Luan, H., & Tsai, C.-C. (2021). A Review of Using Machine Learning Approaches for Precision Education. *Educational Technology & Society*, *24* (1), 250–266.

A Review of Using Machine Learning Approaches for Precision Education

Hui Luan[1] and Chin-Chung Tsai[1, 2*]
[1]Institute for Research Excellence in Learning Sciences, National Taiwan Normal University, Taiwan //
[2]Program of Learning Sciences, National Taiwan Normal University, Taiwan // hluanv@gmail.com //
tsaicc@ntnu.edu.tw
*Corresponding author

ABSTRACT: In recent years, in the field of education, there has been a clear progressive trend toward precision education. As a rapidly evolving AI technique, machine learning is viewed as an important means to realize it. In this paper, we systematically review 40 empirical studies regarding machine-learning-based precision education. The results showed that the majority of studies focused on the prediction of learning performance or dropouts, and were carried out in online or blended learning environments among university students majoring in computer science or STEM, whereas the data sources were divergent. The commonly used machine learning algorithms, evaluation methods, and validation approaches are presented. The emerging issues and future directions are discussed accordingly.

Keywords: Precision education, Personalized learning, Individualized learning, Machine learning, Individual differences

1. Introduction

A key goal of education is to cultivate the talents of all students. It is commonly believed that each student's learning experiences are unique. Therefore, it is imperative to teach in line with each individual's ability or rhythm (Corno & Snow, 1986). However, in the traditional education paradigm, the one-size-fits-all approach is adopted with a focus on average students (Cook et al., 2018). It is almost impossible for the teacher to implement tailor-made pedagogical tools to cater to students' diverse learning styles and needs.

Personalized learning refers to "instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner. Learning objectives, instructional approaches, and instructional content (and its sequencing) may all vary based on learner needs. In addition, learning activities are meaningful and relevant to learners, driven by their interests, and often self-initiated" (U.S. Department of Education, 2017, p. 9). Educational technologies in personalized learning (e.g., e-learning system adaptive to learners' learning style, knowledge level, interest, and preference) help students to learn more effectively than pure educational psychology theories or methods (e.g., Huang et al., 2012; Klašnja-Milićević et al., 2011; Tseng et al., 2008). To date, a large body of these personalized systems used traditional computers or devices. In contrast, smart devices such as wearable devices, smartphones, and tablet computers were less frequently used, and artificial intelligence has a significant impact on these personalized learning systems (Xie et al., 2019).

In the field of education, with the rapid advances in artificial intelligence and data science, accurate and rich learning data are able to be collected and to reveal learning patterns and specific learning needs. Accordingly, an "optimal" personalized learning path or feedback can be provided. As a result, there is a clear progressive shift from a one-size-fits-all approach to precision education (Lu et al., 2018; Tsai et al., 2020). Precision education considers the individual differences of learners in their learning environments, identifies at-risk students as early as possible and provides timely and tailoring intervention accompanied with proper teaching materials and strategies, and learning strategies and activities (Cook et al., 2018; Frey, 2019; Lu et al., 2018). Mirroring precision medicine (Collins & Varmus, 2015), described as "an innovative approach to disease prevention and treatment that takes into account individual differences in people's genes, environments, and lifestyles" (The White House, 2015), precision education aims to advance the diagnosis, prediction, treatment, and prevention of at-risk students (Yang, 2019). According to Hart (2016), the more immediate goals of precision education are to obtain an accurate understanding of the learner's unique individual needs through profiling or diagnosis. In contrast, its ultimate goals are to implement individualized treatment or prevention and to enhance individual student's learning outcomes. Regarding the means to achieve its goals, precision education stresses the importance of advanced computational technologies such as learning analytics, artificial intelligence, and machine learning (Williamson, 2019; Yang, 2019).

Situated at the core of AI and data science, machine learning is one of the most rapidly growing techniques and has come to be expected as an essential means to achieve precision education and optimize learning. Machine learning addresses the question of how to construct computer systems that can learn automatically from past experiences without explicit programming (Jordan & Mitchell, 2015). Machine learning algorithms can classify profiling and patterns, provide new models and insights, and make predictions and recommendations to customize each individual's needs and circumstances. With the availability of adequate training data and low-cost data analytics tools, the data-intensive machine learning methods are widely used to facilitate evidence-based decision making in commerce, medicine, science, agriculture, and manufacturing (Kourou et al., 2015; Liakos et al., 2018; Lin et al., 2011; Ramprasad et al., 2017; Voyant et al., 2017; Wu et al., 2017). Machine learning has attracted growing interest in education recently (Gobert & Sao Pedro, 2017; Zhou et al., 2018). By adopting machine learning in education, the learning paths can be changed dynamically and personalized based on the learner's progress and pace (Kuch et al., 2020). Therefore, individualized learning, which is adaptive to individual needs in real-time, has recently gained increasing attention from educational researchers (Lu et al., 2018).

The ideas of "personalized learning," "individualized learning," and "precision education" are often interchangeable, while the concept of precision education is relatively new. The term "precision education" first appeared in 2016 (Hart, 2016). Since then, a growing number of studies in this research area have adopted machine learning methods. The application of machine learning in education has been reviewed in science assessment (Zhai et al., 2020) and educational technology (Korkmaz & Correia, 2019). Nevertheless, a systematic review of the applications of machine learning in precision education is lacking. The development, trends, and challenges of technology-supported adaptive/personalized learning have recently been systematically reviewed (Xie et al., 2019). However, Xie et al. (2019) found that one study adopted deep neural network techniques among the 70 studies published from 2007 to 2017 (Shi & Weninger, 2017). To provide insights into the educational benefits of machine learning, a comprehensive review is needed to fill the gaps and shed light on the current status, major challenges, and potential future directions of using a machine learning approach for precision education. Five specific research questions guide this study:

- What are the primary research purposes of using a machine learning approach for precision education (e.g., diagnosis, prediction, treatment, or prevention)?
- In which learning environments, domains, education levels, samples, and data sources have machine learning been applied for precision education?
- What are the learner's individual differences and learning outcomes of using machine learning in precision education?
- What are the algorithms, evaluation measures, and validation approaches of using machine learning in precision education?
- Are there significant relationships among these aforementioned categorical variables by using chi-square analysis?

2. Methods

2.1. Literature search

For this review, we selected peer-review articles employing machine learning techniques for precision education, published in journals that are indexed in the Web of Science database. This is a highly reputable database in terms of research quality. As machine learning and precision education have become popular since 2016, we set our search to articles published from January 2016 to July 2020. We further limited the document type to journal or early access articles written in English to ensure the consistent quality of the recruited studies. The keywords used for this search included "machine learn*," "machine-learn*," "precision," "personal* (not personality)," "individual*," and "education." Based on the above search parameters, a total of 151 articles were retrieved. Figure 1 demonstrated the process of selecting the eligible studies for this review. We then screened the articles by reading the titles and abstracts. Those studies that matched our inclusion criteria were retained. The inclusion criteria are fourfold: (1) empirical studies (not a position paper or review paper), (2) in a learning setting, (3) using machine learning techniques, and (4) measuring individual differences. When one of the inclusion criteria was not met, the study was excluded. For instance, Koutsouleris et al. (2016) adopted a machine learning approach to predict the treatment outcomes in patients with first-episode psychosis. This study was excluded because it belongs to the field of psychiatry. By the end of this stage, a total of 34 studies were eligible, while 22 studies were uncertain as the information provided in the title and abstract was insufficient to make a judgment. We then reviewed all of the full-text articles for the uncertain studies. After applying our selection criteria, the final dataset comprised 40 empirical studies.

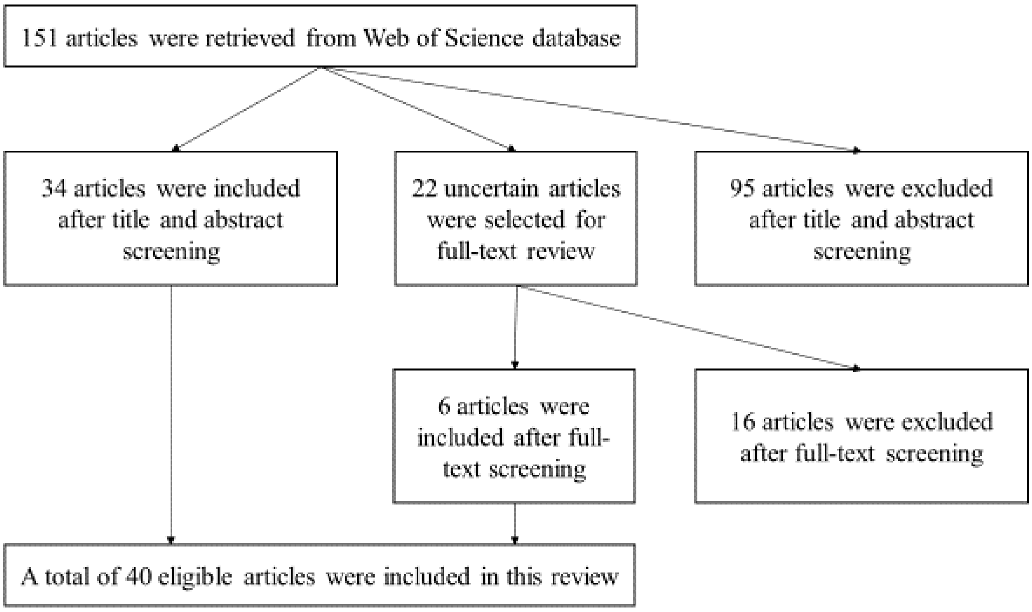

Figure 1. The selection of eligible studies

2.2. Coding scheme

To analyze the current status and future trends of machine-learning-based precision education, all studies were qualitatively coded. The coding scheme consists of eight main categories, including research purpose, general information, individual differences, learning outcomes, machine learning algorithms, evaluation of algorithms, validation of algorithms, and major research findings. Table 1 illustrates the overall coding scheme of this study.

