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A Systematic Literature Review on Personalised Learning in the Higher Education Context

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Abstract

Personalised learning (PL) is learning in which the stage of learning and the instructional approach are optimised for the needs of each learner. The concept of PL allows e-learning design to shift from a 'one size fits all' approach to an adaptive and student-centred approach. This paper aims to provide a literature review of PL based on: the PL components used to analyse learner diversity, the PL features offered, the methods used in developing the PL model, the resulting model, the learning theories applied and the impact of PL implementation. Thirty-nine out of 1654 articles published between 2017 and 2021 which were found by Kitchenham method were studied and analysed. The results are derived from synthesized through qualitative synthesis using thematic analysis. The results reveal that most of the articles used knowledge level and learner characteristics to analyse learner diversity. The teaching materials and learning path were the most widely offered PL features in PL model. There is a trend in determining PL features using the knowledge graph method and the use of machine learning classification algorithms to analyse learner diversity. The results also show that PL implementation improves learning outcomes and increases learner's satisfaction, motivation, and engagement. Research analysing the impact of PL implementation on learning is limited. In addition, only a few studies explicitly referred to learning theory in relation to PL model development. Further research topics are suggested.

Keywords Personalised learning · Adaptive learning · Personalised model · Personalised component learning · Learning strategy

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1 Introduction

Personalised learning (PL) is learning in which the stage of learning and the instructional approach are optimised for the needs of each learner (Xie et al., 2019). The concept of PL allows e-learning design and implementation to shift from a 'one size fits all' approach to an adaptive and student-centred approach (Hoic-Bozic et al., 2016). PL focuses on personalising learners in a model and using that model in conventional e-learning design. This personalisation is reasonable because learners are diverse in terms of, for example, their learning style, approach to learning and orientation to studying, and intellectual development (Felder & Brent, 2005).

The study of PL has developed rapidly in recent years. This can be seen in the number of studies and publications in this field since 2017. To gain an understanding of the development of PL studies, several literature reviews have been carried out. For example, a review conducted by Raj and Renumol (2021) discusses teaching content on recommender systems as a form of PL. Rodriguez and Martinell (2019) also reviewed recommender systems as a form of PL. Xie et al. (2019) and Shemshack and Spector (2020) discuss PL from a technology perspective. Shemshack & Spector (2021) also reviewed the components used in PL. Chen and Wang (2020) conducted a review of studies on individual student differences and how they relate to PL. Another review by Zawacki-Richter et al. (2019) and Costa et al. (2019) discussed how Artificial Intelligence applied in higher education can be beneficial in the context of PL; while Zhong et al. (2020) emphasized deep learning-based PL recommendation. Alamri et al. (2020) emphasized technological models that support PL within blended learning environments. Maier and Klotz (2022) discussed personalised feedback as PL aspect of digital learning environments. However, those literature reviews addressed only area- or topic-specific; each review addressed one specific topic of PL (i.e., recommender system, technology, student differences, and Artificial Intelligence implementation). Only a few systematic reviews covered broader aspects of PL, such as the review by Bernacki et al. (2021) and Li & Wong (2021). Bernacki et al. (2021) discussed who studies PL; what populations of learners have been studied PL; and what learner characteristics and design elements have been investigated in PL studies. Li & Wong (2021) conducted a review to identify what aspects of learning have been personalised, how PL has been practiced, and what are key success factors in implementing PL. However, both studies discussed PL in the general context, not in the higher education context. It is necessary to get a more complete picture of PL implementation in higher education to identify the trends, development, and potential future research directions. Therefore, this systematic review of the literature on PL aims to analyse and summarize research in the field of PL on a broader aspect, from the component to the impact of PL implementation in higher education context. Specifically, this review will discuss the following: PL components the studies used to analyse learner's diversity, the PL features offered in the PL model, the methods the studies used in developing each PL model, the resulting model or framework, the learning theories applied and the impact of PL implementation on the learning process. It is hoped that this literature review can provide a broad overview of PL research and provide direction for further research in this field.

Related to the objective of the current study, the review questions (RQ) in this literature review are:

RQ1: What PL components are used in the PL model in the higher education context?
RQ2: What PL features are offered in the PL model in the higher education context?

RQ3: What methods are used for developing the PL model in the higher education context? What are the most frequently used methods for developing PL models in the higher education context?
RQ4: What are the models/frameworks offered/produced in the PL model in the higher education context?
RQ5: What learning theories underpin the development of the PL model in the higher education context?
RQ6: What are the learning impacts of the implementation of the PL model in the higher education context?

2 Relevant Literature

2.1 Personalised Learning

The concept of PL has deep roots in the world of education. Jean-Jacques Rousseau in the 1700s and John Dewey in the first half of the 1900s are often credited with being the forefathers of PL (Yonezawa et al., 2012). In the early 1900s, Dewey "promoted the idea of building on students' interests and incorporating outside experiences into education to meet students' individual needs" (Yonezawa et al., 2012, p. 10). In 1919, inspired by the progressive ideologies of John Dewey and Maria Montessori, Helen Parkhurst developed the Dalton Plan, a new school model designed to tailor each student's programme to his/her needs, interests, and abilities.

In the 1980s, Theodore Sizer launched the Essential Schools Coalition, which was based on nine general principles, one of which was the fulfillment of learning objectives through learner personalisation. In 2010, a national symposium on "the need for a redesign of the basic education system to a system centered on the personalised learning needs for each student" (Wolf et al., 2010, p. 5) was organised by the Software & Information Industry Association and the Council of Chief State School Officers CCSSO.

Keifer and Effenberger (1967) stated that PL is a student-driven learning model in which students are deeply involved in determining the desired learning objectives/outcomes. PL can be incorporated through the design of the curriculum and its implementation to evaluation of the curriculum. The curriculum can be designed to be tailored by knowing the background of the students (Ferguson et al., 2001). Powell and Kusuma (2011) note that the challenge facing today's teacher is to teach each unique student in a global classroom situation. The key is to know the students with all their different interests, cultures, backgrounds, intellectual abilities, and learning styles.

There are several learning theories underpinning PL, namely humanism learning theory, constructivism, connectivism, and collaborative learning (Jones & McLean, 2018; McLoughlin, 2013; Xiaoqiong et al., 2013). Humanism learning theory proposed the concept of learning objectives of unifying knowledge and emotions and the concept of a student-centered learning model (Xiaoqiong et al., 2013). In this theory, feelings and knowledge are both important to the learning process and should not be separated. Learners were encouraged to take control of their education. This theory fosters engagement to inspire students to become self-motivated to learn (Western Governors University, 2020).

Constructivism learning theory states that learning is a personal construct process, learners construct personal knowledge from the learning experience itself. Therefore learning is an active process and learners are given more opportunities to develop their knowledge rather than just being given instructions (Ertmer & Newby, 2013; Mödritscher, 2006). One of the famous constructivists is Lev Vygotsky with his sociocultural theory. This theory states that knowledge is built through the learner's social interaction with the environment. Collaborative learning in PL is strongly related to this theory.

