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Personalized Education in the Artificial Intelligence Era

What to expect next

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The objective of personalized learning is to design an effective knowledge acquisition track that matches the learner's strengths and bypasses his/her weaknesses to ultimately meet his/her desired goal. This concept emerged several years ago and is being adopted by a rapidly growing number of educational institutions around the globe. In recent years, the rise of artificial intelligence (AI) and machine learning (ML), together with advances in big data analysis, has introduced novel perspectives that enhance personalized education in numerous ways. By taking advantage of AI/ML methods, the educational platform precisely acquires the student's characteristics. This is done, in part, by observing past experiences as well as analyzing the available big data through exploring the learners' features and similarities. It can, for example, recommend the most appropriate content among numerous accessible ones, advise a well-designed long-term curriculum, and connect appropriate learners by suggestion, accurate performance evaluation, and so forth. Still, several aspects of AI-based personalized education remain unexplored. These include, among others, compensating for the adverse effects of the absence of peers, creating and maintaining motivations for learning, increasing the diversity, removing the biases induced by data and algorithms, and so on. In this article, while providing a brief review of state-of-the-art research, we investigate the challenges of AI/ML-based personalized education and discuss potential solutions.

Introduction

The last decade has witnessed an explosion in the number of web-based learning systems due to increasing demand in higher-level education, the limited number of teaching personnel, advances in information technology and AI, and, more recently, COVID-19. In the past few years, to enhance conventional classrooms, to bridge the constraints of time and distance, and to improve fairness by making high-quality education accessible, most universities have integrated massive open online course (MOOC) platforms in their education systems. Also, several schools have added online labs to their structures, where

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students, especially those who cannot access physical labs, can perform experiments.

In addition, there has been significant growth in the development of other online educational tools that simplify learning. These include, for example, the software used for text summarization in different domains and also to produce questions and tests, followed by evaluation, which can be of great assistance to not only students but also to teachers. Several advantages of these systems over traditional classroom teaching are that 1) they provide flexibility to the student in choosing what and when to learn, 2) they do not require the presence of an interactive human teacher, and 3) often, the capacity in terms of the number of participants is significantly larger than the synchronous-presence teaching form. Figure 1 shows the baseline ecosystem of online personalized education, including all the stakeholders, together with the crucial factors and performance metrics.

However, currently available online teaching platforms have significant limitations. To a large extent, personalized education has been limited mainly to a specific type of recommender system, although its potential goes far beyond advising a series of lectures on an online platform that might be interesting to a specific user. One fundamental difference between existing recommender systems and personalized education is the optimization objective: The former focuses on some form of user engagement to maximize profit, which is system centric and relatively easy to quantify, whereas the latter focuses on some form of learning outcomes, which is student centric and hard to define.

ML/AI-enabled education is a response with great potential to overcome the current shortcomings. It creates a new and more flexible learning technology genre that adapts to student learning and allocates resources as obliged. It takes advantage of the strengths of both online tools and individual tutoring. As such, AI-enabled personalized education promises to yield many of the benefits of one-on-one instruction at a per-student cost similar to that of large university lecture classes. The system applies to both online courses and courses with a hybrid of classroom and online instruction. As displayed in Figure 2, ML/AI-enabled education comprises a large set of decision-making strategies that collectively map the available data together with the individual features to a variety of personalized educational materials and recommendations.

Data can be collected on performance in both traditional assignments (problem sets, computer programs, and laboratories) as well as online exercises and tests. It includes built-in assessment tools as an essential part of its optimization of lesson sequences. As such, it supports the educational community in developing new teaching modalities in a broad range of disciplines. However, despite intensive research efforts conducted during this decade, a variety of aspects of personalized

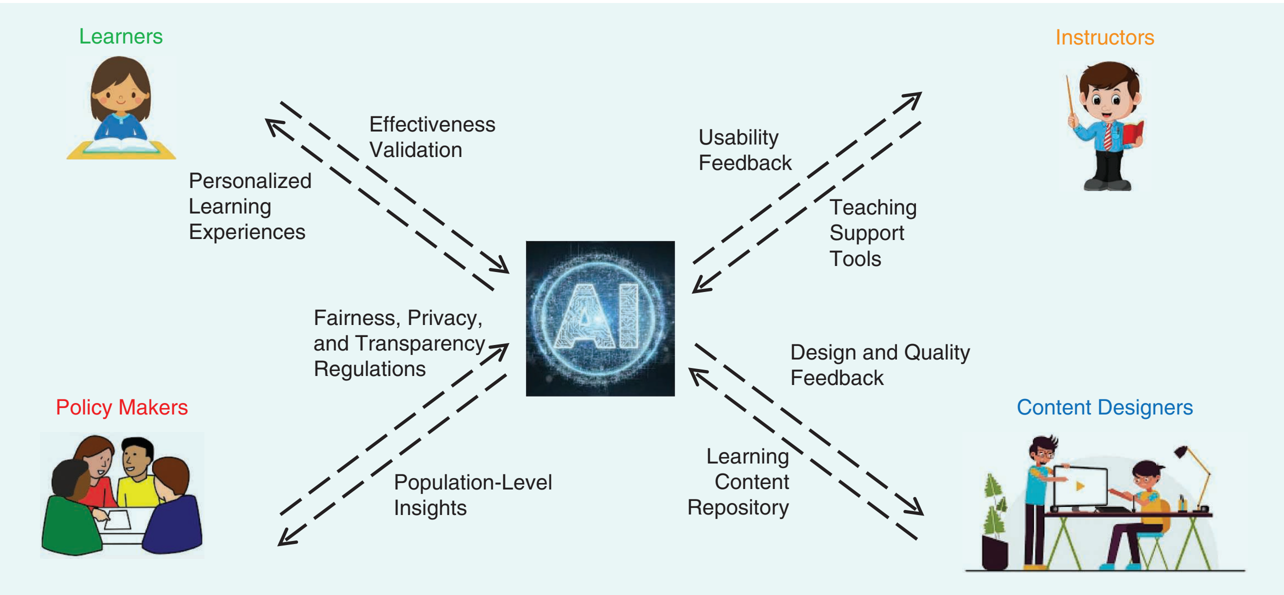

FIGURE 1. The baseline ecosystem of AI-empowered personalized education.