As suggested by Yang (2019), the coding for the research purpose includes diagnosis or profiling (e.g., introverts, extroverts), prediction (e.g., dropout, performance), treatment or intervention (e.g., plan-making intervention, value-relevance intervention), prevention, and recommendations (e.g., personalized learning paths, learning contents).

The coding for general information comprises publication year, learning environment, learning domain, learners' educational level, sample size, data source. The coding for the learning environment can be further divided into classroom, online, blended (combining classroom and online learning; Graham, 2006), and others (e.g., laboratory). The coding for the learning domain is grouped into four main categories, including one multiple domains and three single domains. That is, multiple domains with many disciplines in a single study, computer sciences domain (e.g., programming, internet of things, data science), STEM domain (e.g., engineering, mathematics, digital design, electronic technology), and social sciences domain (e.g., finance, statistics, psychology, and language learning). Note that the main reason for selecting computer sciences as a separate category is that computer sciences are very closely linked with precision education in terms of that precision education places great emphasis on data-intensive digital technologies (Williamson, 2019). In addition, the STEM domain, an interdisciplinary domain that encompasses disciplines of science, technology, engineering, and mathematics, is categorized as a single primary domain in this study for two reasons. The first is that STEM education has gained increasing prominence in the past decade (Honey et al., 2014). The second is that STEM topics are often step-based and well-defined problems, where artificial intelligence tools and techniques can be relatively easily applied (Humble & Mozelius, 2019; Roll & Wylie, 2016). The coding for learners' educational level includes K-12 students, university students, and others (e.g., teachers, working adults). The coding for sample size is classified into 1-999, 1,000-9,999, more than 10,000, and others (e.g., number of responses in training dataset). The coding for the data source is divided into four major categories, including log files from a learning platform (e.g., MOOCs, e-learning system, Facebook, Mobile app), learning records or surveys (e.g., prior grades, past performance, satisfaction), institutional database (e.g., SAT scores, financial status), and physiological records (e.g., EEG signals, eye-movement data).

The coding for individual differences consists of seven categories: demographic (e.g., gender, age), academic (e.g., past performance, prior knowledge), cognitive (e.g., reasoning, working memory), affective (e.g., self-concept, motivation, learning styles, relationships with teachers and peers), behavioral (e.g., log activities, time and efforts for learning activities), pedagogical. In particular, pedagogical category refers to the factors relevant to course difficulty, learning content, or classroom characteristics. The coding for learning outcomes includes performance and dropout/ attrition/retention. If a learning outcome could not be categorized into these categories, the coder tagged it as others and wrote down the specific information.

Based on Moreno-Marcos et al.'s (2018) and Zhai et al.'s (2020) review studies, the coding for machine learning algorithms includes the commonly used ones such as K-Nearest Neighbors (KNN), Naïve Bayes, Regression, Random Forest, Decision Tree, Support Vector Machine (SVM), and Neural Networks. The relatively infrequent algorithms are categorized into the "others" category. This classification and the definitions of each type of algorithm evaluation and validation approaches were adopted from Zhai et al.'s (2020) review study on the applications of machine learning methods in science assessment. The coding for evaluation measure of algorithms covers the most frequently used indicators, including accuracy, precision, recall/sensitivity, F1-score, Area under the ROC Curve (AUC), and Receiver Operating Characteristic (ROC). The less often used evaluation indicators are classified as others. In this review, the validation approaches of algorithms are classified into self-validation, split validation, and cross-validation.

Table 1. Coding scheme of this study

Coding categories	
1. Research Purpose Diagnosis (e.g., introverts, extroverts) Prediction (e.g., dropout, performance) Intervention (e.g., plan-making intervention, value-relevance intervention) Prevention Recommendations (e.g., personalized learning paths, learning contents) **2. General information** Publication year Learning environment • Classroom • Online • Blended • Others Learning domain • Computer sciences • STEM • Social sciences • Multiple Learners' education level • K-12 students • University students • Others Sample size • 1-999 • 1,000-9,999 • >=10,000 • Others Data source • Log files from learning platform (e.g., log activities in MOOCs) • Learning records or surveys (e.g., prior grades, satisfaction) • Institutional databases (e.g., SAT scores, financial status) • Physiological records (e.g., EEG signals, eye-movement data)	**3. Individual differences** Demographic (e.g., gender, age) Academic (e.g., past performance, prior knowledge) Cognitive (e.g., reasoning, working memory) Affective (e.g., self-concept, motivation, learning styles, relationships with teachers and peers) Behavioral (e.g., log activities, time and efforts for learning activities) Pedagogical (e.g., learning contents, course difficulty) **4. Learning outcomes** Performance Dropout/ attrition/retention Others **5. Machine learning algorithms** KNN Naïve Bayes Regression Random Forest Decision Tree SVM Neural Networks Others **6. Evaluation of algorithms** Accuracy Precision Recall/sensitivity F1-score AUC ROC Others **7. Validation of algorithms** Self-validation Split validation Cross-validation **8. Major research findings**

Finally, among the coding scheme, individual differences, machine learning algorithms, evaluation of algorithms, and validation of algorithms are coded with multiple responses as a single study generally measures several individual characteristics (e.g., demographic, academic, behavioral) and adopted more than one algorithm, evaluation measures, and validation approach. As a result, the sum of these factors may exceed 40. In contrast, the rest of the coding categories are multiple-choice items, while the sums are all 40.

3. Results

In this section, the results of the analyses of the 40 empirical studies are presented. By and large, the distribution of the publication year clearly indicated that there is a growing trend. There was only one paper published in 2016, two in 2017, and three in 2018. In the year of 2019, there were 17 studies published. This year was obviously the turning point, as there were 17 articles employing machine learning techniques for precision education within the first seven months of 2020. This result corroborates the rising popularity of this topic. These 40 reviewed studies were analyzed following five major research questions regarding the research purpose, general information, learners' characteristics and learning outcomes, and machine learning algorithms and algorithms' evaluation. Each research question is in its own subsection. In addition to descriptive analysis, Chi-square analysis was also conducted to examine whether there are statistically significant relationships among the aforementioned categorical variables with multiple-choice items. The significant results are reported accordingly.

3.1. What are the primary research purposes of using a machine learning approach for precision education?

As shown in Figure 2, the analyses indicated that among the 40 studies, the majority (25 studies) adopted machine learning methods to make predictions, and nine aimed for diagnosis and profiling. Only three studies carried out intervention research such as using behavioral intervention (e.g., self-regulation, value-relevance; Kizilcec et al., 2020) and machine learning-generated individual eye movement feedback (Krol & Krol, 2019). It was noted that no study employed prevention. Furthermore, three studies provided recommendations such as appropriate learning contents through an individualized AI tutor (Kim & Kim, 2020). Among these 40 studies, only two adopted an experimental design (Kizilcec et al., 2020; Krol & Krol, 2019), and two adopted a quasi-experimental design (Magana et al., 2019; Ninaus et al., 2019).