Connectivism has emerged as a key concept in the information age and assumes that learners have ubiquitous access to network technologies. This theoretical approach focuses on establishing and maintaining network connections that are relevant, updated, and flexible enough to support student-centered learning. Connectivism also assumes that the role of the learner is not to memorize everything but to have the capacity to find and apply knowledge when and where it is needed (McLoughlin, 2013).

2.2 Learner Diversity/Differences

Considering the literature on the concept of PL described in the previous section, it can be concluded that the foundation of PL is an understanding of the uniqueness of and differences between individual learners. Therefore, it is important to discuss the diversity of learners. Felder & Brent (2005) states that learner diversity can be seen through three important aspects: their learning styles; approaches to learning and orientations to studying; and intellectual development.

Learning styles are defined as cognitive, affective, and psychological characteristics that act as indicators of how students perceive, interact with and respond to their learning environment (Keefe, 1979 as cited in Felder & Brent, 2005). For example, some learners are appropriate with theories; others prefer learning with facts and observable phenomena. Some learners prefer active learning and others make reflection; some prefer visual presentation of information and others prefer verbal explanations.

Many learning style theories can be used to analyse learner diversity. A review conducted by Chen and Wang (2020) shows that the models of learning styles that are widely used in the analysis of learner diversity are the Felder-Silverman learning style model, Honey and Mumford's learning styles model, the model determined by the Myers–Briggs Type Indicator and Fleming's Visual, Aural, Read/Write and Kinesthetic (VARK) learning styles model.

Despite widespread and appealing usage of learning style, there are arguments against learning style and its implementation in learning due to lack of empirical and scientific evidence. Several studies state that learning style is a myth (Furey, 2020; Kirschner, 2017; Newton, 2015; Newton & Miah, 2017). Some weaknesses that have been criticized in learning styles used in learning are (1) there is no adequate scientific evidence to support the effectiveness of using learning styles in learning (Kirschner, 2017; Pashler et al., 2009), (2) validity and reliability for the learning style measurement of often shows inconsistencies (Kirschner, 2017). Some learning-style studies even use appropriate methods but have negative results (Constantinidou & Baker, 2002; Cook et al., 2009; Massa & Mayer, 2006; Rogowsky et al., 2015).

Nevertheless, the use of learning styles in the PL design is still carried out by researchers. Several studies have stated empirical evidence on the significance of using learning styles in the PL application to the learning process, such as (1) improving/optimizing learning outcomes (Deng et al., 2018; Joseph, 2019; Laksitowening, 2020; Sfenrianto, 2014; Sihombing et al., 2020); (2) increasing student satisfaction in using e-learning (Bourkoukou & Bachari, 2018; Jeevamol & Renumol, 2021; Nafea et al., 2019); (3) improving/

optimizing the learning process (Laksitowening, 2020; Sfenrianto, 2014; Sweta & Lal, 2017); and (4) make the self-learning process more effective and efficient (Saleh & Salama, 2018).

According to Felder & Brent (2005), another term of learner diversity is the orientation to studying which is strongly related to the approach to learning. Learners can have a surface approach, a deep approach, or a strategic approach. Learners with a surface approach learn something with memorize facts but do not try to fit them into a larger context. These learners commonly exhibit an extrinsic motivation to learn. The learners who have a deep approach not only memorize something but also focus on understanding it. They have an intrinsic motivation to learn. Learners with a strategic approach do whatever to get the best grade. They are well organized and efficient in their studying. Each approach has different orientation to studying. An orientation to studying is a tendency to adopt one of the approaches in a broad range of situations and learning environments (Ramsden, 2003, as cited in Felder & Brent, 2005). According to Felder & Brent (2005), the learners who adopt a surface approach have a reproducing orientation; those who adopt a deep approach have a meaning orientation; while those with a strategic approach have an achieving orientation. We can see that the orientation to studying describes learning objectives, motivation, and engagement in learning. Therefore, this orientation to studying is closely related to the metacognitive aspect such as planning and self-monitoring.

Analyse learner diversity can also be conducted based on the cognitive aspect of learners such as learner's level of knowledge. For example, classification of learner into beginner, intermediate, or advanced knowledge level. In a review of learner diversity in the PL context, Chen and Wang (2020) suggested that several studies used not only learning styles as aspects of learner diversity but also combined with learner's level of knowledge.

2.3 Personalised Learning Model

Personalization cannot take place without technology. PL is enabled by PL systems (Wolf et al., 2010). The development of the PL concept and the web technologies that support it as well as the development of big data and deep learning technologies have brought changes to the field of e-learning (Hoic-Bozic et al., 2016). Developing PL system begins with developing PL model.

The authors have defined some terminologies to be used in this paper to explain the content better and easier:

(1) A PL component is defined as aspects of a learner that is used in analysing learner diversity/differences. From this analysis, we can classify the learner.
(2) A PL feature is an aspect of learning and teaching that is personalised as a learning strategy given to learners according to their classification.
(3) Learner model is learner classification based on its PL component. For example, the classification of learner based on their knowledge level will form a learner model with three categories: a basic, middle, or advanced learner.
(4) A PL model is a model that describes how PL was conducted by providing the PL features to learners according to their classification.
(5) A PL system, a personalised learning system developed based on the PL model. The system can generate learning strategies for personalising learners' learning according to their classification.

From the review of studies on PL, it can be concluded that the development of a PL model generally includes two major stages: (1) the analysis of learner diversity/differences and (2) the development of PL features. Stage one generates a learner model, while stage two generates a PL feature. Both a learner model and a PL feature will form a PL model. Stage one begins with classifying learners based on the diversity/differences described in Sect. 2.2. The classification mechanism can be done by using a conventional approach such as using a questionnaire (Sanjabi & Montazer, 2020; Sihombing et al., 2020) or an automated approach with the help of deep learning technology (Anantharaman et al., 2019; Garrido et al., 2016; Gu et al., 2017; Han et al., 2018; Jagadeesan & Subbiah, 2020; Lagman et al., 2020). The PL model will then be developed into a PL system.

This paragraph describes a study by Sihombing et al. (2020) as an example of developing a PL model and its implementation into a PL system (e-learning). Sihombing et al. (2020) developed e-learning for providing personalised learning content based on learners' learning style. The study classified learners based on their learning styles according to FSLSM (Felder-Silverman Learning Style Model). The FSLSM consists of four categories (Felder & Silverman, 1988), grouped learners into the following: (1) sensing or intuitive learners, based on how information is perceived. Sensing learners tend to perceive information in the form of data or facts, while intuitive learners tend to perceive information in the form of a theory or concept; (2) visual or verbal learners, based on information-reception. Visual learners learn best by seeing while verbal learners learn best by reading; (3) active or reflective learners, based on how information is processed. Active learners learn by doing activities, while reflective learners learn by watching or observing activities; and (4) sequential or global learners, based on how information is understood. Sequential learners like to be presented with information in a sequential perspective, while global learners, which not really care about the order like to learn holistically. Classifying learners generate a learner model (i.e., a learner with his/her learning style).