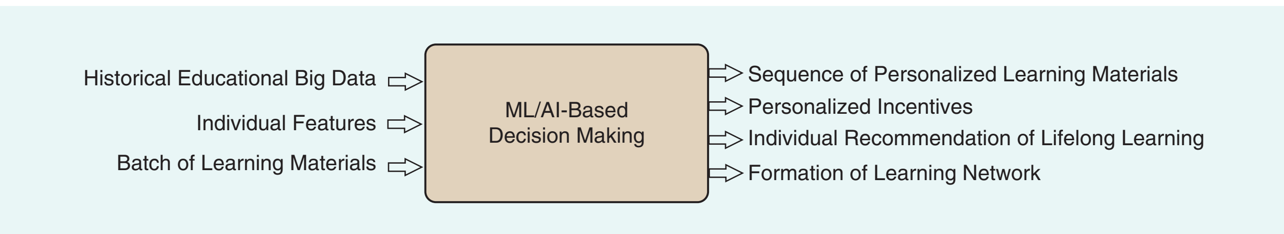

FIGURE 2. The basic concept of AI-empowered personalized education.

education remain unexplored, including both dark and bright sides. In this article, we discuss six core topics, review existing work, outline their limitations, and propose future research directions (see Figure 3 for an overview).

When discussing any form of education, *quality* is an inevitable keyword. The quality of education depends largely on the quality of the available learning content and on the quality of the personalized recommendations that guide each learner to the most suitable learning content. Thus far, researchers have studied the production of learning content, from developing AI-driven smart learning content such as intelligent, interactive textbooks and game-based learning platforms, to automatically generating learning content from the wild. The authors in [1], for example, develop a sentence-deletion method for text simplification. In [2], the authors investigate the effectiveness of discourse in multimedia to extract the knowledge from textbooks. Moreover, a large body of the existing work investigates the recommendation of both macro- and microlevel learning content, including courses in learners' degree plans as well as specific remedial content, such as lecture notes, videos, and practice problems. For example, in [3], the authors take advantage of a multiarmed bandit framework to optimize the selection of learning resources and questions to satisfy the needs of each individual student. Furthermore, another paper has developed an e-learning recommender system framework based on two concepts: peer learning and social learning, which encourage students to cooperate and learn jointly. Despite great effort, there remain several challenges to address, including content recommendation at heterogeneous levels, the recommendation of a bundle of related content followed by performance evaluation, and the Pareto-optimization of conflicting objectives in the content recommendation. We discuss these progress and future steps in the "Content Production and Recognition" section.

Historically, education has been tightly coupled with evaluation. In personalized education, assessment and evaluation concern both the learner's performance and the effectiveness of the intelligent learning platform. The early approaches that were

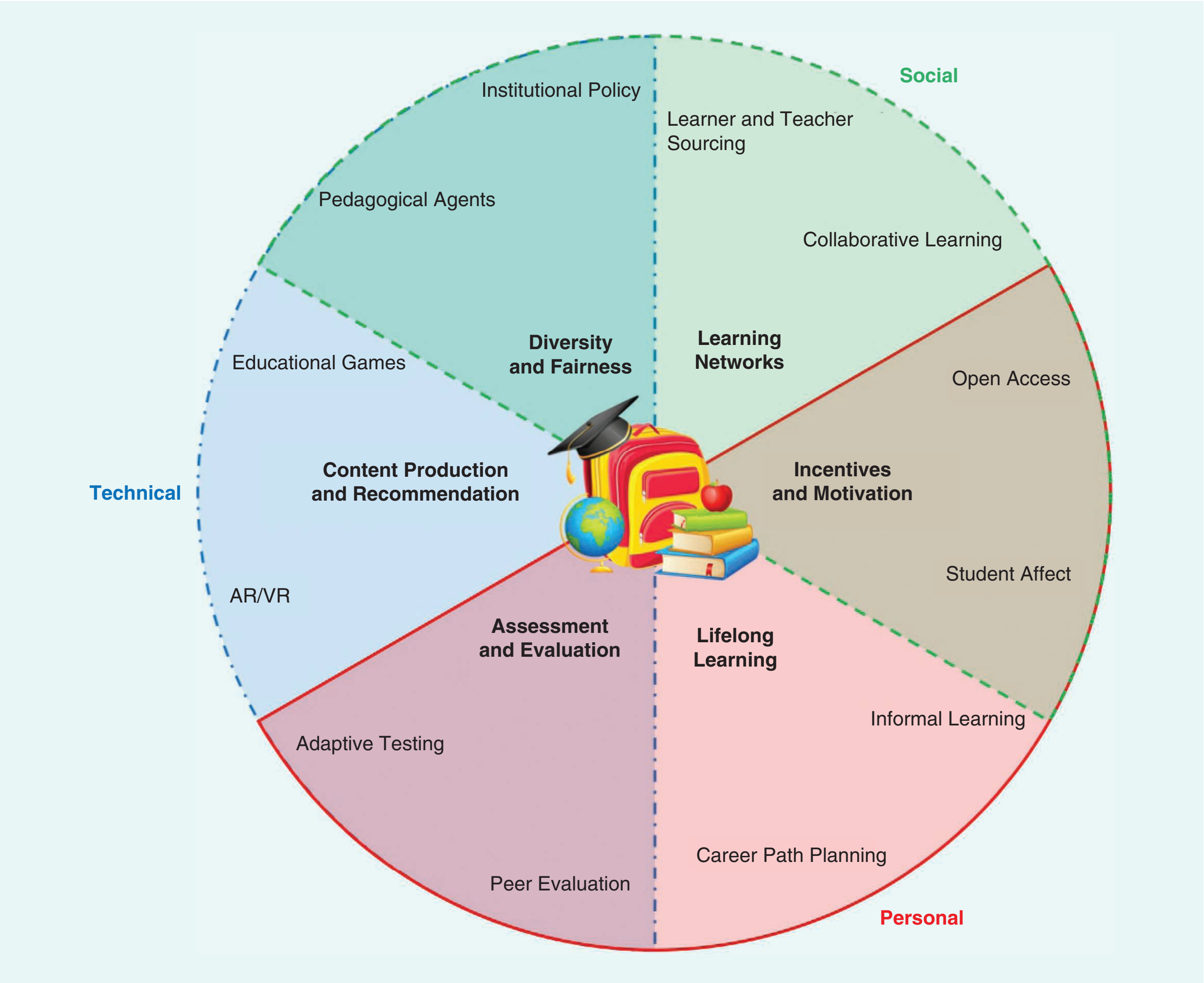

FIGURE 3. A list of (some of) the topics in personalized education, organized according to three different aspects: technical, personal, and social. In this article, we focus on six of the topics. AR/VR: augmented reality/virtual reality.