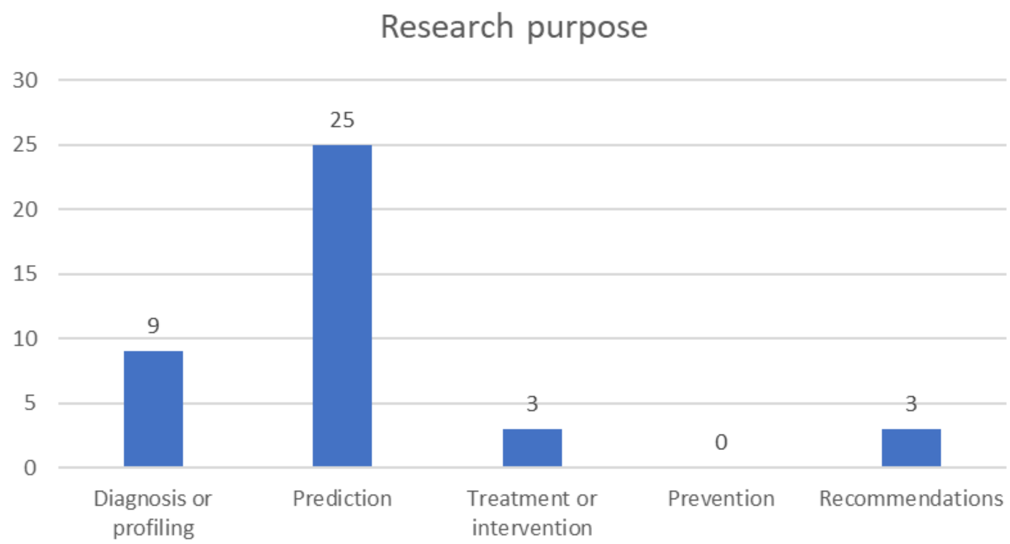

Figure 2. Distribution of research purposes

3.2. In which learning environments, domains, education levels, samples, and data sources have machine learning been applied for precision education?

In terms of the learning environments in which machine learning was employed, four categories were defined: classroom, online, blended, and others (Figure 3). The most used learning environment was online learning (18 out of 40 studies), followed by classroom learning (9 studies) and blended learning (8 studies). The studies not specified, and the study conducted in a game-based learning environment were tagged as others (5 studies).

With regard to the learning domain, most studies recruited learners from multiple domains (n = 10) partially due to the large dataset of these studies (Figure 4). Concerning specific learning domains, STEM (n = 10; e.g., engineering, mathematics, digital design, electronic technology) and computer science (n = 9; e.g., programming, internet of things, data science) related domains were most popular. Machine learning was also used in social sciences (n = 7) such as finance, statistics, psychology, and language learning. Besides, there were four studies which did not specify the learning domain.

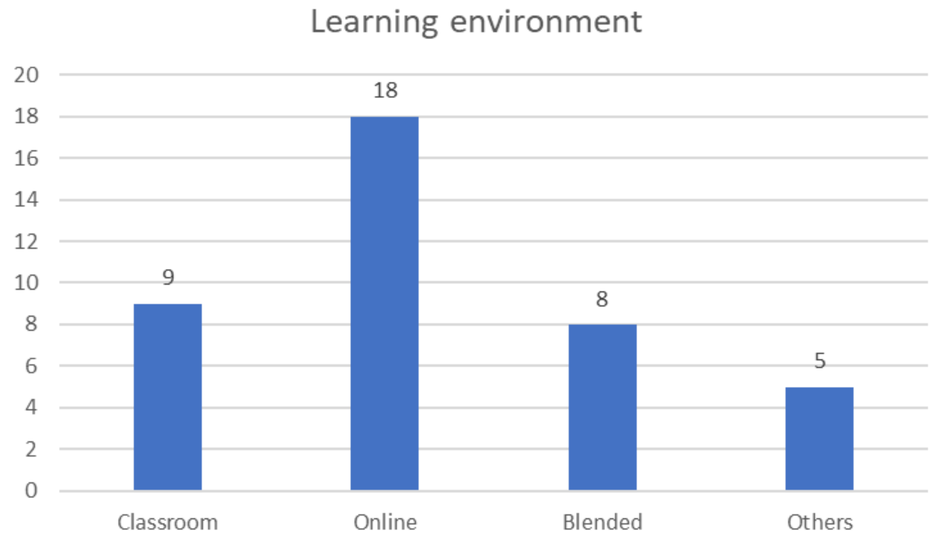

Figure 3. Distribution of the learning environment

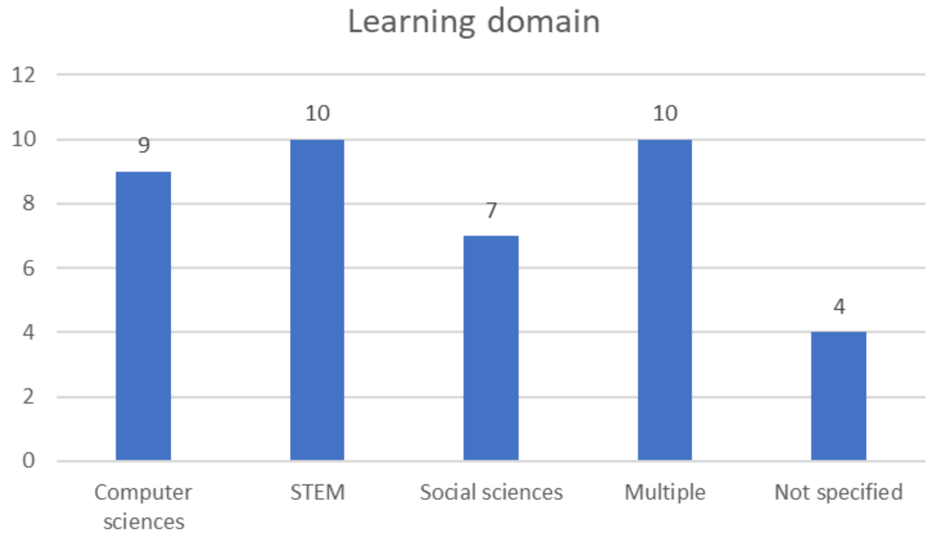

Figure 4. Distribution of the learning domain

As shown in Figure 5, the overwhelming majority of studies recruited university students (24 out of 40 studies), whereas five focused on elementary students and secondary students. Among the 40 reviewed studies, nine were tagged as others. The reason is that these studies recruited participants from heterogeneous groups by using MOOCs or other large databases. Among the nine studies categorized as others, one solicited participants from teachers who were taking a computer science course (Spatiotis et al., 2020). Besides, there were two studies which did not specify the learners' education level.

To train a good machine learning algorithm model, a certain amount of data is required. Of the 40 studies included in this paper, the number of students ranged from 6 to 269,169. Among them seven studies' sample size was beyond 10,000, and six studies recruited 1,000-9,999 students. Surprisingly, the sample size of most of the studies (22 studies) fell into the 1-999 range. There were three studies which reported the numbers of responses for the training data instead, namely 3,000, 11,156, and 76,936, respectively. The training responses ranged from 650 to 9,966,292. For the study which recruited six students (Kurilovas, 2018), the responses used for training data were 5,658. There were three studies found with no sample size or training response information. Figure 6 illustrates the distribution of sample size.