Sihombing et al. (2020) then used learning content as a PL feature. Learning content is categorized into several types based on FSLSM, for examples: (1) sensory-visual material-content, to accommodate learning content for sensory and visual learners, and (2) sensory-verbal material-content to accommodate learning content for sensory and verbal learners; and so on. This step generates PL features. To implement PL model and PL features into PL system (e-learning), Index Learning Styles (ILS) questionnaire is integrated into the e-learning system to classify learners. An algorithm then is embedded in the e-learning system so the users (learners) get learning content and have a learning flow according to their learning style.

3 Methodology

The method used in this systematic literature review (SLR) was adapted from the Kitchenham methods version 1.0 and 2.3 (Kitchenham, 2004; Kitchenham & Charters, 2007). According to Kitchenham, there are three stages in SLR process, namely, planning, conducting, and reporting.

The planning stage includes the identification of SLR needs and the preparation of a review protocol. SLR needs include topics that will be explained or elaborated on through the literature study which are stated in the review question(s) (RQ). The review protocol includes a literature search strategy, the type of literature to be selected, quality test checks, data extraction strategies, and data synthesis strategies.

The conducting stage includes study selection criteria, study selection process, study quality assessment, data extraction, and data synthesis. The reporting stage involves writing up the results of the review. The conducting stage is discussed further in the following subsection.

3.1 The Study Selection

The study selection consists of three phases: the initial search; the title and abstract selection; and the selection of the entire text. The strategy employed for the initial search was to identify conference proceedings and journal articles ranked Q1 and Q2 (based on Scimago journal rankings). Since PL implementation is closely related to the use of ICT, to maintain the latest technology and methods used, the literature to be searched was limited to the last five years from various sources: IEEE Xplore, ACM Digital Library, SpringerLink, Science Direct, and Scopus. The literature search was conducted using the boolean string ("personalized learning" OR "personalized e-learning" OR PL OR "personalized online learning") AND (model OR framework OR technique OR application OR implementation OR concept).

The inclusion and exclusion criteria were applied to those three phases of selection. The initial search, title and abstract selection, and entire text selection were conducted by Rida Indah Fariani and validated by Kasiyah Junus and Harry Budi Santoso. The detail of inclusion and exclusion criteria is shown in Fig. 1. The next phase is performing a quality test for the selected studies.

3.2 Assess the Study Quality

In the next phase, a quality test was performed by checking the completeness of the selected studies. The quality test questions were (1) Does the article clearly describe the research objectives?; (2) Does the article include a literature review, background, and research context?; (3) Does the article display related work from previous research to show the main contribution of the research?; (4) Does the article describe the proposed model

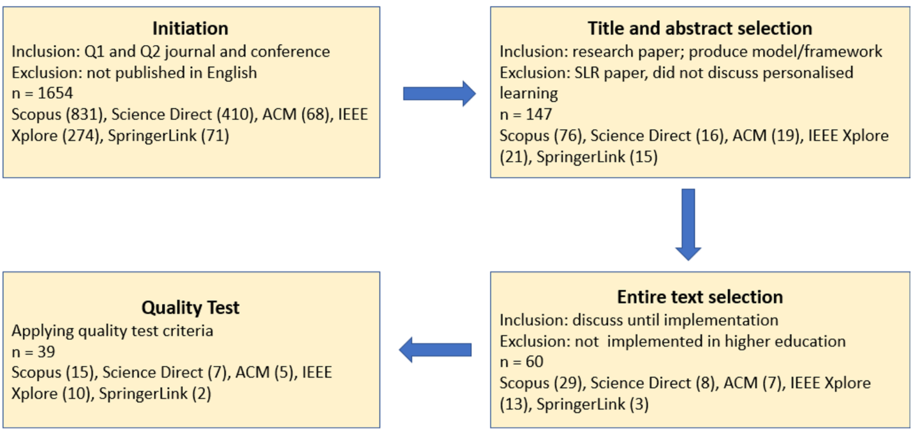


Fig. 1 The selection process of the articles to be analysed

architecture or the methodology used?; (5) Does the article have research results?; (6) Does the article present conclusions that are relevant to the research objectives/problems?; and (7) Does the article recommend future work or improvements for the future? Only articles that met these seven criteria were included in the review. The overall selection process and the number of articles for each stage are described in Fig. 1. Of the initial 1,654 articles selected, 39 articles met the selection criteria and were included in the analysis.

3.3 Data Analysis

To analyse the selected studies, data extraction and synthesis were performed on the selected 39 studies. Data were extracted into a table for comparison to cater RQs: the PL components used to analyse learner diversity, the PL features offered, the methods used in developing the PL model, the resulting model, the learning theories applied, and the impact of PL implementation. Once the data were extracted, data synthesis was performed.A qualitative synthesis was conducted using thematic analysis with the inductive approach. Thematic analysis is a "method for identifying, analysing, organising, describing, and reporting themes found within a data set" (Nowell et al., 2017, p. 2). The inductive approach was used since deriving meaning and creating themes from the data without any preconceptions (Crosley, 2021). An inductive approach means the themes identified are strongly linked to the data themselves. Therefore the coding process of the data is data-driven. This coding process is conducted without trying to fit it into a pre-existing coding frame (Braun et al., 2006).

Thematic analysis was performed for each data extracted in relation to the research questions and was guided by the phases proposed by Nowell et al. (2017): familiarising with data, generating initial codes, identifying themes, reviewing themes, defining and naming themes, and reporting the results. Lists of phrases from the data extracted were generated and developed into codes by Rida Indah Fariani. For identifying themes, similar coded-phrases were grouped to form a preliminary themes. During the reviewing theme phase, the preliminary themes were reviewed whether they form a specific theme. The sub-themes, which are the detail of the specific themes were also identified. The themes and sub-themes are then named. All synthesis process was conducted by Rida Indah Fariani and verified by Kasiyah Junus and Harry Budi Santoso. Thus, all authors collaborated on coding and categorising the themes and sub-themes.

4 Results and Discussion

In this section, some statistics from the selected studies will be described and an analysis was conducted for addressing several aspects regarding predetermined RQ in Sect. 1.

Figure 2 shows the distribution per year of the 39 studies obtained from the selection process, and Table 1 describes the distribution of studies from the five academic resources. Overall, there has been a tendency to increase the number of publications on PL studies for the last five years. This indicates that PL is an attractive area in research.

Table 1 shows that most studies, 22 articles (56%), were published in journals, while 17 articles were published for conferences (44%). The source of the majority of the studies was Scopus, with 15 articles, followed by IEEE Xplore with 10 articles.