used for learner assessment, such as classical testing theories (CTTs), utilized graded standardized test summaries. Recent approaches include item response theory (IRT) models, which facilitate the estimation of latent-knowledge mastery levels, and knowledge tracing (KT) models, which pursue the evolution of a learner's knowledge. In [4], the authors compare CTTs and IRTs. Methods such as computerized adaptive testing improve the efficiency of assessments. The current approaches employed to evaluate learning platforms use rigorous experiments, often large-scale, randomized, and controlled trials. In this area, open problems include the prediction of learners' future performance, which enables providing better recommendations and more accurate feedback. This is referred to as the *KT* problem, for which several methods have been developed in the past few decades. As an example, among many others, some papers discuss a Bayesian framework for KT. Another challenge is to reduce the information loss while grading the arrived input from the learner through the accurate interpretation of knowledge level based on the test design. We elaborate on and address such challenges in the "Assessment and Evaluation" section.

Significant advances in science, technology, and health care have changed the working life of humans. Individuals have many more alternatives when choosing a job; he/she tends to change jobs more frequently than before, is more open to mobility, and has a long career span. As such, continuing education, which aims at advancing one's educational process, as well as lifelong learning, i.e., pursuing additional professional qualifications, are important components of educational policy in the world. Implementing these two concepts successfully has a significant impact on social welfare by developing new skills that enhance personal and professional lives.

During the past decade, AI-/ML-based personalized education has been under intensive investigation from several perspectives; nonetheless, the aforementioned aspects are largely neglected. Indeed, personalized education shall accompany the learner throughout his/her life, which can be difficult and costly to implement. Other challenges include a lack of appropriate data, a potentially long delay to receive feedback, high diversity, and fast dynamics in the environment. For instance, in [5], the authors design a new genre of educational technology, personal computer systems, which support learning from any location throughout a lifetime. Another research direction is to enable the learning system to learn continuously. Parisi et al. [6], for example, investigate the ability of neural networks to provide lifelong learning. We elaborate more on this topic in the "Lifelong Learning" section.

Similar to any other task, humans require motivation for learning. Generally, incentives for learning can be defined as *an inducement or supplemental reward that serves as a motivational device for intended learning* [7]. Presumably, the most conventional models of incentive are the grade and the certificate, which are implemented as a part of learning platforms to motivate students. The strength of such motivation depends on the validity and acceptance of such certificates by different authorities, such as employers. Nonetheless, employing AI methods for personalized education enables incentive design far beyond the issuance of a certificate. This includes monetary rewards in the form of bonuses for online learning materials. The incentives can also be introduced using soft methods, such as gamification based on the learner's characters to promote continuous learning, or by adapting the features of the learning environment based on the learner's traits to engage him/herself in the learning process for as long as possible. In [8], the authors investigate the effects of gamification on students' motivation from several perspectives. We discuss these challenges and methods in the "Incentives and Motivation" section.

Education is social, and learners can benefit meaningfully from their peers. It is therefore urgent to develop effective ways to build networks that serve as a conduit of knowledge for learners to interact with each other. In its current form, personalized education suffers from a lack of student–student and student–teacher connections and interactions, which, unquestionably, have a positive impact on learning, through discussions, joint efforts, and brainstorming. For example, Vesely, et al. [9] investigated and compared the influence of such communities from both students' and teachers' perspectives. As another example, in state-of-the-art research, authors have studied the building and sustaining community in asynchronous learning networks, i.e., when the learners are physically separated.

Despite past research efforts, we believe that by capitalizing on AI and ML methods, online platforms have more to offer, especially for building the knowledge and expertise networks that facilitate the assimilation and dissemination of information, and, consequently, by enabling close interactions (in terms of mentorships, friendships, coworkers, and so on), creating knowledge. Personalized education platforms can promote autonomous network formation by encouraging learners to interact. Moreover, the platforms can establish links among those learners that satisfy some similarity conditions and can hence be useful to each other for cooperation, inspiration, and motivation. Still, it is vital to note that online contacts can be lost easily, and the learners, especially at early ages, are more prone to feeling isolated and depressed. We elaborate on these issues in the "Building Learning Networks" section.

In many different ways, education affects the well-being of humans, and society at-large, both in the short and long term. As such, fairness is a highly important aspect of education, regardless of whether it occurs in conventional classrooms or in modern platforms that can personalize the learning experience. Despite this great importance, personalized education, similar to its traditional counterpart, might result in and strengthen inequality. This arises, for example, due to unequal access to learning platforms, biases in training data, inaccuracies in algorithm design, and so forth. Indeed, existing research shows that some subgroups of students—many of whom are also privileged with respect to conventional education platforms—would profit more from personalized education than would their peers. To address this issue more specifically, there have been intensive efforts to develop appropriate fairness models [10]. Moreover, several research works have studied the fairness of predictive algorithms in educational settings.

Another crucial issue is diversity. Today, it is well established that diversity promotes innovation and efficiency in the working place. Nonetheless, given the social responsibility of education, recruiting only diverse talents does not suffice. An AI-based personalized education platform can help diversify the education environment, for example, by rewarding collaborative learning in diverse networks. We discuss these topics in the "Diversity, Fairness, and Biases" section.

Content production and recommendation

Ultimately, the quality of education depends on the quality of the learning content. Creating new content requires the wisdom of human content designers and educational experts; to date, AI methods have not shown the capability of creating learning content on their own. However, they still have plenty to offer in content production by automating mundane jobs and helping humans in tasks where human input is necessary. Specifically, the role of AI should be to 1) take away repetitive tasks that can be automated and 2) assist humans by providing the feedback extracted from data during the process of content production in a human-in-the-loop manner. The following section detail ample future research directions in content production.