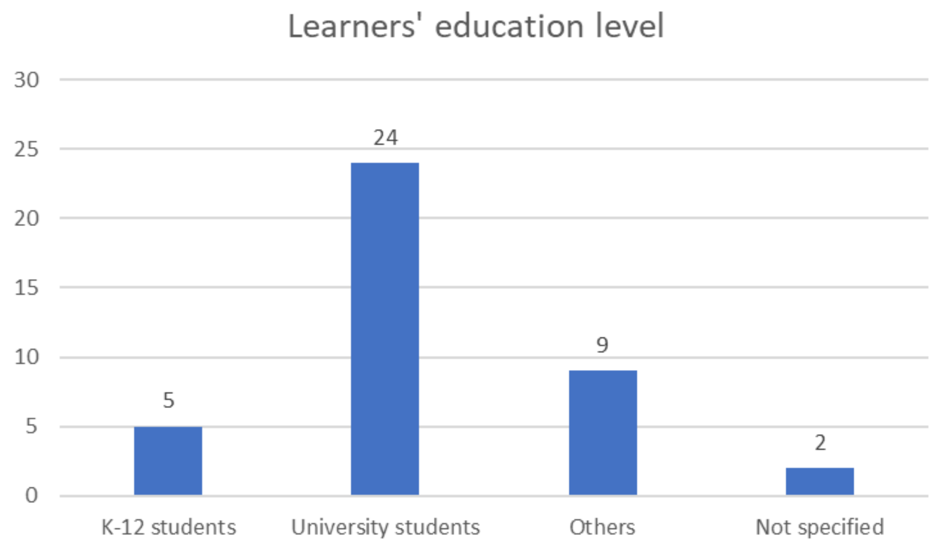

Figure 5. Distribution of learners' education level

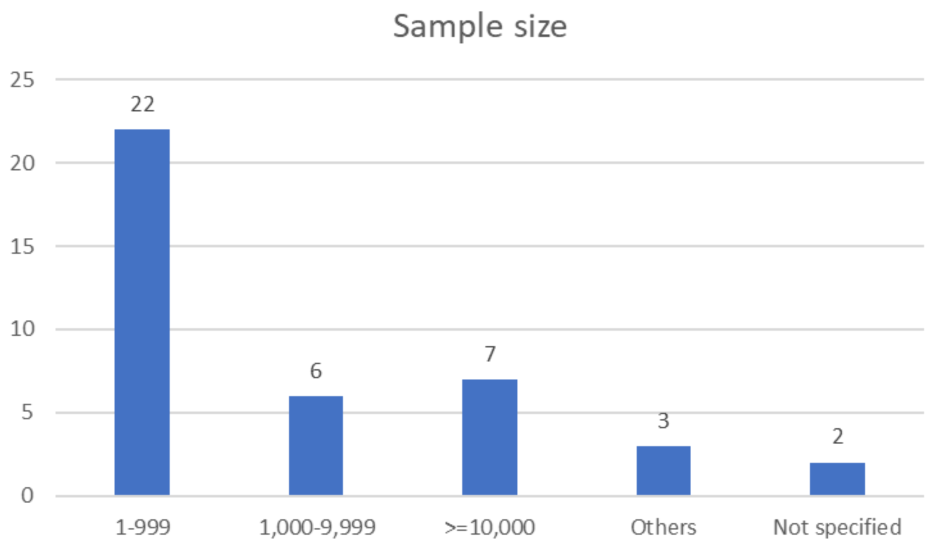

Figure 6. Distribution of sample size

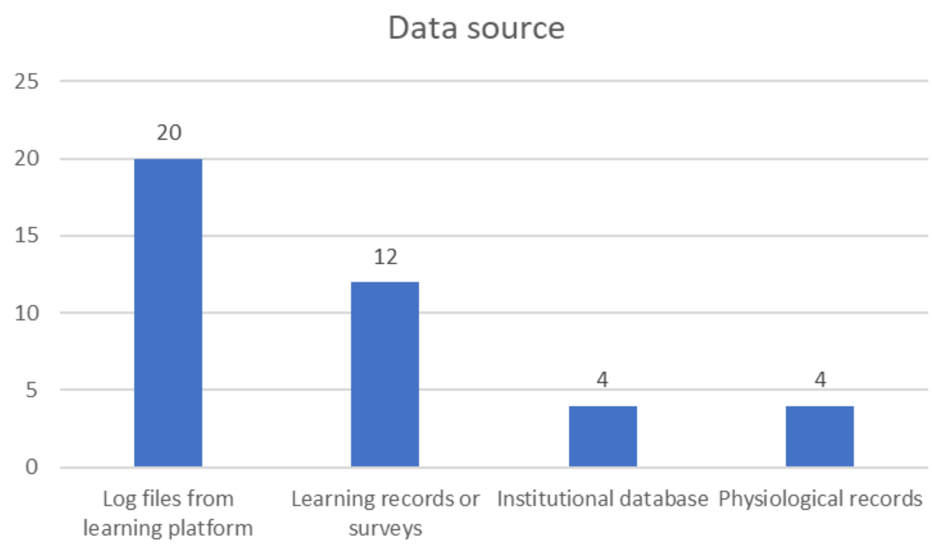

Figure 7. Distribution of data sources

As shown in Figure 7, the distribution of major data sources varied. Most of the studies collected students' log files from a learning platform (20 studies; e.g., MOOCs, e-learning system, Facebook, Mobile app), followed by learning records or surveys (12 studies; e.g., prior grades, past performance, satisfaction) and institutional databases (4 studies). It is worth noting that several neuroscience studies began to adopt machine learning to analyze the physiological records (4 studies). In particular, there were two studies which collected data from EEG signals (Luo & Zhou, 2020; Rajkumar & Ganapathy, 2020), and two which analyzed eye-movement data employing a machine learning approach (Krol & Krol, 2019; Lee et al., 2019).

3.3. What are the learners' individual differences and learning outcomes of using machine learning in precision education?

For the machine learning training model's features, the individual characteristics were grouped into six main categories as described in the coding scheme section (Figure 8). Among them, the behavioral characteristics (e.g., log activities, time and efforts for learning activities) were mostly investigated (18 studies), followed by affective factors (16 studies). The affective factor included self-concept, motivation, attitudes, learning styles, learning strategies, coping strategies, relationships with teachers and peers, time management, etc. For example, Rajkumar and Ganapathy (2020) compared Chatbot and machine learning algorithms' classification accuracy. Based on the VARK (Visual, Auditory, Read/Write and Kinesthetic) learning style, individuals were classified as Introverts or Extraverts. Introverts prefer to study alone in calm places. Extraverts prefer to study in a group and like to learn with music and audiobooks. Participants first answered questionnaire questions via the Chatbot, then their learning beta brain waves were recorded through a non-invasive EEG sensor while they were processing visual and auditory learning content. The result showed that the classification accuracy of the Chatbot and machine learning algorithms was similar, whereas the Chatbot was fast and convenient. There were 14 studies which used demographic information and 13 which examined the academic characteristics (e.g., past performance, prior knowledge). There were six studies which involved cognitive factors (e.g., reasoning, working memory) as independent variables in the training model. Finally, among the 40 studies, five examined pedagogical factors relevant to course difficulty or classroom characteristics, such as learning materials (e.g., Coussement et al., 2020; Kassak et al., 2016), teaching strategies or interventions (Kizilcec et al., 2020).

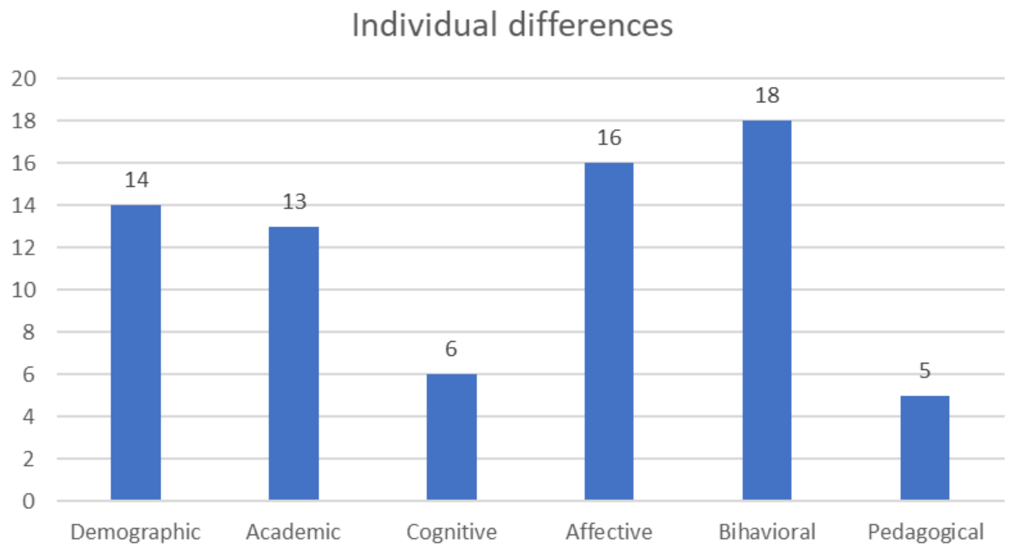

Figure 8. Distribution of individual differences

Investigating the learning outcomes, as shown in Figure 9, the majority of studies focused on learning performance (15 studies) and dropout/attrition/retention (11 studies). This finding was consistent with the research purpose, as most of the studies aimed to make predictions or profiling and tried to identify at-risk students as early as possible. Of the 40 reviewed studies, nine were categorized as others, such as emotion engagement (Ninaus et al., 2019), satisfaction (Spatiotis et al., 2020), decision quality (Krol & Krol, 2019), behavior intentions (Arpaci, 2019), and brain organization (Astle et al., 2019). For instance, using an artificial neural network algorithm named Self Organising Maps, Astle et al. (2019) grouped 530 heterogeneous struggling children into four clusters with distinctive cognitive profiles. The group comparison showed that they were significantly different in terms of their learning performance (e.g., reading, math), behavioral scores (e.g., executive function, communication), and patterns of brain organization. Besides, Ninaus et al. (2019) examined emotional engagement differences in game-based and non-game-based learning by using the SVM algorithm. There were five studies which were tagged as not applicable.

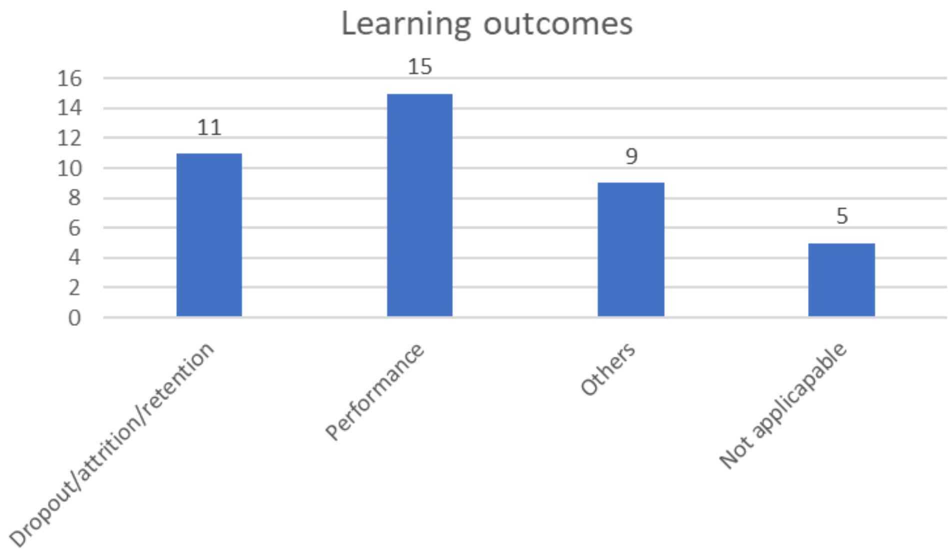

Figure 9. Distribution of learning outcomes

3.4. What are the algorithms, evaluation measures, and validation approaches for using machine learning in precision education?