Fig. 2 The distribution of the selected research articles on PL from January 2017 to August 2021

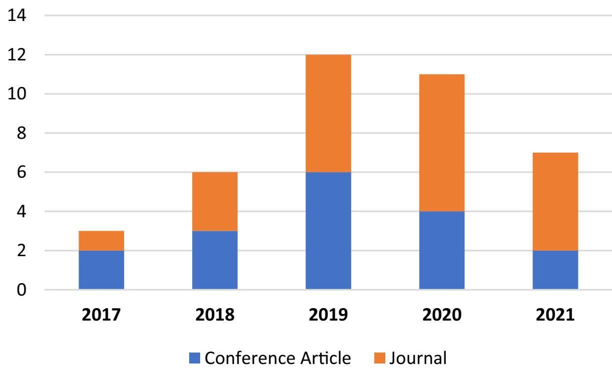


Table 1 The distribution of the selected studies in five academic resources

Resource	Type of Publication		Number of Studies
	Conference Articles	Journal	
Scopus	6	9	15
Science Direct	1	6	7
ACM Digital Library	4	1	5
IEEE Xplore	5	5	10
SpringerLink	1	1	2
Total	17	22	39

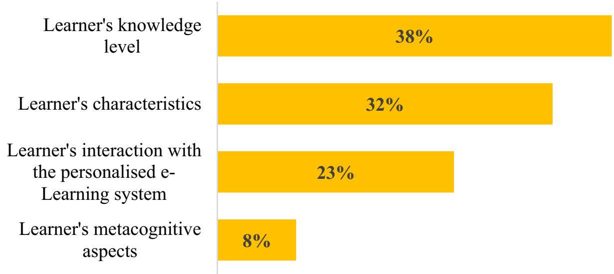
4.1 Addressing RQ1: What PL Components are used in the PL Model in the Higher Education Context?

As defined in Sect. 2.3, the PL component is aspects of a learner that is used to identify learner differences. From the review, PL components can be classified into four major categories: the learner's knowledge level, characteristics, interaction with the personalised e-learning system, and metacognitive aspects.

The knowledge level is mainly used for determining the learners' knowledge level, both current and prior knowledge as background knowledge. The knowledge level was usually attained from the results of the assessment or feedback. Thus, knowledge level can be divided into sub-components, namely the learner's background/prior knowledge level, current knowledge level, and feedback results. Learner characteristics are mainly used for describing the learners and can be divided into the following sub-components (1) profile data, including gender, age, education, and demographic data; (2) learning style, and (3) learner personality. Personality is described as psychological characteristics which define people's behavior and cognitive style (Mount et al., 2005 as cited by Tlili et al., 2019). Personality, such as introvert or extrovert, is mainly used for game-based learning.

Interaction with e-learning is mainly for detecting learners' behavior and patterns dynamically by mining data learners when using e-learning. The data is usually obtained from server logs. Therefore, this PL component is used in PL research where case studies are carried out at institutions that have implemented e-learning. The sub-components

Fig. 3 The distribution of PL components used in analysing learner diversity



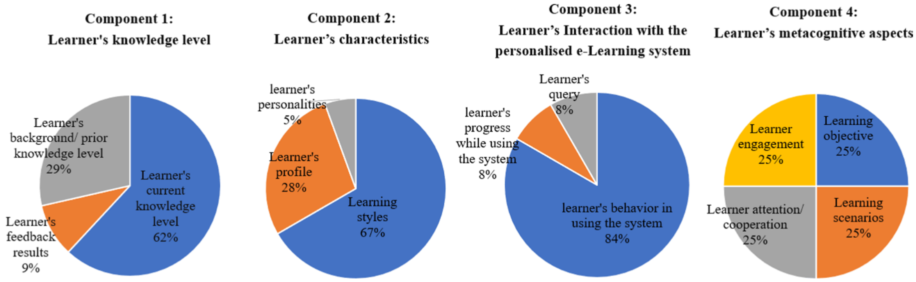


Fig. 4 The distribution of sub-components for each PL component

of learners' interaction with personalised e-learning are the learners' behavior in using the system, their progress while using the system, and learners' queries on the system. The learners' behaviors examples are (1) learning habits Bourkoukou & Bachari (2018), (2) learning activities like total learning time, frequency of forum posts, frequency of taking a topic or course (Cuong et al., 2018; Deng et al., 2019; Hidayat et al., 2020; Perišić et al., 2018; Syed & Nair, 2018), and (3) browsing history ().

Metacognition is defined as cognition about cognition or thinking about thinking, it is knowledge of one's thinking process (Dabarera et al., 2014). Metacognitive is a person's awareness, belief, and knowledge about the process and way of thinking to improve the learning process (i.e. learning objectives, learning strategies, learning engagement, and evaluation of whether the learning objectives have been achieved or not). The sub-components of learners' metacognitive aspects are learning objectives, learning scenarios, learner attention/cooperation, and learner engagement.

The learner's knowledge level was the most widely used PL component in the selected PL study (38%), followed by the learner's characteristics (32%), interaction with the personalised e-learning system (23%), and metacognitive aspects (8%) (Fig. 3). In terms of the learner's knowledge level, the learner's current knowledge level was the most widely used sub-component, and the learning style was the most widely used sub-component of the learner's characteristics (Fig. 4). These results show that despite many criticisms of learning styles and their implementation in learning, the learning styles remains one of the most widely used PL components today.

Summary of the PL components used in analysing learner diversity is shown in Table 2.

Some studies used a combination of PL components in analysing learner diversity. For example, Raj and Renumol (2021) used learning styles and learner's background/prior knowledge. Grivokostopoulou et al. (2019) and Huang and Shen (2018) used learning

Table 2 Summary of PL components used in analysing learner diversity

	PL Component	Studies
Learners' knowledge level		
1	Learners' current knowledge level	Araujo et al., 2020, Cagliero et al., 2019, Deng et al., 2019, Wang et al., 2021a, 2021b, Huang & Shen, 2018, Wang & Fu, 2021, Jeevamol & Renumol, 2021, Lagman et al., 2020, Muangprathub et al., 2020, Nafea et al., 2019, Troussas et al., 2021, Vanitha & Krishnan, 2019
2	Learners' background/prior knowledge level	Jeevamol & Renumol, 2021, Shi et al., 2020, Supic, 2018, Troussas et al., 2020, Troussas et al., 2021, Zhu et al., 2018
3	Learners' feedback results	Gu et al., 2017, Pliakos et al., 2019
Learners' interaction with e-learning		
1	Learners' behavior using the system	
	Bourkoukou & Bachari, 2018, Cuong et al., 2018, Deng et al., 2019, Wang & Fu, 2021, Hidayat et al., 2020, Perišić et al., 2018, Syed & Nair, 2018, Wang et al., 2021a, 2021b, Shou et al., 2020, Su, 2020	
2	Learners' progress using the system	Azcona et al., 2019
3	Learners' Query	Ibrahim et al., 2020
Learners' characteristics		
1	Learners' profile	Gu et al., 2017, Grivokostopoulou et al., 2019, Nafea et al., 2019, Pliakos et al., 2019
2	Learning style	Araujo et al., 2020, Bourkoukou & Bachari, 2018, Cuong et al., 2018, Deng et al., 2019, El Guabassi et al., 2018, Hidayat et al., 2020, Jeevamol & Renumol, 2021, Muangprathub et al., 2020, Nafea et al., 2019, Perišić et al., 2018, Shou et al., 2020, Wang et al., 2021a, 2021b
3	Learners' personalities	Tlili et al., 2019
Learners' metacognitive aspects		
1	Learning objectives	Wang & Fu, 2021, Zhu et al., 2018
2	Learning scenarios	Zhu et al., 2018
3	Learners' attention/cooperation	Araujo et al., 2020
4	Learner engagement	Zhen et al., 2021

styles and learner's current knowledge level. Deng et al. (2019) and Bourkoukou & Bachari (2018) used learning styles and interaction with the e-learning system.