Content summarization and question generation

In many educational domains, knowledge is factual. For example, in history, one often needs to remember specific detailed facts about historical events. Even in scientific domains such as biology, there is also factual knowledge, e.g., the size and life span of an animal. In this case, there are many natural language processing (NLP)-based tools that can be used for content production. For example, text summarization tools can sort through long, sometimes redundant, textbook sections and extract key facts for remedial studies. This is not only helpful but also sometimes crucial to certain learner groups, such as those with learning disabilities. Moreover, automatic question generation can effectively produce high-quality factual assessment questions that have short, textual answers [11]. An example of automated question generation is shown in Table 1: We reversed a long short-term memory network-driven question-answering pipeline trained on common question-answering data sets, turned it into a question-generating pipeline, and applied it to textbooks. Human experts have indicated that the quality of generated questions is higher than those produced from other methods [11].

Multimodal content understanding

Many educational domains involve multimodal learning content, such as text, formulas, figures, and diagrams. When a learner fails to answer an assessment question correctly, personalized education systems need to automatically retrieve relevant content to help the learner resolve his/her confusion (by retrieving examples and explanations) or give the learner more practice opportunities (by retrieving assessment questions). Retrieving content within the same modal is relatively easy; for example, when a learner answers a textual question incorrectly, it is possible to use information-retrieval methods to extract relevant textbook chunks or lecture slides. However, when the most helpful content is in another modality, such as when a Venn diagram is the most effective at helping a learner clear up a misconception in a probability question involving text and mathematical formulas, it is hard to retrieve the diagram. Therefore, more work needs to be done when the domain includes multimodal content. To understand these content modalities and use them for content production, we need to learn universal representations across all modalities, possibly using embedding approaches to map multiple modalities into a shared vector space.

Human-in-the-loop content design

Even for humans, learning content is not created in one shot. Similar to textbooks, which have different editions, learning content is frequently edited and updated over time. Therefore, during this multistep process, we can use AI methods to act as (possibly even interactive) assistants to content designers. The duties that can be assigned to AI methods include 1) analyzing learners' data to identify the areas of priority for new content and assessment questions that need to be improved (see the "Assessment and Evaluation" section for discussions on how existing learner assessment models can also provide information about question quality), 2) providing drafts of instructor responses and perform automated checking of human-generated content using NLP tools, and 3) using crowdsourcing to put the learning content together by soliciting on-demand feedback. The third task is especially important in online educational settings, where learning occurs during frequent exchanges between learners and human instructors and assistants [12].

Even with high-quality learning content, the presentation, i.e, the personalized recommendation of the right learning content to the right learner at the right time is crucial to optimizing learning outcomes. Fortunately, this is an area at which AI methods can excel: By automatically deploying recommendations and analyzing the data of learners' performance, they can quantify the effect of the learning content on certain learners in terms of specific learning outcomes to detect the most effective ones. On the contrary, humans, including educational experts in the past, use theoretical models of learning and do not fully take advantage of this data. In the following sections, we discuss a few directions for future research in this area.

Recommendations at the microscopic and macroscopic levels

Learning content is organized at multiple levels, down to individual paragraphs and assessment questions, up to courses and

Table 1. An example of two automatically generated assessment questions for two different answers with the same input context from a textbook. The answers are underlined and marked with different colors in the input context.

Context (Biology): On each chromosome, there are thousands of genes that are responsible for determining the genotype and phenotype of the individual. A gene is defined as *a sequence of DNA that codes for a functional product.* The human haploid genome contains **3 billion base pairs** and has **between 20,000 and 25,000** functional genes.

3 billion base pairs	Between 20,000 and 25,000
How many base pairs are on the human genome?	How many functional genes are on the human haploid genome?

textbooks that organize several pieces of learning content together. Therefore, we need to study content recommendations at multiple levels: 1) microscopic, which comprises individual questions and lecture video suggestions [13], and 2) macroscopic, which includes course recommendation, especially for learners taking MOOCs [14].

Efficient experimentation and synthetic learner models

Traditionally, the fields of learning science and education have relied on rigorous A/B testing to validate the educational impact of learning content, usually in terms of its ability to improve learning outcomes for learners in the experimental group over those in the control group. However, this approach leads to long experimental cycles because 1) typically, only one learning content at a time can be validated and 2) metrics such as long-term learning outcomes naturally require long experimental cycles. Therefore, it is imperative to search for novel tools that enable rapid experimentation. Possible solutions include employing Bayesian optimization to test multiple contents simultaneously, or utilizing reinforcement learning (RL) as more and more learners use a piece of learning content. In the past, using RL to learn instructional policies (content recommendation can be viewed as a form of the instructional policy) has been limited due to a lack of large-scale real learner data; however, recent approaches have looked at using data- or cognitive theory-driven synthetic learner models to simulate learner data.

Conflicting objectives

There is no unified objective in personalized learning because learning outcomes themselves are defined at multiple time scales. The optimal action may differ across different objectives. For example, the learning content used in a practice session that maximizes a learner's performance on the midterm exam tomorrow may differ from the one that maximizes their overall course grade, which may differ from the one that maximizes their chance of getting a specific job after graduation. Therefore, we need to develop personalization algorithms that can balance multiple objectives and even resolve potential conflicts among these objectives. We also need to understand how these objectives interact with each other; for example, what skills taught in courses and schools carry over after graduation—a key issue in lifelong learning (discussed in detail in the "Lifelong Learning" section).

