and systems available that can provide a unique learning experience for all. Chatti and Muslim (2019) and Peng et al. (2019) suggested that SLEs and LA are essential tools to allow learners to meet their learning goals by providing tools that promote awareness, recommendation, self-reflection, assessment, feedback, and motivation, which are essential components of personalized learning.

Smart learning environments

Chatti and Muslim (2019) brought attention to the necessity of SLE to support personalized learning by providing systems that foster awareness, recommendation, self-reflections, assessment, feedback, and motivation. Hwang (2014, as cited in Zhang et al., 2018) argued that an SLE could offer instant and adaptive support to learners by immediate analysis of individual learners' needs from different perspectives.

Intelligent tutoring systems

Another system that supports personalized learning experience is intelligent tutoring systems (ITS), which employ computational algorithms or models to deliver immediate feedback and learning instructions to learners without human teachers (Psotka et al., 1988). ITS incorporates built-in expert systems to monitor a learner's performance and personalize instructions based on adaptation to the learners' learning style, current knowledge level, and appropriate teaching strategies in e-learning systems (Phobun & Vicheanpanya, 2010). Walonoski and Heffernan (2006, as cited in Hwang et al., 2012) pointed out that Intelligent tutoring systems are such learning systems that provide personalized learning supports or feedback to help individual students improve their learning performance based on their personal information, such as the records in their profiles or learning portfolios. They discussed the adaptive learning systems could be viewed as a special kind of intelligent tutoring system that adapts the presentation of educational materials to students' needs.

Canfield, Kaklauskas et al., Woo et al. (2001, 2006 as cited in Wang & Liao, 2011) explained that adaptive learning systems that are implemented in the context of computer-mediated instruction are called intelligent tutoring systems (ITSs), and ITSs dynamically adapt the learning content, the pedagogical model, and human–computer interaction to the objectives, needs, and preferences of individual users for effective learning and teaching. However, they do not explain why they needed to differ ITS instead of claiming it as a supportive tool to adapt/personalize the learning. By collecting students' learning styles, preferences, and performances by tracking their knowledge, work, and feedback, the system can make inferences from students' learning strengths and weaknesses to suggest additional work (Kaklauskas et al., 2006; Woo et al., 2006). Furthermore, ITS has always been used in e-learning and long-distance learning, not in blended classroom instruction. We do not see a need for separating a learning approach for distance learning versus in-class learning anymore.

Data mining and learning analytics

Zhu and Guan (2013) suggested that two applications that provide big data in education are data mining and learning analysis. These two applications are expected to collaborate on promoting learning by using registered learning data more effectively in evaluating learning methods, predicting anticipated performance, and identifying possible problems.

LA can play an essential role in examining data collected from multiple learning environments, promoting customized activities according to different learners' needs and goals, contributing insights and perception into how learners function in these environments and how to support the learners best in the process. LA allows promoting personalization by providing insights and understanding how learners learn and meet their goals and needs. Chatti and Muslim (2019) also pointed out the increased interest in LA to promote personalized learning. Siemens (2010, as cited in Zhang et al., 2018) defined learning analytics (LA) as the use of learners' data and analysis models to identify information and social connections and predict and guide learning. Zhang et al. (2018) supported the idea of LA and SLEs.

Another approach that allows personalizing the learning is learner profiles, which aim to portray the individual characteristics of each learners' strengths, preferences, motivations, etc.; competency-based progression evaluates the learners' progress by continuously measuring the proper completion of the learner's learning objectives; personal learning is to provide a learner with a path to personal advancement; flexible learning environment as a flexible and intelligent learning environment can provide adequate support for the adaptive modification of teaching strategies.

Wearable devices

Borthwick et al. (2015, as cited in Xie et al., 2019) brought up that wearable personal learning, 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, individual learning data acquisition can be used for artificial intelligence to acquire content-specific knowledge and skills. They also pointed out that higher order thinking skills and communication have attracted little attention in terms of both learning outcomes and the process of personalized learning due to the difficulty of measurement and the limited learning support types (Shemshack & Spector, 2020). Recently, virtual reality techniques have started to support collaborative and immersive learning environments, which will increase the possibility of cultivating higher order thinking skills and communication in personalized systems soon.

Moreover, all these systems assert the goal-driven personalized learning that is a cyclical process and composed of different dynamic phases. Although using different labels, all approaches share typically identifiable phases that include goal setting by analyzing tasks, planning, activating goals, self-motivation, executing performance, and evaluating through self-reflection, feedback, monitoring, controlling, appraisal, regulating, adapting, and reacting (Panadero, 2017).