4.2 Addressing RQ2: What PL Features are Offered in the PL Model in the Higher Education Context?

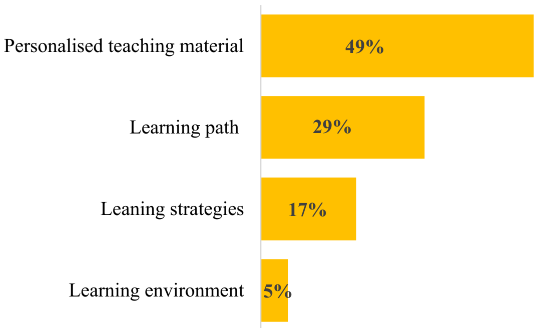
A PL feature is defined as an aspect of learning and teaching that is personalised as a learning strategy given to learners according to their classification. Based on in-depth analysis from the selected studies, there are four main PL features, namely, learning strategies, learning paths, personalised teaching materials, and learning environments. As shown in Fig. 5, personalised teaching materials were the most widely used PL features in the PL model (49%), followed by learning paths (29%), learning strategies (17%), and learning environments (5%).

Teaching material is learning objects that are used for teaching and learning. In this study, learning object is defined as a reusable learning resource having specific learning goals that can be utilised to support learning (Apoki, 2021). A learning path is a sequence of learning objects (concepts or activities) that is followed by a learner during the learning process (Cui & Wang, 2020). Learning strategies focus on strategies that facilitate the learning process for achieving success. Learning strategies can be instructional design (Bourkoukou & Bachari, 2018; Cuong et al., 2018), reward factors for increasing learners' motivation (Gu et al., 2017), recommendation of concept to study (Grivokostopoulou et al., 2019), learning suggestions, feedback, and scaffolding. Learning environment in this review means an environment for game-based learning such as game elements.

Each PL feature can be divided into sub-groups. The sub-groups of each PL feature are shown in Fig. 6. Personalised teaching materials can be further grouped by learning content, teaching guides, module topics, and teaching support. The learning strategy features can be grouped by scaffolding, learning suggestions, feedback, and personalised instruction. The learning environment features were mainly for game-based learning and can be grouped by suggested game peer and game elements. The summary of PL features in the studies' PL models is shown in Table 3.

Personalised teaching material was a commonly used PL feature in PL model. It is noteworthy that this review found that learning paths were also increasingly becoming a PL feature. Researchers have realised that the learning path has a great impact on learning quality (Shi et al., 2020). Shemshack & Spector (2021) concluded that most educators and researchers agreed on was facilitating students to learn at their own pace, which is an

Fig. 5 The distribution of PL features in the PL models



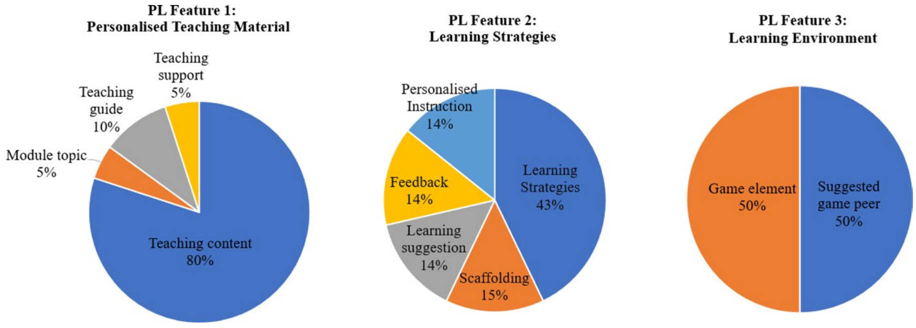


Fig. 6 The distribution of sub-group for each PL feature

advantage that PL provides. Thus the learning path is widely used as a PL feature due to its usefulness in supporting the flexibility of learning pace. Learning path for the fast learners will be shorter than the slow learners.

4.3 4.3. Addressing RQ3: What Methods are used for Developing the PL Model in the Higher Education Context? What are the Most Frequently used Methods for Developing PL Models in the Higher Education Context?

As explained in Sect. 2.3, most of the selected PL research included two major stages in the development of their PL models: (1) the analysis of learner diversity/differences and (2) the development of PL features. Therefore, the methods that will be discussed in this paper are related to these two stages, namely, (1) the methods for analysing learner differences (classifying learners based on their PL components to obtain the learner model) and (2) the methods used to generate PL features.

The most frequently used method to analyse learner diversity/differences was assessment (29%), followed by questionnaires (17%). In addition, several of the selected studies use machine learning algorithms, such as decision tree, k-means, classification, fuzzy logic, support vector machine (SVM), cluster analysis, k-nearest neighbor (KNN), long-short term memory (LSTM), and artificial neural network (ANN) to analyse learner diversity/differences. The methods used in analysing learner diversity/differences are shown in Fig. 7.

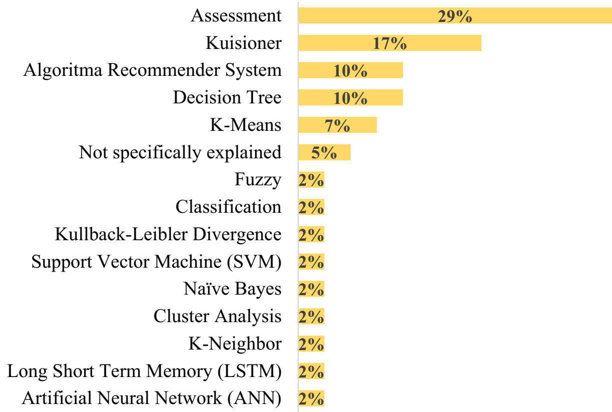
Almost half of the selected studies (49%) applied methods with machine learning algorithms to analyze learner diversity/difference. This result shows that the use of machine learning technology is increasingly being used in research in the PL field. Technology has a significant role in personalized learning systems by collecting learners' data (Shemshack & Spector, 2021). The machine learning algorithm is one such technology.