Figure 4 depicts the interplay between different elements, such as context, prediction, feedback, and so on to optimize course recommendation. It is worth noting that the approaches described previously are generic in the sense that they have wide applicability to different educational areas, including signal processing, possibly with minor domain-dependent adaptations. As an example, in [15], the authors apply several of the aforementioned ideas to develop eTutor, a personalized, web-based education system that learns the optimal sequence of teaching materials to present, based on the student's context

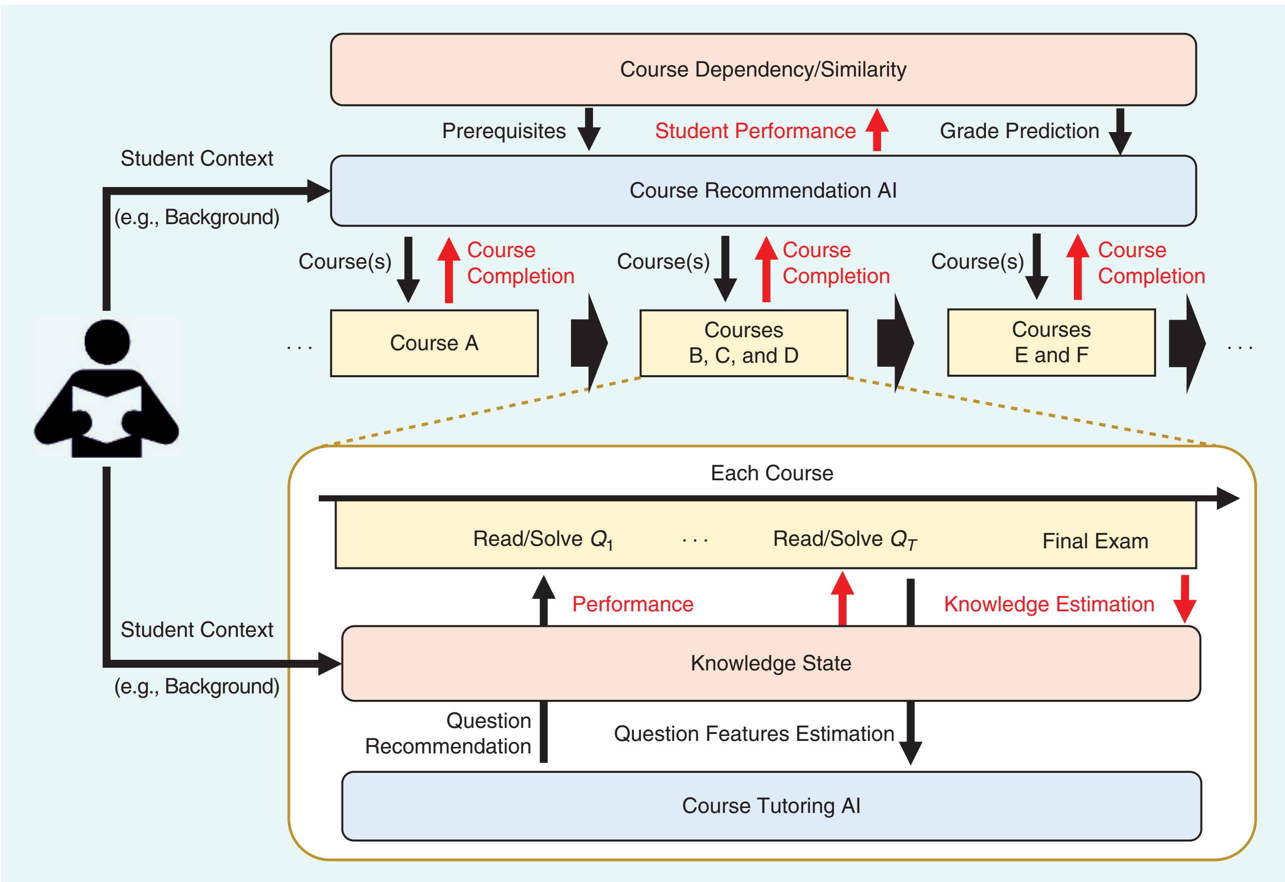

FIGURE 4. A detailed framework of course recommendation.

and feedback, previously shown teaching materials. In an experiment, they apply the eTutor system in the following scenario: The students have studied digital signal processing in the past. The role of eTutor is to recommend learning materials to the students with the goal of refreshing their minds about discrete Fourier transform in the least amount of time. The eTutor shows better performance compared to random- and fixed-selection rules.

Assessment and evaluation

A key problem in learner assessment is estimating how well he/she will master each knowledge component/concept/skill from the responses to assessment questions. Related works can be broadly classified into two model categories: 1) static, which analyze the generated data as learners take an assessment (assuming that each learner's knowledge remains constant during the assessment) and 2) dynamic, which track a learner's progress throughout a (possibly long) period as their knowledge levels evolve. The following is a short overview of each category:

- *Static models—IRT*: The basic 1PL IRT model characterizes the probability that a learner answers a question correctly as

$$P(y_{i,j}=1)=\sigma(a_j-d_i),$$

where $y_{i,j}$ denotes the binary-valued graded response of learner j to question i, where 1 implies a correct response and 0 otherwise. Moreover, $a_j \in \mathbb{R}$ and $d_i \in \mathbb{R}$ are scalars that correspond to the learner's ability and the question's difficulty, respectively. Also, $\sigma(\cdot)$ is a link function that is usually the sigmoid function or the inverse probit link function. Later extensions include 2PL IRT models, which add another multiplicative scaling parameter. This parameter corresponds to the ability of each question, differentiating high-capacity learners from low-capacity ones. Further, 3PL IRT models add another scalar outside of the link function, which corresponds to the probability that an item can be guessed correctly. Finally, multidimensional IRT models use vectors instead of scalars to parameterize strengths and weaknesses to capture multiple aspects of one's ability. Using the aforementioned models, one can 1) obtain relatively stable estimates of learners' ability levels by denoising learners' responses and 2) estimate the quality of each assessment question.

- *Dynamic models—KT*: KT models consist of the learner performance $[f(\cdot)]$ and learner knowledge evolution models $[g(\cdot)]$, expressed as

$$y_t \sim f(a_t), \quad a_t \sim g(a_{t-1}),$$

where t denotes a discrete-time index. Early KT models, such as Bayesian KT [16], treat knowledge (h_t) as a binary-valued scalar that characterizes whether or not a learner masters the (single) concept covered by a question. Performance and knowledge evolution models are simply noisy binary channels. Later, factor-analysis-based KT models used a set of handcrafted features, such as the number of previous attempts; successes; and failures on each concept, to represent a learner's knowledge levels. These models require expert labels to associate questions to concepts, resulting in excellent interpretability because they can effectively estimate the knowledge level of each learner on expert-defined concepts. Recent KT models incorporate deep learning, especially recurrent neural networks into the KT framework, where knowledge is represented as a latent vector $\mathbf{a}_t$. These models achieve state-of-the-art performance in predicting future learner responses, although in some cases, the advantage is not significant despite the loss of some interpretability.