The machine learning experts developed different kinds of algorithms to train the models. Depending on the data characteristics, selecting some algorithms may result in better performance. Various indicators can evaluate the quality of the model according to the research purpose. Also, in machine learning, whether a trained model can be generalized to an independent dataset like a testing dataset is essential. This process refers to model validation. Investigating these reviewed studies, the commonly used algorithms were KNN, Naïve Bayes, regression, random forest, neural networks, decision tree, and SVM. In contrast, the innovative or uncommon machine learning algorithms were numerous (see Figure 10).

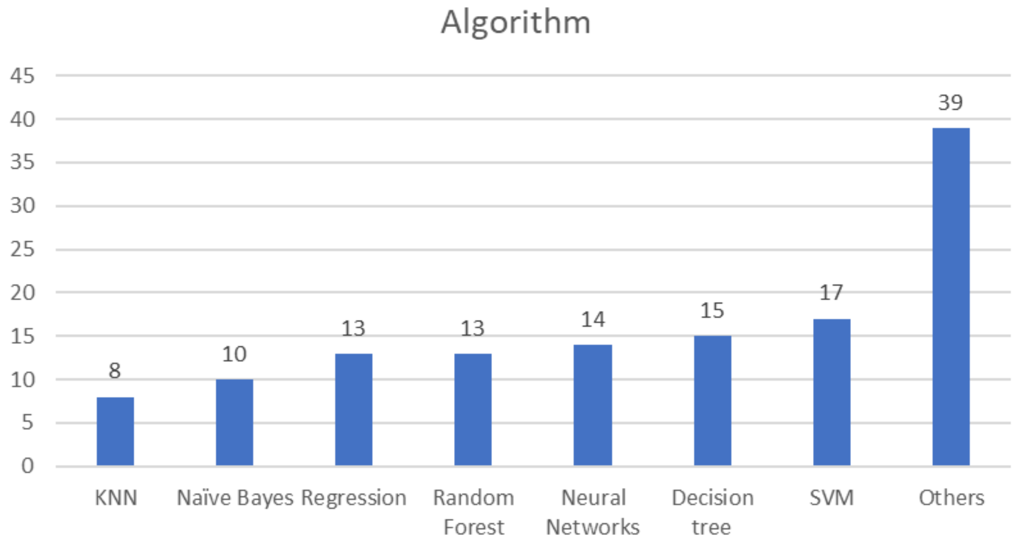

Figure 10. Distribution of machine learning algorithms

As shown in Figure 11, the models were often evaluated by using accuracy, precision, recall/sensitivity, F1-score, AUC, and ROC, while other measures were also used, such as specificity, PR curve, and RMSE. There were two studies which did not specify the algorithm used in their study.

As shown in Figure 12, adopting Zhai et al.'s (2020) classification and definitions, three validation approaches were classified in this review: self-validation, split validation, and cross-validation. Self-validation did not divide data into a training set and test set; in contrast, the same data were used to build the algorithmic model and to evaluate the model. Split validation divided data into two sets: a training dataset to train the model, and a testing dataset to evaluate the model. The generalizability of the algorithm was improved by using split validation.

However, there were only two datasets, and the validation indicator still may vary when the settings of the training and testing data were changed. Therefore, in machine learning, cross-validation is more commonly used. Cross-validation divides data into n subsets (n-fold; the number of n might be 4, 5, or 10), while with this process, each subset was used to be both the training set and the testing set. Figure 12 demonstrates that cross-validation was most frequently used in our review sample, too; that is, 24 out of 40 studies used cross-validation, followed by self-validation (16 studies) and split validation (10 studies).

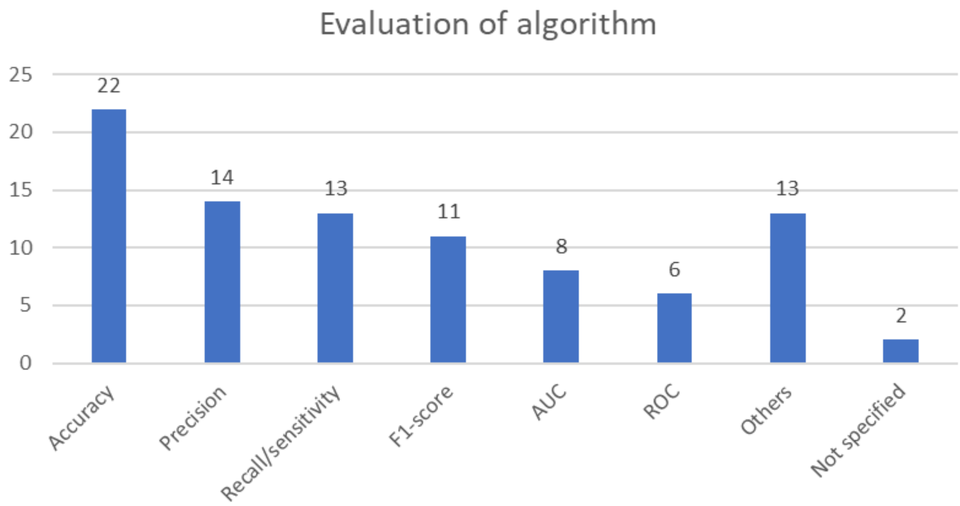

Figure 11. Distribution of machine learning algorithm evaluation

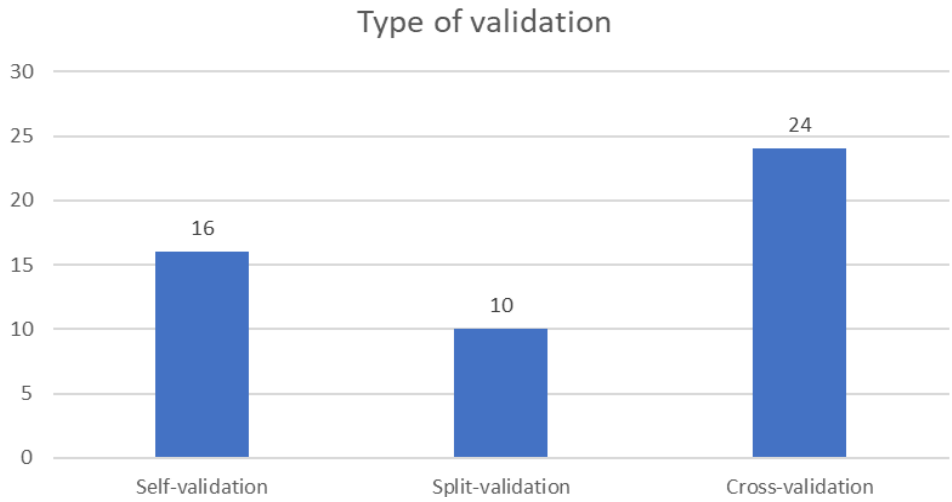

Figure 12. Distribution of validation of machine learning algorithms

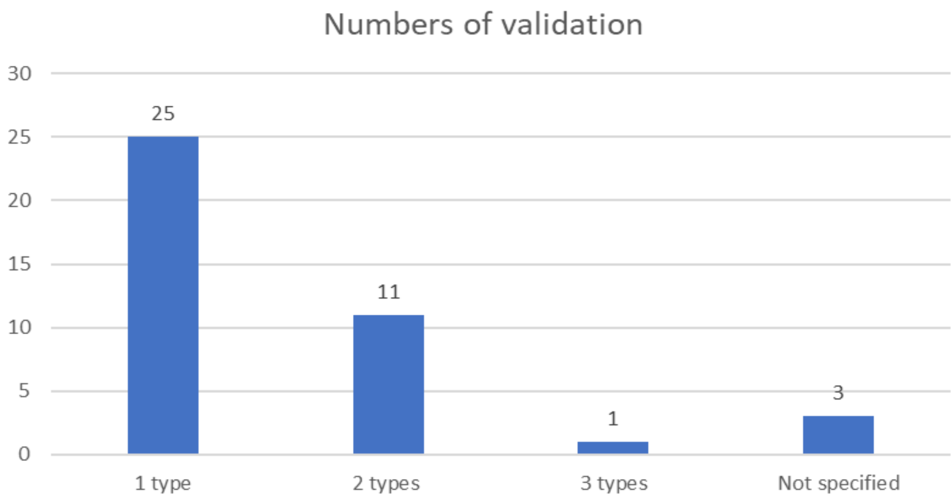

Figure 13. Distribution of validation types of machine learning algorithms

Figure 13 further presents how many types of validation approaches were used in our reviewed studies. The result showed that a single method was dominant (26 studies), followed by two mixed validation approaches (10 studies), and three types of validation used together (1 studies). Among the 40 reviewed studies, three did not report the validation approach.