Having identified learner differences and diversity, the next stage is to generate the PL features. Figure 8 shows the method used in generating PL features in the development of the PL model from the studies. As can be seen in Fig. 8, the most frequently used method for generating PL features is the ontology/semantic web rules method (16%), followed by knowledge graph (13%) and fuzzy logic (13%). Other methods used were collaborative filtering, ant colony algorithm, decision tree, euclidian distance, rule-based SRL, content-based filtering, generalised sequential pattern, association rule

Table 3 Summary of PL features used in PL model

	PL Feature	Studies
Learning strategies		
1	Learning strategies	Bourkoukou & Bachari, 2018, Gu et al., 2017, Grivokostopoulou et al., 2019
2	Scaffolding	Su, 2020
3	Learning suggestion	Troussas et al., 2020
4	Feedback	Azcona et al., 2019
5	Personalised instruction	Cuong et al., 2018
Learning path	Wang et al., 2021a, 2021b, Huang & Shen, 2018, Iatrellis et al., 2017, Joseph, 2019, Lagman et al., 2020, Wang et al., 2021a, 2021b, Shi et al., 2020, Shou et al., 2020, Supic, 2018, Sweta & Lal, 2017, Vanitha & Krishnan, 2019, Zhu et al., 2018	
Teaching materials		
1	Learning content	Araujo et al., 2020, Bourkoukou & Bachari, 2018, Cagliero et al., 2019, Cuong et al., 2018, Deng et al., 2019, El Guabassi et al., 2018, He et al., 2019, Hidayat et al., 2020, Ibrahim et al., 2020, Jeevamol & Renumol, 2021, Muangprathub et al., 2020, Nafea et al., 2019, Perišić et al., 2018, Saleh & Salama, 2018, Sweta & Lal, 2017, Troussas et al., 2021
2	Module topics	Syed & Nair, 2018
3	Teaching guides	Araujo et al., 2020, Wang & Fu, 2021
4	Teaching support	Zhen et al., 2021
Learning Environment (mainly for game-based learning)		
1	Suggested game peer	Troussas et al., 2020
2	Game elements	Tlili et al., 2019

Fig. 7 Methods for analysing learner diversity/differences



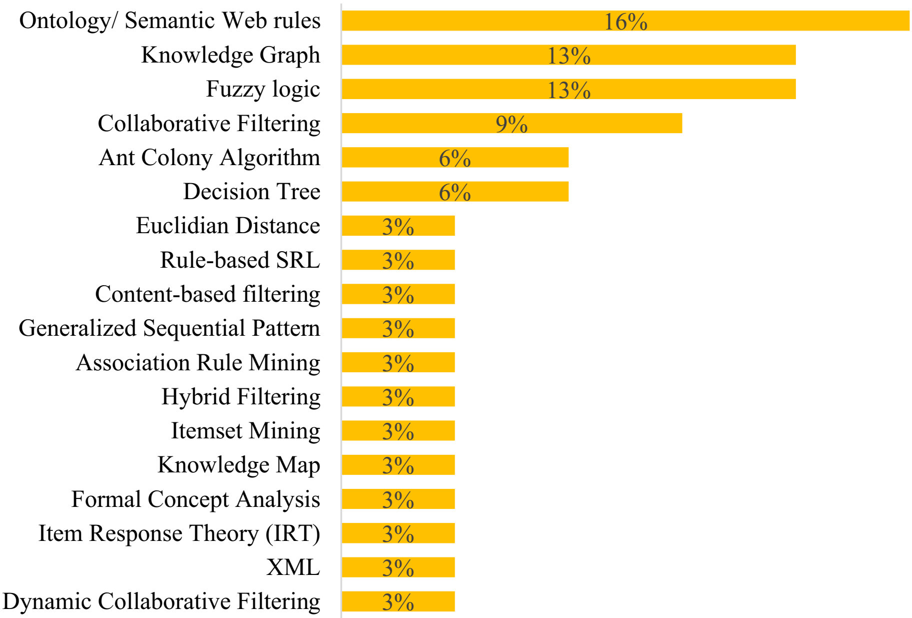


Fig. 8 Methods for generating PL features

mining, hybrid filtering, itemset mining, knowledge map, formal concept analysis, item response theory, XML, and dynamic collaborative filtering.

Table 4 shows the summary of methods used for generating PL features over the last five years. The review indicates a growing trend in the use of knowledge graphs for generating PL features in the last two years. This is in line with the findings in Sect. 4.3 that the learning path was quite widely used as a PL feature in the PL models developed in the selected study (29%). Shi et al. (2020) stated that knowledge graphs are widely used in research that recommends the provision of learning paths in the learning process.

Table 4 Summary of methods used for generating PL features in the selected studies from 2017 to 2021

Year	Method
2017	Ontology/ Semantic web rules (Iatrellis et al., 2017) Fuzzy logic (Sweta & Lal, 2017) Decision Tree (Gu et al., 2017)
2018	Ontology/ Semantic web rules (Cuong et al., 2018; Perišić et al., 2018) Fuzzy logic (Cuong et al., 2018); CF (Bourkoukou & Bachari, 2018) Ant Colony Algorithm (Huang & Shen, 2018) Decision Tree (Syed & Nair, 2018) XML (El Guabassi et al., 2018) Knowledge Map (Zhu et al., 2018) Association Rule Mining (Bourkoukou & Bachari, 2018) Generalised Sequential Pattern (Bourkoukou & Bachari, 2018) Euclidian Distance (Supic, 2018)
2019	Ontology/ Semantic web rules (Grivokostopoulou et al., 2019) CF (Bourkoukou & Bachari, 2018; He et al., 2019; Hidayat et al., 2020) Ant Colony Algorithm (Vanitha & Krishnan, 2019) Item Response Theory (IRT) (Pliakos et al., 2019) Itemset Mining (Cagliero et al., 2019) Hybrid Filtering (Nafea et al., 2019)
2020	Knowledge Graph (Shi et al., 2020) Fuzzy logic (Ibrahim et al., 2020; Troussas et al., 2020) CF (Bourkoukou & Bachari, 2018; He et al., 2019; Hidayat et al., 2020) Formal Concept Analysis (Muangprathub et al., 2020) Rule-based SRL (Su, 2020)
2021	Knowledge Graph Wang et al., 2021a, 2021b; Wang et al., 2021a, 2021b; Zhen et al., 2021) Ontology/ Semantic web rules (Jeevamol & Renumol, 2021) Dynamic collaborative filtering (Wang & Fu, 2021) Content-based filtering (Troussas et al., 2021)

Machine learning algorithms, data mining technology, knowledge graph, and artificial intelligence seem to continue to be the most widely used methods in recent PL studies. For example, a LSTM model is built to consider video-watching preference features, clusters of students, and learning paths to recommend personal learning paths suitable for each student (Chen et al., 2022). In another study, data mining is used for establishing the main position of students in learning and improve learning effectiveness (Shang, 2022). Wei and Yao (2022) used knowledge graph to construct a class model in their PL study. Artificial intelligence is used for determining appropriate learning contents for each learner in the study conducted by Murtaza et al., (2022). Another study used artificial intelligence to reveal the intelligent recommendation mechanism of online learning resources (Yang et al., 2022).

4.4 Addressing RQ4: What are the Models/Frameworks Offered/Produced in the PL Model in the Higher Education Context?

The resulting models/frameworks in the selected PL studies can be classified into four main categories: (1) model/framework built into PL system in the form of personalised e-learning; (2) model/framework integrated with existing learning management system (LMS)/e-learning; (3) model/framework built into PL systems in the form of a recommender system

(RS), and (4) model/framework built into PL systems in the form of an intelligent tutoring system (ITS). As shown in Fig. 9, the model built into the personalised e-learning system was the most widely produced (53%), followed by the model integrated with an existing LMS/e-learning system (21%), the model built into RS (16%), and model built into ITS (11%). The summary of the models/frameworks produced by the selected PL studies is shown in Table 5.