Discussion

Current personalized learning models heavily rely on technology, which allows us to implement personalized learning in our current learning environments with less effort. Machine learning, data mining, and human behavior are determining factors that shape personalized learning. Among many different models and systems that focus on personalized learning experiences for all, it is found that they all based on each human being is unique, so their needs are. As a result, there have been attempts to personalize the learning by considering individuals' specific differences (Shemshack & Spector, 2020). The most used component for personalized learning is learning style. Graf et al. (2009) argued that even though learning styles have been a controversial topic, the learning style models agree that learners have different ways in which they prefer to learn.

Furthermore, many educational theorists and researchers consider learning styles as an essential factor in the learning process. They agree that incorporating learning styles in education has the potential to facilitate learning for students. Graf and Kinshuk (2006) suggested that detecting learners' needs (learning style) is challenging but essential for providing learning adaptivity. While Hwang et al. (2013) found that even learning style improves learning, it was observed that if the choice was given to learners, they did not choose the learning style that helped them learn better.

This finding raises the question that should control over their learning style be given to learners, or should the data collected from learners determine the learning style? Several studies and learning theories showed that when the learner was given control over their learning, they learned better; however, we need to define what it means to give control to the learner. Self-pacing learning is one way to give control to the learner, which is found to improve learning while giving control over how to learn did not end up with learners to choose the right learning style for themselves.

As a result of the focus of this study what components need to be included in a comprehensive, personalized learning approach, it was concluded that one of the components that most educators and researchers agreed upon is allowing students to learn at their own pace, which is a strength and advantage that personalized learning provides. While self-pacing learning seems to be one of the critical components of personalized learning systems, which has been proven to increase learning, learner needs and previous knowledge are the main goals to provide content accordingly to learners. Adapting content according to the learner's responses allows the learner to interact and choose the content. Furthermore, learning profiles that considered personality and cognitive styles showed the importance of including personality and cognitive styles in personalized learning approaches. Panadero (2017) claimed that self-regulated learning (SRL) is one of the most critical areas in education; however, there is no clear definition of how SRL should look and how to empower the learner self-organize the learning materials. Cognitive type: engagement, cognitive processing habits, personal relevance, choice, and learner responsibility; cognitive styles: prior knowledge and learning style; and non-cognitive factors such as gender, mood, learning motivation, interest, learning habits, and personal styles are other learning characteristics that have been considered for different personalized learning systems.

Similarly, as different personalized systems were analyzed to find out the similarities and differences of used components of personalized learning approaches, it was found that while at first cognitive components were the focus of for personalized learning systems such as learning styles and self-pacing were main components considered, the focus of researchers have broadened to non-cognitive components as we learned more about human learning. The cognitive components used for personalized learning are listed in Table 1, and non-cognitive components are listed in Table 2 to provide a more systemically presentation of the results described and evaluated.

Furthermore, the following analysis helped compare different personalized learning models, so any relationship between used systems/models and components could be identified. Peng et al. (2019)'s definition of personalized learning as a technology-empowered effective pedagogy that can adaptively modify teaching strategies timely based on real-time monitoring, which is enabled by smart

Table 1 The summary of cognitive components used for personalized learning

Cognitive components	
Assessment	Chatti and Muslim (2019), Peng et al. (2019)
Ability	Ehrman (2001), Ehrman and Oxford (1995), Liu and Yu (2011), Reiff (1992)
Feedback	Chatti and Muslim (2019), Curry (1991), Kaklauskas et al. (2006), Peng et al. (2019), Psotka et al. (1988), Shaughnessy (1998), Walonoski and Heffernan (2006), Wang and Liao (2011)
Adaptive content delivery	Canfield (2001), Kaklauskas et al. (2006), Lee et al. (2018), Miliband (2006), Phobun and Vicheanpanya (2010), U.S. Department of Education (2017), Woo et al. (2006)
Learner engagement	Borthwick et al. (2015), Curry (1991), Erumit and Cetin (2020), Panadero (2017), Shaughnessy (1998), Wang and Liao (2011)
Cognitive processing habits	Curry (1991), Panadero (2017), Shaughnessy (1998), Wang and Liao (2011)
Learning styles	Atkinson (2006), Graf and Kinshuk (2006), Hwang et al. (2013), Kaklauskas et al. (2006), Panadero (2017), Phobun and Vicheanpanya (2010), Tseng et al. (2008), Wang and Liao (2011)
Cognitive styles	Chen et al. (2016), Panadero (2017), Triantafillou et al., 2003, Wang and Liao (2011)
Learner choice	Erumit and Cetin (2020), FitzGerald et al. (2018), Panadero (2017), Scanlon et al. (2012)
Personal relevance	FitzGerald et al. (2018), Panadero (2017), Scanlon et al. (2012)
Learner responsibility	FitzGerald et al. (2018), Panadero (2017), Scanlon et al. (2012)
Self-reflection and self-regulation	Canfield (2001), Chatti (2010), Chatti and Muslim (2019), Kaklauskas et al. (2006), Woo et al. (2006), Peng et al. (2019), Panadero (2017)
Prior knowledge	Chen et al. (2016), Kaklauskas et al. (2006), Panadero (2017), Phobun and Vicheanpanya (2010)
Flexible pacing	Sturgis and Patrick (2010), Lee et al. (2018), Miliband (2006), U.S. Department of Education (2017)