3.5. Are there significant relationships among these aforementioned categorical variables by using chi-square analysis?

The Chi-square analysis showed that for the studies' sample size larger than 10,000, the data were mainly collected in online environments, whereas for the studies with sample sizes ranging from 1 to 999, the data were collected through classroom, online, or blended environments ($\chi^2 = 22.44$, $p = .033$). For the studies focused on a single learning domain (e.g., computer science), the data source is mainly from log files from the learning platform and learning records, while the studies which covered multiple learning domains also obtained data from institutional databases ($\chi^2 = 22.69$, $p = .031$).

Concerning learning outcomes, learning performance and dropout/attrition/retention were mostly measured by the studies aimed to make predictions, while learning outcomes were less often measured for the studies mainly focused on profiling or recommendations ($\chi^2 = 24.32$, $p = .004$). Furthermore, learning performance is equally important among all learning environments, while "other" learning outcomes are often measured in "other" learning environments ($\chi^2 = 28.07$, $p = .001$); for instance, emotional engagement was measured in game-based learning environments (Ninaus et al., 2019), or brain organization was evaluated by laboratory study (Astle et al., 2019).

With respect to the validation of algorithm, self-validation and split-validation were seldom used together ($\chi^2 = 6.07$, $p = .013$), whereas self-validation was more often combined with cross-validation ($\chi^2 = 5.52$, $p = .019$). Cross-validation tent to be used as the only validation approach, followed by combination with another type of validation (e.g., self-validation, split-validation; $\chi^2 = 9.62$, $p = .008$). Split-validation were often paired with cross-validation, followed by using alone ($\chi^2 = 6.14$, $p = .047$).

4. Discussion

In this paper, we systematically reviewed the emerging field of using a machine learning approach for precision education. After a series of screening steps, a total of 40 studies remained. To date, profiling and prediction were the primary research purpose. In short, most studies were carried out in an online or blended learning environment among university students majoring in computer science or STEM with heterogeneous data sources, such as MOOCs, institutional datasets, learning records, etc. The results indicated that using a machine learning approach for precision education is a fast-growing area with high potential. The emerging issues and future directions are presented in the following section.

4.1. From personalized learning to individualized learning

In the traditional education setting, personalized learning is resource-heavy and time-consuming. With the development of society and technology, data-driven personalized learning or precision education has become an achievable education paradigm. Among the potential methodologies to realize precision education, machine learning is viewed as one of the most promising means that emphasizes individual-level support rather than class- or group-level assistance. Harnessing big data, machine learning approaches are capable of extracting meaningful patterns and making individualized predictions. Correspondingly, this review study showed that diagnosis and prediction were the most prevalent research types, consistent with the results from an earlier review study on artificial intelligence applications in higher education (Zawacki-Richter et al., 2019). Only a handful of studies ($n = 3$) delivered interventions, similar to the proportion of review studies adopting learning analytics in higher education (Sonderlund et al., 2019; Viberg et al., 2018). There was as yet no study that provided prevention. The rapid advances in automatic emotion detection techniques are opening up new possibilities to monitor students' real-time emotions (Ninaus et al., 2019) and to provide immediate individualized feedback or learning materials. Real-time feedback or interventions are encouraged in future studies to realize the machine learning technique's full potential. That is, the research focus may shift from personalized learning to individualized learning (Luan et al., 2020).

4.2. Domain and population generalization issues

To date, most studies have been carried out among university students majoring in computer sciences and STEM. It is reasonable that the researchers with information technology expertise and in-depth domain knowledge were more familiar with machine learning techniques and gained greater access to students in these domains. On the other hand, the step-based and well-defined problems in computer sciences and STEM topics were more likely for machine learning researchers to design and implement personalized educational tools or systems (Humble & Mozelius, 2019; Roll & Wylie, 2016). Since the number of published articles in the first seven months of the year of 2020 was equal to the total of the year of 2019, the adoption of machine learning in education might experience a growth spurt, as occurred with AI-based precision medicine (Kourou et al., 2015; Krittanawong et al., 2017; Rajkomar et al., 2019) and precision psychiatry (Bzdok & Meyer-Lindenberg, 2018). Perhaps future research could broaden the learning domain from computer sciences and STEM to a more general knowledge area and include more learners at lower education levels such as kindergartens, elementary and secondary students.

4.3. Convergence of machine learning and neuroscience

The other notable line in research employing machine learning methods for precision education is the convergence of machine learning and neuroscience, similar to the existing trends in psychiatry (Janssen et al., 2018). The vast amount of data generated by EEG and Eye-movement devices is a perfect match for machine learning. The algorithmic models can be utilized to classify the patterns of cognitive ability such as working memory (Luo & Zhou, 2020) and styles of attention in financial decision making (Krol & Krol, 2019). Real-time feedback provided by machine learning techniques enables students to significantly improve their performance (Krol & Krol, 2019). The knowledge and insights from different forms of learning data are converging to create a new interdisciplinary science of learning that is capable to provide differentiated educational practices (Kuch et al., 2020).

4.4. Integration of innovative technologies and classic learning theories

Last but not least, we noticed that most of these reviewed studies selected features based on data availability; thus, past performance and log activities were frequently used in the training models. These data-intensive machine learning technologies might be integrated with learning theories to more effectively enhance students' learning (X. Chen et al., 2020; Hew et al., 2019). It is essential to help students become active participants in their own learning process and facilitate their self-directed learning (Loftus & Madden, 2020). Depending on the individual needs and specific educational purposes, pedagogical tools and learning strategies can be designed from different education perspectives such as behaviorism, information processing theory, social cognitive theory, and constructivism (Schunk, 2020).

5. Conclusion

In this review, we systematically reviewed 40 empirical studies regarding machine-learning-based precision education and showed that this field is a rapidly expanding area. This study uncovered the research gaps and provided an overview of the recent progress to help researchers understand essential topics in this emerging field. The results indicated that the majority of studies focused on the prediction of learning performance or dropouts, and were carried out in an online or blended learning environment among university students majoring in computer science or STEM, whereas the data sources were divergent and the sample size was 1-999. The commonly used machine learning algorithms, evaluation methods, and validation approaches were presented. This study offered valuable insights into the state-of-the-art machine learning techniques in precision education. We also discussed the emerging issues and critical directions to inspire the researchers interested in this field to conduct more empirical studies in the future. Furthermore, the research findings provided beneficial information for teachers and practitioners. The learning patterns and needs, and the predictions of learning outcomes generated by machine learning methods can help teachers make more precise decisions and reduce educational waste in time and resources.

This review study has several limitations. First, it should be noted that the current study mainly conducted a descriptive quantitative analysis of the current status of machine-learning-based precision education. Research synthesis and meta-analysis are recommended to provide more critical information. Second, we limited our search to journal articles to ensure the research quality, while book chapters and conference papers were excluded. Third, we set our search in published journal articles indexed in a highly reputable database, namely the Web of Science. Future studies can search for papers without these limitations to obtain more eligible items.

Compared to studies of other more mature educational technologies such as augmented reality and virtual reality (e.g., M. P. Chen et al., 2020; Cheng & Tsai, 2020; Jong et al., 2020), research using a machine learning approach for precision education is in its infancy. There is a long way to go in promoting learning and teaching by using machine learning methods. An in-depth understanding of the relationships between AI/machine learning techniques and an individual's characteristics calls for more subsequent research in this field.

Acknowledgement

This work was financially supported by the "Institute for Research Excellence in Learning Sciences" of the National Taiwan Normal University (NTNU) from the Featured Areas Research Center Program within the framework of the Higher Education Sprout Project by the Ministry of Education (MOE) in Taiwan.

References

(*Note.* References marked with stars (*) are the 40 reviewed studies in this paper)

*Abidi, S. M. R., Hussain, M., Xu, Y., & Zhang, W. (2019). Prediction of confusion attempting algebra homework in an intelligent tutoring system through machine learning techniques for educational sustainable development. *Sustainability*, *11*(1), 105. doi:10.3390/su11010105

*Arpaci, I. (2019). A Hybrid modeling approach for predicting the educational use of mobile cloud computing services in higher education. *Computers in Human Behavior, 90*, 181-187.

*Astle, D. E., Bathelt, J., Team, C., & Holmes, J. (2019). Remapping the cognitive and neural profiles of children who struggle at school. *Developmental Science, 22*(1), e12747. doi:10.1111/desc.12747

*Azcona, D., Hsiao, I. H., & Smeaton, A. F. (2019). Detecting students-at-risk in computer programming classes with learning analytics from students' digital footprints. *User Modeling and User-Adapted Interaction, 29*(4), 759-788.