Building personalized e-learning from the scratch based on the PL model is the most widely developed rather than integrated into the existing e-learning/LMS. This is probably due to the varied PL models so that it is easier and more effective to build from the scratch.

It is worth noting that two of the studies, Tlili et al. (2019) and Troussas et al. (2020), used the personalisation model in game-based learning. Troussas et al. (2020) claimed that incorporating personalisation into game-based learning can further assist students in higher education.

4.5 Addressing RQ5. What Learning Theories Underpin the Development of the PL Model in Higher Education Context?

The review found that only a few of the selected articles explicitly explained the learning theory used in their PL research. Among the 39 studies, only 18% (7 articles) clearly stated what learning theory was used. Some of the learning theories stated are constructivism (Huang & Shen, 2018; Wang & Fu, 2021), collaborative learning (Troussas et al., 2020; Zhen et al., 2021), and case-based learning (Supic, 2018). Critical thinking and metacognition were used in one of the studies (Gu et al., 2017). Furthermore, self-regulated learning was expressed as implicit knowledge that is used to facilitate PL (Su, 2020).

This result indicates that researchers rarely use explicitly what learning theories guided them in developing PL models. One implication of this result is that researchers are encouraged to be explicit in using learning theories that underpin PL studies.

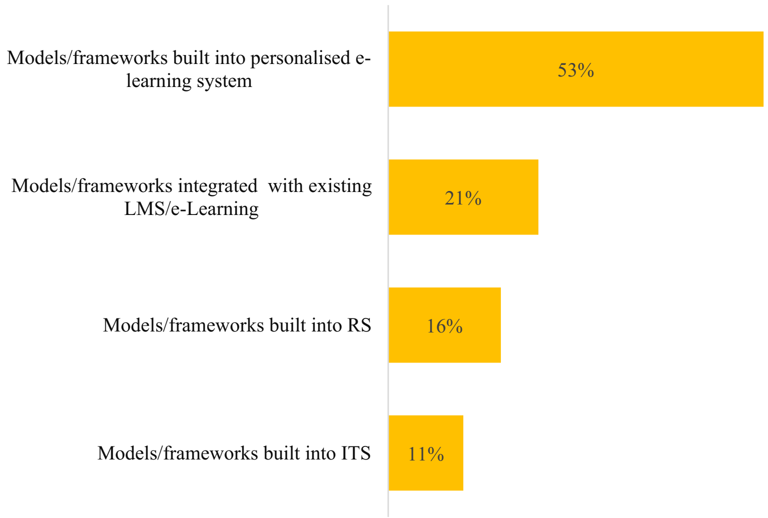


Fig. 9 Models/frameworks produced in the selected PL studies

Table 5 Summary of the models/frameworks produced by the selected PL studies

	Models/Frameworks	Studies
Models/frameworks built into personalised e-learning system		
1	Personalised programming learning strategy recommendation approach (PPLSRA)	Gu et al., 2017
2	QuizTime	Troussas et al., 2020
3	EDUCATE (EDU8)	Iatrellis et al., 2017
4	Personalised Game-Based Learning	Tlili et al., 2019
5	Model Knowledge Point	Wang et al., 2021a, 2021b
6	Ubiquitous Learning	El Guabassi et al., 2018
7	Multiconstraint Learning Path recommendation	Zhu et al., 2018
8	PredictCS (automatically detect "at-risk" student)	Azcona et al., 2019
9	Personalised E-learning System Architecture (PESA)	Araujo et al., 2020
10	Framework for generating Knowledge Graph (KG)	Zhen et al., 2021
11	ThoTHLab, personalised framework for hands-on	
in the Lab	Deng et al., 2019	
12	Adaptive Learning System: LearnFit	Bourkoukou & Bachari, 2018
13	Course Delivery System	Saleh & Salama, 2018
14	Rule-based self-regulated learning assistance scheme (SRL-RuAS)	Su, 2020
15	Framework Self-learning System	Wang et al., 2021a, 2021b
16	Model Case-based reasoning	Supic, 2018
17	FCTools	Araujo et al., 2020
18	The model with the algorithm to produce a learning path	Su, 2020, Vanitha & Krishnan, 2019
Models/frameworks integrated with existing LMS/e-learning system		
1	Adaptive e-learning	Lagman et al., 2020
2	E-learning with an adaptive recommendation	Shi et al., 2020
3	Moodle with personalisation	He et al., 2019, Joseph, 2019, Nafea et al., 2019, Perišić et al., 2018

Table 5 (continued)

	Models/Frameworks	Studies
4	Personalised adaptive learner model	Sweta & Lal, 2017
5	The model algorithm based on collaborative learning	Shou et al., 2020
Models/frameworks built into RS		
1	Ontology-based RS	Jeevamol & Renumol, 2021
2	Fog-based RS	Ibrahim et al., 2020
3	PLE Application RS	Hidayat et al., 2020
4	Personalised recommendation based on bidirectional self equation	Wang & Fu, 2021
5	LMS with Most Recently Referred (MTR) and All Time Referred (ATR)ara>	Syed & Nair, 2018
6	Model RS with a solution for 'cold start problem'	Pliakos et al., 2019
Models/frameworks built into ITS		
1	ITS	Cuong et al., 2018, Muangprathub et al., 2020, Troussas et al., 2021
2	ITS with model generic ontology	Grivokostopoulou et al., 2019

Self-regulated learning continues to be used for underpinning the development of PL models in some recent PL studies. In a study conducted by Ingkavara et al. (2022), PL was used as an approach for implementing self-regulated online learning with positive results. Another study proposed a PL system to integrate self-regulated learning components such as planning, monitoring, evaluating the learning commitment, activating alert of student achievement, and further intervention by the instructor (Izzudin & Judi, 2022).

4.6 Addressing RQ6: What are the Learning Impacts of the Implementation of the PL Model in the Higher Education Context?

Not all the studies discussed the impacts of implementing the PL system that developed based on the PL model. A total of 20 studies (51%) measured the impacts (academic and/or non-academic) of implementing the PL system on learning.

From an academic perspective, the impact was an improvement in learning outcomes. Some of the selected studies (Cuong et al., 2018; Deng et al., 2019; Grivokostopoulou et al., 2019; Huang & Shen, 2018; Joseph, 2019; Muangprathub et al., 2020; Perišić et al., 2018; Shou et al., 2020; Su, 2020; Supic, 2018; Troussas et al., 2020; Vanitha & Krishnan, 2019) used a control group and an experimental group to measure the impact of a PL system implementation. The control group was a group of learners who used the PL system, and the experimental group was a group of learners who used conventional e-learning. All their results showed an improvement in learning outcomes. Another study (Azcona et al., 2019), which did not involve a control group, also showed a significant improvement in learning outcomes after the implementation of the PL system.