Table 2 The summary of non-cognitive components used for personalized learning

Non-Cognitive components	
Gender	Atkinson (2006), Chen et al. (2016), Panadero (2017), Wang and Liao (2011)
Learning motivation, concentration degree	Chatti and Muslim (2019), Curry (1991), Liu and Yu (2011), Panadero (2017), Peng et al. (2019), Shaughnessy (1998), Tseng et al. (2008), Wang and Liao (2011)
Mood	Liu and Yu (2011), Panadero (2017)
Learning habits	Li et al. (2013), Panadero (2017)
Interest, emotions; confusion, engagement, frustration, boredom, curiosity, etc., preferences	Calvo and D'Mello (2010), Canfield (2001), FitzGerald et al. (2018), Kaklauskas et al. (2006), Lee et al. (2018), Liu and Yu (2011), Miliband (2006), Panadero (2017), Scanlon et al. (2012), Woo et al. (2006)
Personal styles, individual characteristics, personality, learner profiles	Gomez et al. (2014), Lee et al (2018), Miliband (2006), Liu and Yu (2011), Panadero (2017), Peng et al. (2019), Triantafillou et al. (2003), Walonoski and Heffernan (2006)
Individual academic performance	Ehrman, (2001), Ehrman and Oxford (1995), Reiff (1992), Kaklauskas et al. (2006), Peng et al. (2019), Sturgis and Patrick (2010), Tseng et al. (2008), Walonoski and Heffernan (2006)
Needs	Canfield (2001), Gomez et al. (2014), Graf and Kinshuk (2006), Hwang (2014), Kaklauskas et al. (2006), U.S. Department of Education (2017), Woo et al. (2006)
Awareness	Chatti and Muslim (2019), Peng et al. (2019)
Personalized recommendation	Chatti and Muslim (2019), Peng et al. (2019)
Personalized learning path	Sturgis and Patrick (2010)

technology that considers learners' differences changes in individual characteristics, individual performance, and personal development summarizes the components and elements of personalized learning very well. This definition clarifies that technology tools have a significant role in personalized learning systems by collecting learners' data and seamlessly feeding the data into each function.

SLEs and LA are essential tools to allow learners to meet their learning goals by providing tools that promote awareness, recommendation, self-reflection, assessment, feedback, and motivation, which are essential components of personalized learning. Also, LA can play an essential role in examining data collected from multiple learning environments, supporting customized activities according to different learners' needs and goals, contributing insights and perception into how learners function in these environments, and how to empower the learners best in the learning process. LA allows personalization by providing insights and understanding how learners learn and meet their goals and needs by connecting the previous history of each learner's data.

Another system that supports personalized learning experience is intelligent tutoring systems (ITS), which employ computational algorithms or models to deliver immediate feedback and learning instructions to learners without human teachers (Psotka et al., 1988). Intelligent tutoring systems (ITSs) dynamically adapt the learning content, the pedagogical model, and human–computer interaction to the objectives, needs, and preferences of individual users for effective learning and teaching by collecting students' learning styles, preferences, and performances by tracking their knowledge.

Two main applications that provide big data in education are data mining and learning analysis. These are two approaches that allow personalizing the learning by using learner profiles, which aim to portray the individual characteristics of each learners' strengths, preferences, motivations, etc.; competency-based progression evaluates the learners' progress by continuously measuring the proper completion of the learner's learning objectives; personal learning is to provide a learner with a path to personal advancement; flexible learning environment as a flexible and intelligent learning environment can provide adequate support for the adaptive modification of teaching strategies.

All these systems and tools would be exemplified by the holistic personalization element and have a high level of sophistication, considering many learning characteristics that can help personalized learning by capturing learner data and modeling their emotions via facial recognition, processing voice-recorded data, sentiment analysis of student comments, and heart rate detection using video cameras.

It is observed that, as Miliband (2006, as cited in Lee et al., 2018) argued, the goal of personalized learning is to help and support everyone to reach their maximum potential by customizing instruction, including content, instruction delivery, and the pace at which it is learned, to meet unique needs, such as diverse student characteristics and interests of learners by considering the most common components have been used for different personalized learning systems.