The existing learner assessment models have several bottlenecks. First, there are not many models with both the ability to achieve state-of-the-art performance in data fitting, (i.e., future performance prediction) as well as feedback generation (i.e., providing interpretable feedback to learners and instructors for downstream tasks, such as personalization). Therefore, it is imperative to develop new deep learning-based models that not only inherit the flexibility of neural networks to accurately predict learner performance but also build in cognitive theory-inspired structures to promote interpretability and enable the generation of meaningful feedback. As an example, in the recently developed attentive KT (AKT) model [17] (Figure 5), we combined state-of-the-art attention networks with cognitive theory-inspired modules. We used a monotonic attention mechanism where weights exponentially decay over time and question embeddings are parameterized by the 1PL IRT model to prevent overfitting. Experimental results show that the AKT model not only outperforms existing KTs but also exhibits some interpretability [17]. The existing learner assessment models operate almost exclusively on graded learner responses; however, converting raw learner responses to graded responses leads to considerable information loss.

For multiple-choice questions, different distractor options are not created equal; choosing certain incorrect options over others might indicate that a learner exhibits a certain misconception. However, this information is lost when the learner's option choice is converted to a graded response. Moreover, due to their superior pedagogical value, open-response questions have been widely adopted; the specific open-ended response a learner enters contains rich information about his/her knowledge state. Therefore, it is vital to develop models that go deeper than the graded response level and into the raw response level. These models allow for personalization at even finer levels; for example, after each step as a learner solves an open-ended mathematical problem step by step and by enabling personalized education systems to attend to learner difficulties in a more timely manner.

Another consideration in effective learner evaluation is that assessment and performance prediction models must be tailored to different learning environments and platforms. For instance, the accurate prediction of students' future college performance based on their ongoing academic records is crucial to carrying out effective pedagogical interventions so that on-time, satisfactory graduation is ensured. However, foretelling student performance in completing degrees (e.g., college programs)

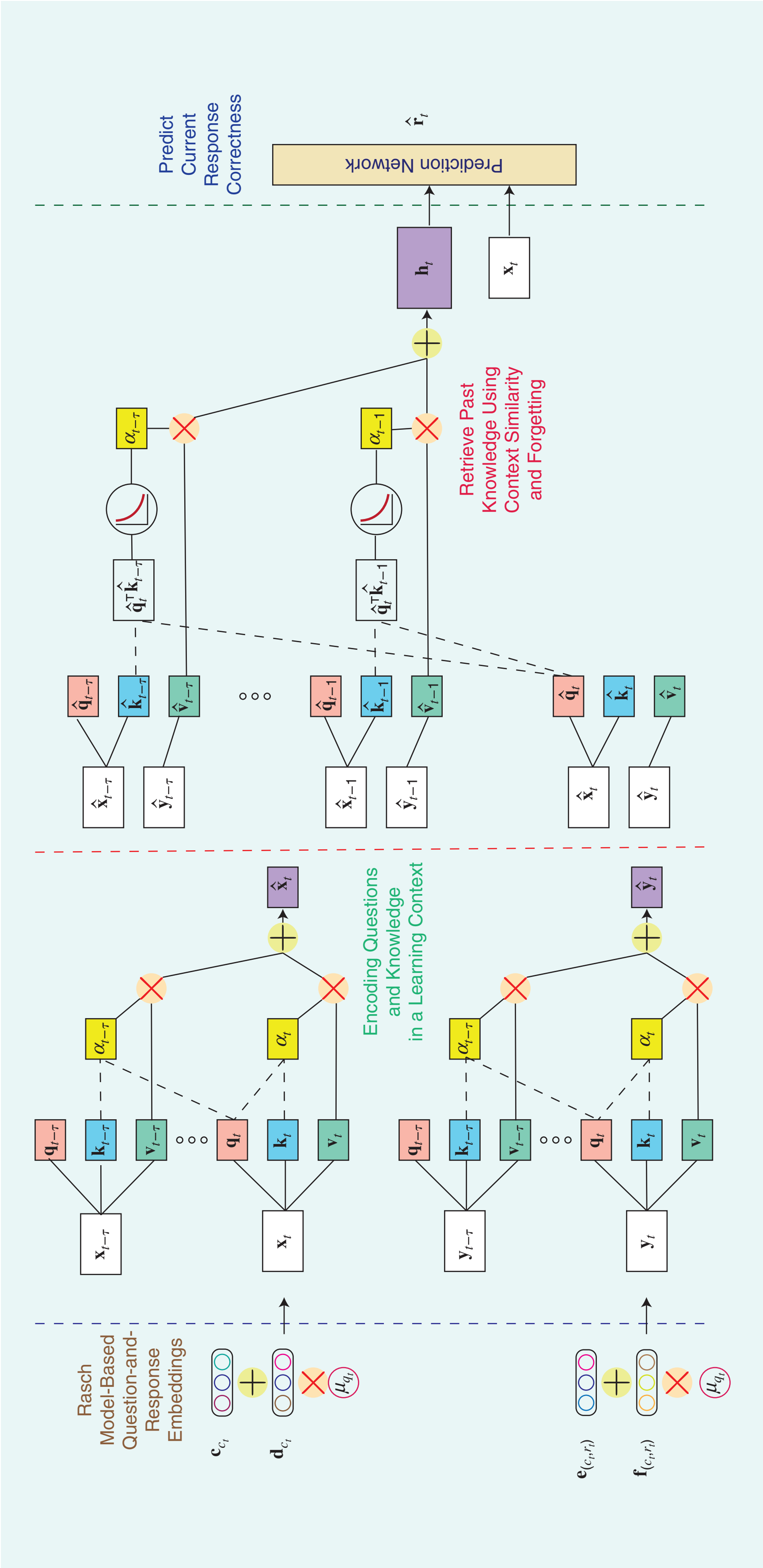

FIGURE 5. An overview of the AKT method. We used IRT-based raw embeddings for questions and responses. We computed context-aware representations of questions and responses using two encoders. We then used a knowledge retriever to retrieve past-acquired knowledge for each learner using a monotonic attention mechanism, which is used for performance prediction.

is significantly different from that for in-course assessment and intelligent tutoring systems. The following describes the most important reasons for why this is so.