Bzdok, D., & Meyer-Lindenberg, A. (2018). Machine learning for precision psychiatry: Opportunities and challenges. *Biological Psychiatry-Cognitive Neuroscience and Neuroimaging*, *3*(3), 223–230.

Chen, M.-P., Wang, L.-C., Zou, D., Lin, S.-Y., Xie, H., & Tsai, C.-C. (2020). Effects of captions and English proficiency on learning effectiveness, motivation and attitude in augmented-reality-enhanced theme-based contextualized EFL learning. *Computer Assisted Language Learning*, 1-31.

Chen, X., Xie, H., Zou, D., & Hwang, G.-J. (2020). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *1*, 100002. doi:10.1016/j.caeai.2020.100002

Cheng, K. H., & Tsai, C. C. (2020). Students' motivational beliefs and strategies, perceived immersion and attitudes towards science learning with immersive virtual reality: A Partial least squares analysis. *British Journal of Educational Technology, 51*(6), 2139-2158.

Collins, F. S., & Varmus, H. (2015). A New initiative on precision medicine. *New England Journal of Medicine*, *372*(9), 793-795.

Cook, C. R., Kilgus, S. P., & Burns, M. K. (2018). Advancing the science and practice of precision education to enhance student outcomes. *Journal of School Psychology*, *66*(SI), 4–10.

Corno, L., & Snow, R. E. (1986). Adapting teaching to individual differences among learners. In *Handbook of research on teaching* (pp. 605-629). Chicago, IL: Rand McNally.

*Coussement, K., Phan, M., De Caigny, A., Benoit, D. F., & Raes, A. (2020). Predicting student dropout in subscription-based online learning environments: The Beneficial impact of the logit leaf model. *Decision Support Systems,* 113325. doi:10.1016/j.dss.2020.113325

*Delen, D., Topuz, K., & Eryarsoy, E. (2020). Development of a Bayesian belief network-based DSS for predicting and understanding freshmen student attrition. *European Journal of Operational Research, 281*(3), 575-587.

Frey, J. R. (2019). Assessment for special education: diagnosis and placement. *The ANNALS of the American Academy of Political and Social Science*, *683*(1), 149-161.

Gobert, J. D., & Sao Pedro, M. A. (2017). Digital assessment environments for scientific inquiry practices. In A. A. Rupp, & J. P. Leighton (Eds.), *The Wiley Handbook of Cognition and Assessment: Frameworks, Methodologies, and Applications* (pp. 508-534). West Sussex, UK: John Wiley & Sons Ltd.

*Gontzis, A. F., Kotsiantis, S., Panagiotakopoulos, C. T., & Verykios, V. S. (2019). A Predictive analytics framework as a countermeasure for attrition of students. *Interactive Learning Environments*, 1-15.

Graham, C. R. (2006). Blended learning systems. In *the Handbook of Blended Learning: Global Perspectives, Local Designs* (pp. 3-21). San Francisco, CA: Pfeiffer.

*Guerrero-Higueras, Á. M., Fernández Llamas, C., Sánchez González, L., Gutierrez Fernández, A., Esteban Costales, G., & Conde González, M. Á. (2020). Academic success assessment through Version Control Systems. *Applied Sciences, 10*(4), 1492. doi:10.3390/app10041492

Hart, S. A. (2016). Precision education initiative: Moving toward personalized education. *Mind Brain and Education*, *10*(4), 209–211. doi:10.1111/mbe.12109

Hew, K. F., Lan, M., Tang, Y., Jia, C., and Lo, C. K. (2019). Where is the "theory" within the field of educational technology research? *British Journal of Educational Technology*, *50*(3), 956–971.

Honey, M., Pearson, G., & Schweingruber, H. (Eds.). (2014). *STEM integration in K-12 education: Status, prospects, and an agenda for research*. Washington, DC: National Academies Press.

Huang, Y. M., Liang, T. H., Su, Y. N., & Chen, N. S. (2012). Empowering personalized learning with an interactive e-book learning system for elementary school students. *Educational Technology Research and Development*, *60*(4), 703-722.

Humble, N., & Mozelius, P. (2019). Artificial intelligence in education—A Promise, a threat or a hype? In *European Conference on the Impact of Artificial Intelligence and Robotics 2019 (ECIAIR 2019)* (pp. 149–156). Oxford, UK: Academic Conferences and Publishing International Limited.

*Hussain, M., Zhu, W., Zhang, W., Abidi, S. M. R., & Ali, S. (2018). Using machine learning to predict student difficulties from learning session data. *Artificial Intelligence Review, 52*(1), 381-407.

Janssen, R. J., Mourão-Miranda, J., & Schnack, H. G. (2018). Making individual prognoses in psychiatry using neuroimaging and machine learning. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *3*(9),798-808. Doi: 10.1016/j.bpsc.2018.04.004

Jong, M. S. Y., Tsai, C. C., Xie, H., & Kwan-Kit Wong, F. (2020). Integrating interactive learner-immersed video-based virtual reality into learning and teaching of physical geography. *British Journal of Educational Technology*, *51*(6), 2063-2078.

Jordan, M. I., and Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255-260.

*Kassak, O., Kompan, M., & Bielikova, M. (2016). Student behavior in a web-based educational system: Exit intent prediction. *Engineering Applications of Artificial Intelligence*, *51*, 136-149.

*Kim, W.-H., & Kim, J.-H. (2020). Individualized AI tutor based on developmental learning networks. *IEEE Access, 8*, 27927-27937.

*Kizilcec, R. F., Reich, J., Yeomans, M., Dann, C., Brunskill, E., Lopez, G., Turkay, S., Williams, J. J., & Tingley, D. (2020). Scaling up behavioral science interventions in online education. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(26), 14900-14905.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers & Education*, *56*(3), 885-899.

Korkmaz, C., & Correia, A. P. (2019). A Review of research on machine learning in educational technology. *Educational Media International*, *56*(3), 250-267.

Kourou, K., Exarchos, T. P., Exarchos, K. P., Karamouzis, M. V., & Fotiadis, D. I. (2015). Machine learning applications in cancer prognosis and prediction. *Computational and Structural Biotechnology Journal*, *13*, 8–17.

Koutsouleris, N., Kahn, R. S., Chekroud, A. M., Leucht, S., Falkai, P., Wobrock, T., Derks, E. M., Fleischhacker, W. W., & Hasan, A. (2016). Multisite prediction of 4-week and 52-week treatment outcomes in patients with first-episode psychosis: A Machine learning approach. *The Lancet Psychiatry*, *3*(10), 935-946.

Krittanawong, C., Zhang, H., Wang, Z., Aydar, M., & Kitai, T. (2017). Artificial intelligence in precision cardiovascular medicine. *Journal of the American College of Cardiology*, *69*(21), 2657–2664.

*Krol, M., & Krol, M. (2019). Learning from peers' eye movements in the absence of expert guidance: A Proof of concept using laboratory stock trading, eye tracking, and machine learning. *Cognitive Science, 43*(2), e12716. doi:10.1111/cogs.12716

Kuch, D., Kearnes, M., & Gulson, K. (2020). The Promise of precision: Datafication in medicine, agriculture and education. *Policy Studies*, 1-20.

*Kurilovas, E. (2018). Advanced machine learning approaches to personalise learning: learning analytics and decision making. *Behaviour & Information Technology, 38*(4), 410-421.

*Kushik, N., Yevtushenko, N., & Evtushenko, T. (2020). Novel machine learning technique for predicting teaching strategy effectiveness. *International Journal of Information Management, 53,*101488. doi:10.1016/j.ijinfomgt.2016.02.006

*Lee, S., & Chung, J. Y. (2019). The Machine learning-based dropout early warning system for improving the performance of dropout prediction. *Applied Sciences, 9*(15), 3093. doi:10.3390/app9153093

*Lee, S., Hwang, Y., Jin, Y., Ahn, S., & Park, J. (2019). Effects of individuality, education, and image on visual attention: Analyzing eye-tracking data using machine learning. *Journal of Eye Movement Research*, *12*(2), 4. doi:10.16910/jemr.12.2.4

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A Review. *Sensors*, *18*(8), 2674. doi:10.3390/s18082674

Lin, W. Y., Hu, Y. H., & Tsai, C. F. (2011). Machine learning in financial crisis prediction: A Survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, *42*(4), 421-436.

*Loftus, M., & Madden, M. G. (2020). A Pedagogy of data and Artificial Intelligence for student subjectification. *Teaching in Higher Education, 25*(4), 456-475.

*López, M. B., Alor-Hernández, G., Sánchez-Cervantes, J. L., del Pilar Salas-Zárate, M., & Paredes-Valverde, M. A. (2018). EduRP: An educational resources platform based on opinion mining and semantic web. *Journal of Universal Computer Science*, *24*(11), 1515-1535.