Furthermore, ITS provide significant support to create dynamic, evolving personalized learning environments that are cyclical and gather data from learner by creating learning profiles that are created by learning analytics. Ongoing input from learner attitudes and patterns allows ITS to adjust the learning activity and content to be adjusted according to the data collected, such as the learner's mood, previous knowledge, skills, motivation, gender, interests, abilities, learning pace, and learning behaviors.

Gomez et al. (2014) stated that the key benefits of a personalized learning approach are that learners are provided with adaptive and personalized learning experiences tailored to their educational needs and personal characteristics to maximize their satisfaction, learning speed, and learning effectiveness. Learning effectiveness is one of the results we have been hoping for, for centuries, and improvements in learning effectiveness motivate us to look for how to improve it more. The research progress in personalized learning shows that as technology develops, personalized learning takes advantage of the benefits technology can offer that increase the components that can be considered to personalize the learning. However, some concerns need to be considered while collecting data from learners, such as privacy concerns and keeping the data collected from individuals safe.

Chatti and Muslim (2019) pointed out that personalized learning models are labeled differently; they all in core assert the goal-driven nature of personalized learning and view personalized learning as a cyclical process composed of different phases.

Limitations

This study had several shortcomings during the review and in its attempt to answer all the research questions. The literature review is a time-consuming process and labor-intensive approach, and especially with personalized learning, there is an enormous number of studies available. The tremendous number of published papers might lead to missing relevant papers as many literature review studies face this problem. Moreover, the extensive effort to construct a search by identifying relevant keywords is critical for the search process. The keyword determination process was conducted using a snowballing process from related studies to identify the reflections or keywords relevant to this study, and it might be subjective. Overlooking articles by omitting important information or keyword combinations is likewise possible due to the authors' limited time frame and misinterpretations.

Nonetheless, this study also confronts the possible limitation originated by the selection criteria. For example, this study focused on only journal articles and was limited to only documents written in English and studies published between 2010 and 2020. Therefore, other pertinent articles that are not written in English and were not published in selected journals or within the same timeline might not have included.

Future research directions and conclusion

Our findings revealed that the range of components being used to personalize learning is widening as technology develops. As we learn more about human learning and what technology can provide us to personalize learning experience, such as gathering data of learners' emotions by using bio-trackers, which might bring up some privacy concerns, we are redefining our understanding of personalized learning. Future research can focus on what privacy concerns we might face and address those concerns and protect learners' privacy.

In conclusion, this study found that a unified evolving personalized learning approach would consider four main components: learner profiles, previous knowledge, personalized learning, and a flexible self-paced learning environment that generates a personalized learning path according to provided dynamic learning analytics. This paper presents a clear understanding of personalized learning components, models, and approaches. This study serves to contribute to future studies and practices on personalized learning and learning in general.

This study's findings support that personalized learning has become a fundamental learning paradigm in the research community of educational technologies. Firstly, the current trends are presented as they relate to the Research Questions;

then, the future direction and limitations are discussed. The study shows that using personality traits and their identification techniques has an enormously positive influence in personalized learning environments.

This study is related to several significant psychology, education, educational, and computer science domains. Likewise, it reveals the integration of personal traits in the adaptive learning environment, which involves many personality traits and identification techniques that can improve learning. Also, it found that there is an increase of interest in two areas that are oriented towards the incorporation and exploration of significant data capabilities in education: Educational Data Mining (EDM) (Shemshack & Spector, 2020) and LA. According to Papamitsiou and Economides (2014), EDM and LA communities seem to add another approach to personalized learning and make it easier modify the learning according to individuals.

Personalized learning for everyone looks different according to the needs, goals, interests, skills (Shemshack & Spector, 2020), and many other individual components throughout the paper. Ennouamani et al. (2020) argued that learners are diverse in terms of their needs, knowledge, personality, behavior (Shemshack & Spector, 2020; Pliakos et al., 2019), preferences, learning style, culture, and the parameters of the mobile devices that they use.

This study has answered some critical research questions, including different components used with personalized learning and systems and models that lead to efficient, effortless personalized learning. Also, some research issues and potential future development directions are presented. According to the discussions and current trends, it was found that personalized learning systems seem to evolve as technology develops. These components may evolve as we learn more about human–machine interaction and learn to use technology to improve learning experiences (Shemshack & Spector, 2020). We suggest that researchers use the components reviewed in this study to guide future studies on the impact of personalized learning on student learning and performance.

To sum up, this study discussed different components used for personalized learning models in detail and how personalized learning evolves as technology develops, and we learn more about human–machine interaction.

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Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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