- First, students differ tremendously in terms of backgrounds as well as the study domains (majors, specializations), resulting in different selected courses. Even if the courses are similar, the sequences in which the students take the courses might differ significantly. Therefore, a key challenge for training an effective predictor is to handle heterogeneous student data. In contrast, solving problems in intelligent tutoring systems often follow routine steps that are identical for all students. Similarly, predictions of students' performance in courses are often based on in-course assessments that are identical for all students.
- Second, although the students often take several courses, not all of them are equally informative for predicting the students' future performance. Utilizing the student's past performance in all courses that he/she has completed not only increases complexity but also introduces noise in the prediction, thereby degrading the performance. For instance, while it is meaningful to consider a student's grade in linear algebra for predicting his/her grade in linear optimization, the student's grade in chemistry lab may have much weaker predictive power. However, the course correlation is not always as obvious as in this example; therefore, to enhance the accuracy of performance predictions, it is essential to discover the underlying correlation among courses.

- Third, predicting student performance in a degree program is not a one-time task; rather, it requires continuous tracking and updating as the student finishes new courses over time. An important consideration is the following: The prediction shall be made based on not only the most recent snapshot of the student's accomplishments but also the evolution of the student's progress, which may contain valuable information to improve the prediction's accuracy. However, the complexity can easily explode because just mathematically representing the evolution of student progress itself can be a daunting task. Treating the past progress as equally as the current performance when predicting the future may not be a wise choice either because old information tends to be outdated.

Finally, we would like to emphasize the following: Similar to an offline system, in AI-powered personalized education, an assessment does not remain limited to evaluating the performance of individual students in different tests in a single online education portal. Indeed, evaluation might be necessary not only for individuals but also for a collection of students as well as other stakeholders, such as educators, policy makers, and the providers of online education. In particular, the fair and precise comparison, analysis, and accreditation of online education portals, as well as the degrees and certificates provided by such portals, are crucial. The reasons include the following: 1) Distance education has grown into a broad industry in the past decade, 2) the majority of learners rely on certificates of online classes as approval for obtaining the necessary knowledge and skills, and 3) online education is inherently international and crosses boundaries. Similar to improving the evaluation of students, AI and ML methods, together with bid data analysis, can assist in the accreditation and comparison of online portals and the degrees and certificates issued; this includes, e.g., comparing the average student's performance with an online degree to that of a traditional, yet accredited, degree. A detailed discussion of such topics has several perspectives and is therefore beyond the scope of this article.

Lifelong learning

Lifelong learning emphasizes holistic education and the fact that learning takes place on an ongoing basis as a result our daily interactions with others and with the world around us in different contexts. These include not only schools but also homes and workplaces, among several others. Because of its ongoing nature, making foresighted learning plans is crucial for lifelong learning to achieve the desired outcome.

In the school context, a specific challenge for developing a learning plan is the course sequence recommendation in degree programs [14]. Recent studies show that the vast majority of college students in the United States do not complete college in the standard time frame. Moreover, today, compared to a decade ago, fewer college students graduate in a timely manner. Although several factors contribute to students taking longer to graduate, such as credit losses resulting from a school transfer, uninformed choices due to low advisor-student ratios, and poor preparation for college, the inability of students to attend the required courses is among the leading causes. If a student selects courses myopically without a clear plan, he/she may end up in a situation where required subsequent courses are offered (much) later, thereby (significantly) prolonging the graduation time. Hence, to accelerate graduation, students should essentially select courses in a foresighted way while taking the course sequences (shaped by courses being mandatory, elective, or prerequisite) into account.

It is also essential to observe the time period in which the school offers various courses. More importantly, as the number and variety (in terms of backgrounds, knowledge, and goals) of students is expanding rapidly, the same learning path is unlikely to best serve all students. Therefore, it is crucially important to tailor the course sequences to students. To this end, it is necessary to learn from the performance of previous students in various courses/sequences to adaptively recommend course sequences for current students. Obviously, this depends on the student's background and his/her completion status of the program to maximize any of a variety of objectives, including the time to graduate, grades, and the tradeoff between the two. To make such plans, AI is a tool of great potential; however, designing AI technologies for personalized, foresighted, and adaptive course planning is challenging in several dimensions, as described in the following.

- First, course sequence recommendation requires dealing with a large decision space that grows combinatorially with the number of courses.
- Second, there is a great deal of flexibility in course sequence recommendation as multiple courses can be taken simultaneously, while it is also subject to many constraints due to prerequisites and availability.
- Third, any static course sequence is suboptimal as the knowledge, experience, and performance of a student develops and evolves during the process of learning.
- Finally, students vary tremendously in their backgrounds, knowledge, and goals.

For example, in [14], we develop an automated course sequence recommendation system to address the aforementioned challenges. To reduce complexity and enable tractable solutions, we solve the problem in two steps, as illustrated in Figure 6:

1) The first step corresponds to offline learning, in which a set of candidate recommendation policies are determined that minimize the expected time to graduation or the on-time graduation probability using an existing data set of anonymized student records based on dynamic programming.
2) The second step corresponds to online learning, in which for each new student, a suitable course sequence recommendation policy is selected depending on this student's background using the learned knowledge from the previous students.

In other lifelong learning contexts (e.g., the workplace), although similar challenges may still be present, new challenges are likely to emerge, and hence, foresighted learning plans must be tailored to the specific context.

Recent research shows a significant gap between the lectures offered in schools and job requirements, especially in emerging disciplines like data science. Soft skills such as communication and teamwork are often even more important than typical technical skills. Future research on lifelong learning shall bridge this gap. Indeed, there is a systematic demand for the research community to identify and study the skills that significantly contribute to professional perspectives instead of maximizing achievement in schools. Educators can take advantage of the findings to adjust school curricula and educational activities to better prepare students for the future. The centerpiece of possible approaches is to fuse a student's school records with future employment outcomes, possibly tracked over a long period, as well as other data sources such as course syllabi and job postings, to identify the crucial skills that extend from the classroom (virtual or otherwise) to the profession. There is also a need for research labor studies to conduct interviews with 1) employers, to understand their requirements; 2) job seekers, to identify the skills to acquire; and 3) training providers, to clarify the skills that can be taught in a part-time or on-the-job way rather than through centralized educational programs, given workers' real-life constraints.