Su's (2020) study showed that the implementation of PL system can reduce learning time. Another study conducted by (Iatrellis et al., 2017) found that the implementation of PL system made learners have good competencies under learning objectives.

From a non-academic perspective, several studies stated that students were satisfied with the results of implementing the PL system (Jeevamol & Renumol, 2021; Nafea et al., 2019; Shi et al., 2020). In addition, there was a high level of acceptance of the PL system (Araujo et al., 2020). The implementation of a PL model also increased student engagement (Deng et al., 2019) and participation (Cuong et al., 2018). In terms of the learning experience, the implementation of PL was found to be able to reduce the cognitive load in learning (Tlili et al., 2019) and able to provide direction for students in learning (Araujo et al., 2020). Summary of these impacts is shown in Table 6.

Figure 10 shows the impact of PL system implementation from the twenty studies. As can be seen in Fig. 10, 13 studies found an improvement in learning outcomes.

The limited number of articles discussing the impacts of implementing PL system in the selected studies indicates several possibilities. The first possibility is that there are still many studies on PL system implementation that do not measure the impact on learning. The second possibility is that the impacts of implementation have been measured but not reported or described by the researcher in these studies. In addition, among the twenty studies, no study talked about implementation impact related to the lecturers such as instructional design and teaching improvement. It would be interesting for future studies to discuss how lecturers reshape their role in PL system implementation.

Table 6 Summary of PL system implementation impact in the selected studies

	Impacts	Studies
Academic Impacts		
1	Improve learning outcome	Azcona et al., 2019, Cuong et al., 2018, Deng et al., 2019, Grivokostopoulou et al., 2019, Huang & Shen, 2018, Joseph, 2019, Muangprathub et al., 2020, Perišić et al., 2018, Shou et al., 2020, Su, 2020, Supic, 2018, Troussas et al., 2020, Vanitha & Krishnan, 2019
2	Reduce learning time	Su, 2020
3	Improve learner competence	Iatrellis et al., 2017
Non-academic Impacts		
1	Increase learner satisfaction	Jeevamol & Renumol, 2021, Nafea et al., 2019, Shi et al., 2020
2	High acceptance level	Araujo et al., 2020
3	Improve learner engagement	Deng et al., 2019
4	Encourage learner participation	Cuong et al., 2018
5	Reduce cognitive load	Tlili et al., 2019
6	Assist learners' learning	Araujo et al., 2020

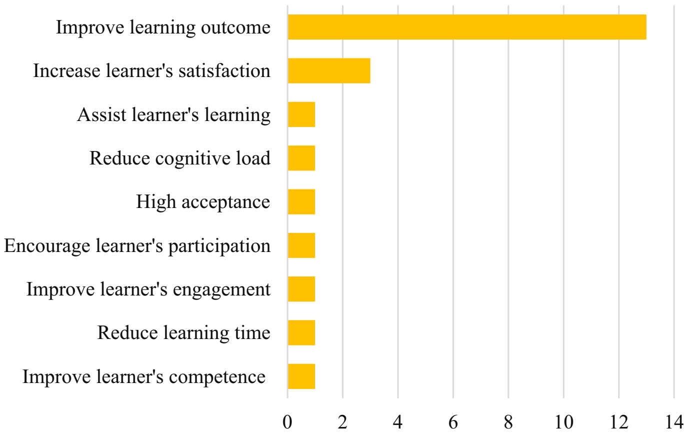


Fig. 10 The identified impacts of PL system implementation in the selected studies

5 Conclusions, Limitations, and Future Research

The results of this study revealed that there has been a tendency to increase the number of publications on PL studies for the last five years. This indicates that the topic of PL has become an attractive area in research and that the opportunities for research development in this field are wide open.

The results of the extraction of PL components in the selected studies show that the analysis of learner diversity/differences is not only limited to learner's level of knowledge and characteristics but has also expanded to learner's metacognitive aspects, such as learning objectives, learning scenarios, learner attention/cooperation, and learner engagement. Nevertheless, from the review, there is no study discuss affective aspects as learner diversity/differences, such as motivation and interest.

Methods using machine learning techniques are increasingly being used to analyse learner diversity/differences as an alternative to assessments and questionnaires. Moreover, the last two years have seen a trend in the use of knowledge graphs, especially to generate PL features in the form of learning paths (i.e., the sequence of learning objects). Knowledge graph can describe the dependencies between learning objects. In addition, the knowledge graph is a data representation of a semantic model built with an ontology (Schrader, 2020). As seen in the results of the review, ontology/semantic web and knowledge graphs were the most widely used methods for generating PL features.

The focus of PL design differs among researchers. Bernacki et al. (2021) stated that the focus of the PL designs differs by the learner characteristics and targeted prioritized outcomes. The results exhibited that the use of PL components seems to be related to the use of PL features. Studies with PL model design provide learning paths and teaching materials as PL features, tend to use knowledge level as PL components. One possible reason is that learners with different knowledge level may have different paces of learning (which is different learning path and teaching materials). Meanwhile, studies with PL model design provide learning strategies, such as scaffolding or personal instructional design, tend to use learner characteristics as PL components. One possible reason is that learners with different characteristics may have different learning preferences.

The impacts of PL implementation on learning do not only concern cognitive aspects, such as learning outcomes, but also the level of learner satisfaction, acceptance PL system rate, and increased learner engagement and participation. Although several of the selected studies showed these positive impacts, the number of articles analysing the impact of PL implementation was relatively low, indicating that PL research that analyses the impact of PL implementation on learning is still limited. This is in line with research conducted by Alamri et al. (2021) which states that there is a lack of independent, data-based research investigating the effectiveness and impact of personalised learning models and technologies on student learning.

Only a few of the selected articles discussed or explicitly used learning theory in the development of a PL model. This indicates that learning theory is not a common theme in PL research. One possible reason is that learning theory can be used implicitly. In real terms, learning does not adhere to only one theory, rather it incorporates multiple theories, as each theory has its limitations and strengths.

This paper has some limitations. This study only analysed research published in English and focused on journals and conference articles. In addition, the review only included studies published in the last 5 years (2017–2021).

Overall, the results suggested four directions for further research on PL: First, due to the still limited number of studies that discuss affective aspects as learner differences, it is recommended that future research consider affective aspects, such as motivation and interest, as PL components in analysing learner diversity/differences.

Second, with the lack of research analysing the impacts of PL implementation on learning, there is a need to conduct further empirical and systematic research on the impact of personalised learning in higher education for both learners and lecturers.

Third, the focus of PL research can be expanded to include the application of learning theory such as critical thinking, self-regulated learning, or metacognition in the formation of PL models. It is hoped that the learning theory can be developed through PL.

Fourth, the focus of PL research can also be expanded by looking at hands-on learning/practice so that the personalisation will include psychomotor aspects in addition to cognitive aspects. Last but not least, education with a high portion of hands-on learning/practice, such as vocational education, can be used as a research context which will be examined in our future work.

Further research directions on this systematic literature review can be beneficial for academics and instructional designers and encourage researchers to further study the field of PL.

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Ethical approval and consent to participate Not applicable.

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