Lu, O., Huang, A., Huang, J., Lin, A., Ogata, H., & Yang, S. J. H. (2018). Applying learning analytics for the early prediction of students' academic performance in blended learning. *Educational Technology & Society, 21*(2), 220-232.

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J. H., Ogata, H., Baltes, J., Guerra, R., Li, P., & Tsai, C.-C. (2020). Challenges and future directions of big data and artificial intelligence in education. *Frontiers in Psychology*. *11,* 580820. doi:10.3389/fpsyg.2020.580820

*Luo, W., & Zhou, R. (2020). Can working memory task-related EEG biomarkers measure fluid intelligence and predict academic achievement in healthy children? *Frontiers in Behavioral Neuroscience*, *14*, 2. doi:10.3389/fnbeh.2020.00002

*Magana, A. J., Elluri, S., Dasgupta, C., Seah, Y. Y., Madamanchi, A., & Boutin, M. (2019). The Role of simulation-enabled design learning experiences on middle school students' self-generated inherence heuristics. *Journal of Science Education and Technology, 28*(4), 382-398.

Moreno-Marcos, P. M., Alario-Hoyos, C., Muñoz-Merino, P. J., & Kloos, C. D. (2018). Prediction in MOOCs: A Review and future research directions. *IEEE Transactions on Learning Technologies*, *12*(3), 384-401.

*Mubarak, A. A., Cao, H., & Zhang, W. (2020). Prediction of students' early dropout based on their interaction logs in online learning environment. *Interactive Learning Environments*, 1-20.

*Musso, M. F., Hernández, C. F. R., & Cascallar, E. C. (2020). Predicting key educational outcomes in academic trajectories: A Machine-learning approach. *Higher Education*, 1-20.

*Ninaus, M., Greipl, S., Kiili, K., Lindstedt, A., Huber, S., Klein, E., Karnath, H.-O., & Moeller, K. (2019). Increased emotional engagement in game-based learning – A Machine learning approach on facial emotion detection data. *Computers & Education, 142*, 103641–103610.

*Pliakos, K., Joo, S. H., Park, J. Y., Cornillie, F., Vens, C., & Van den Noortgate, W. (2019). Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems. *Computers & Education*, *137*, 91-103.

Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine*, *380*(14), 1347-1358.

*Rajkumar, R., & Ganapathy, V. (2020). Bio-inspiring learning style chatbot inventory using brain computing interface to increase the efficiency of e-learning. *IEEE Access, 8*, 67377-67395.

Ramprasad, R., Batra, R., Pilania, G., Mannodi-Kanakkithodi, A., & Kim, C. (2017). Machine learning in materials informatics: Recent applications and prospects. *npj Computational Materials*, *3*(1), 1-13. doi:10.1038/s41524-017-0056-5

*Rodríguez-Martín, M., Rodríguez-Gonzálvez, P., Sánchez-Patrocinio, A., & Sánchez, J. R. (2019). Short CFD simulation activities in the context of fluid-mechanical learning in a multidisciplinary student body. *Applied Sciences*, *9*(22), 4809. doi:10.3390/app9224809

*Rodriguez-Muniz, L. J., Bernardo, A. B., Esteban, M., & Diaz, I. (2019). Dropout and transfer paths: What are the risky profiles when analyzing university persistence with machine learning techniques? *PLoS One, 14*(6), e0218796. doi:10.1371/journal.pone.0218796

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education*, *26*(2), 582–599.

Schunk, D. H. (2020). *Learning theories an educational perspective* (8th ed.) Boston, MA: Pearson.

Shi, B., & Weninger, T. (2017). ProjE: Embedding projection for knowledge graph completion. *Proceedings of the Thirty-first AAAI Conference on Artificial Intelligence, 31*(1), 1236–1242.

Sonderlund, A. L., Hughes, E., and Smith, J. (2019). The Efficacy of learning analytics interventions in higher education: A Systematic review. *British Journal of Educational Technology*, 50(5), 2594–2618.

*Spatiotis, N., Perikos, I., Mporas, I., & Paraskevas, M. (2020). Sentiment analysis of teachers using social information in educational platform environments. *International Journal on Artificial Intelligence Tools*, *29*(02), 2040004. doi:10.1142/S0218213020400047

*Sultana, S., Khan, S., & Abbas, M. A. (2017). Predicting performance of electrical engineering students using cognitive and non-cognitive features for identification of potential dropouts. *International Journal of Electrical Engineering & Education, 54*(2), 105-118.

The White House, Office of the Press Secretary. (2015). *FACT SHEET: President Obama's Precision Medicine Initiative*. Retrieved from https://www.whitehouse.gov/the-press-office/2015/01/30/fact-sheet-president-obama-s-precision-medicine-initiative

Tseng, J. C., Chu, H. C., Hwang, G. J., & Tsai, C. C. (2008). Development of an adaptive learning system with two sources of personalization information. *Computers & Education*, *51*(2), 776-786.

*Tomasevic, N., Gvozdenovic, N., & Vranes, S. (2020). An Overview and comparison of supervised data mining techniques for student exam performance prediction. *Computers & Education, 143,* 103676. doi:10.1016/j.compedu.2019.103676

*Tsai, S.-C., Chen, C.-H., Shiao, Y.-T., Ciou, J.-S., & Wu, T.-N. (2020). Precision education with statistical learning and deep learning: A Case study in Taiwan. *International Journal of Educational Technology in Higher Education, 17*(1), 1-13.

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018) The Current landscape of learning analytics in higher education. *Computers in Human Behavior, 89,* 98–110.

*Wakelam, E., Jefferies, A., Davey, N., & Sun, Y. (2019). The Potential for student performance prediction in small cohorts with minimal available attributes. *British Journal of Educational Technology, 51*(2), 347-370.

*Wang, L., Hu, G., & Zhou, T. (2018). Semantic analysis of learners' emotional tendencies on online MOOC education. *Sustainability, 10*(6), 1921. doi:10.3390/su10061921

Williamson, B. (2019). Digital policy sociology: Software and science in data-intensive precision education. *Critical Studies in Education*, 1-17. doi:10.1080/17508487.2019.1691030

Wu, D., Jennings, C., Terpenny, J., Gao, R. X., & Kumara, S. (2017). A Comparative study on machine learning algorithms for smart manufacturing: Tool wear prediction using random forests. *Journal of Manufacturing Science and Engineering*, *139*(7), 071018. doi:10.1115/1.4036350

*Wu, J. Y., Hsiao, Y. C., & Nian, M. W. (2020). Using supervised machine learning on large-scale online forums to classify course-related Facebook messages in predicting learning achievement within the personal learning environment. *Interactive Learning Environments*, *28*(1), 65-80.

*Xiao, M., & Yi, H. (2020). Building an efficient artificial intelligence model for personalized training in colleges and universities. *Computer Applications in Engineering Education*, 1–9. doi:10.1002/cae.22235

Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A Systematic review of journal publications from 2007 to 2017. *Computers & Education*, *140*, 103599. doi:10.1016/j.compedu.2019.103599

*Xing, W., & Du, D. (2018). Dropout prediction in MOOCs: Using deep learning for personalized intervention. *Journal of Educational Computing Research, 57*(3), 547-570.

*Xing, W., Popov, V., Zhu, G., Horwitz, P., & McIntyre, C. (2019). The Effects of transformative and non-transformative discourse on individual performance in collaborative-inquiry learning. *Computers in Human Behavior*, *98*, 267-276.

*Xu, J., Moon, K. H., & van der Schaar, M. (2017). A Machine learning approach for tracking and predicting student performance in degree programs. *IEEE Journal of Selected Topics in Signal Processing, 11*(5), 742-753.

U.S. Department of Education, Office of Educational Technology (2017). *Reimagining the role of technology in education: 2017 national education technology plan update.* Retrieved from https://tech.ed.gov/files/2017/01/NETP17.pdf

Voyant, C., Notton, G., Kalogirou, S., Nivet, M. L., Paoli, C., Motte, F., & Fouilloy, A. (2017). Machine learning methods for solar radiation forecasting: A Review. *Renewable Energy*, *105*, 569-582.

Yang, S. J. H. (2019). Precision education: New challenges for AI in education [conference keynote]. In *Proceedings of the 27th International Conference on Computers in Education (ICCE)* (pp. XXVII-XXVIII). Kenting, Taiwan: Asia-Pacific Society for Computers in Education (APSCE).

Zawacki-Richter, O., Marín, V. I., Bond, M., and Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1-27. doi:10.1186/s41239-019-0171-0

Zhai, X., Yin, Y., Pellegrino, J. W., Haudek, K. C., & Shi, L. (2020). Applying machine learning in science assessment: A Systematic review. *Studies in Science Education*, *56*(1), 111-151.

[*]Zhou, Y., Huang, C., Hu, Q., Zhu, J., & Tang, Y. (2018). Personalized learning full-path recommendation model based on LSTM neural networks. *Information Sciences*, *444*, 135-152.