Incentives and motivation

Thus far, one crucial aspect of personalized education has been largely left aside, namely, motivation and incentive design. This is unfortunate as these factors significantly contribute to a learner's perseverance and engagement, and thereby, overall student achievement. As such, they affect not only individuals but also the entire society in terms of the efficiency of resource expenditure.

In educational sciences, motivation is regarded as a concept that involves several learning-related features, such as initiation, goal orientation, intensity, persistence, and the quality of behavior [7]. Therefore, as described by Hartnett in [18], *motivation is an unobservable dynamic process that is difficult to measure directly, but it is inferable from observations*. Similar to the other crucial factors of successful education, such as talent and interest, motivation originates and is influenced by personal factors, including goals and beliefs. As such, it is reasonable to conclude that intelligent personalization affects motivation to a large extent.

Motivation can be intrinsic or triggered by external factors. Accordingly, the various features of personalized education, such as recommending a proper series of content or creating educational networks, might implicitly improve a learner's motivation by increasing the engagement level. Such efforts make the learning experience more pleasant, thereby improving a learner's satisfaction level. This is, however, insufficient. It is imperative to integrate direct motivating methods into personalized education and the learning platform. To this end, in the following sections, we describe a few frameworks that can accommodate motivation and its relevant concepts appropriately (see [18] for more information).

Behavioral economics

Any personalized education platform should be able to appropriately connect, interact, and interface with humans. Hence, proper operation significantly depends on various characteristics of the members of the target group that shape their decision making behavior. Indeed, a utility function is the most seminal computational model for the interests of learners. For a rational decision maker, the utility function is conventionally increasingly concave and is to be maximized. However, humans often demonstrate unusual patterns in their utility functions and decision making due to the following reasons:

- Humans make mistakes, often due to inaccurate beliefs and imprecise predictions.
- Humans often act irrationally and based on heuristics.
- Humans think and act in different ways as a result of their unique backgrounds, including personality and experiences [19].

Behavioral economics accommodates and formalizes such aspects; therefore, one can take advantage of behavioral economics for efficient incentive design and motivation in learning platforms [20].

Self-determination theory

This theory asserts that humans have an intrinsic urge to be self-autonomous, competent, and connected with respect to their environments [21]. Although behavioral economics is appropriate for investigating motivations that result from external rewards, self-determination observes motivations from an internal perspective. Indeed, any environment, including the learning platforms that satisfy the aforementioned needs of humans, awakens the intrinsic motivation, rendering external triggers mostly unnecessary. As such, promoting intrinsic

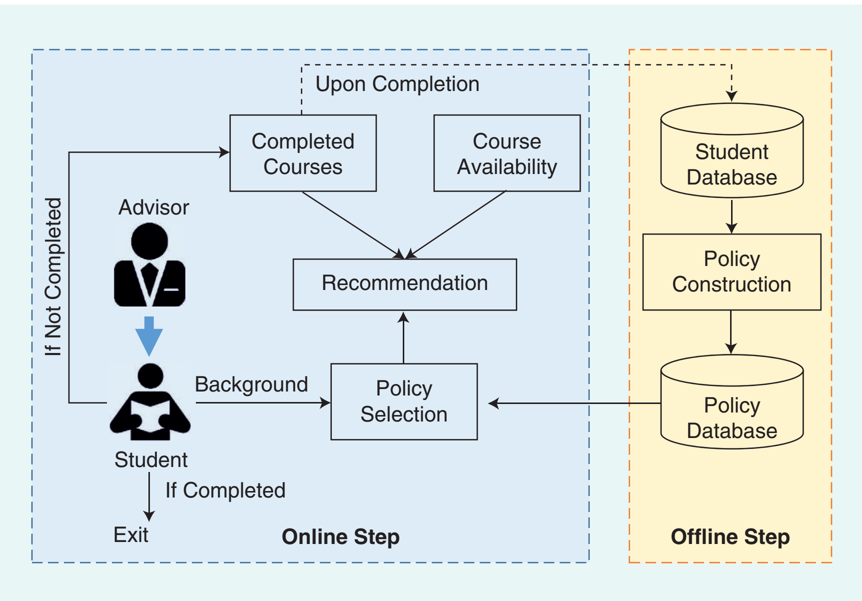

FIGURE 6. The course sequence recommendation.

motivation is significantly more effective than extrinsic motivation as it is often associated with lower cost when compared to material rewarding and has a long-lasting effect [18].

Self-efficacy theory

This concept corresponds to an individual's confidence in his/her capability of performing a specific task to be undertaken; for example, learning in an online learning platform or performing at a certain level [22]. Researchers show that humans constantly assess their self-efficacy, mainly based on the observed information from the environment and past experiences [22]. Similar to the self-determination theory, self-efficacy considers the intrinsic motivation, implying that a feeling of efficacious triggers the internal motivation feeling in learners. Other relevant concepts include interest and goal orientation [18].

The main challenge is how best to utilize AI and ML to motivate the learners of a personalized learning platform, based on the aforementioned theories that formalize and explain human behavior. To clarify this, consider the utility function of a learner in a personalized learning platform as an example [20]. The function quantifies the learner's well-being while using the platform, and, consequently, his/her (future) engagement. Some learners exhibit hyperbolic preferences, overweighting the presents ones so much so that future rewards are largely ignored. Some learners show strong reactions even to nonmonetary rewards, while other learners demonstrate reference-dependent preferences, implying that the utility is largely determined by its distance from a reference point; for example, a predefined goal or the average performance. By using ML and AI methods, a learning platform can take advantage of the available data and a learner's feedback to estimate the utility function of that learner, thereby predicting his/her reaction to the potential triggers of incentive and motivation. Consequently, the platform can adjust and allocate the reward among learners efficiently and fairly.

As another example, consider the self-determination theory. Based on this theory, a sophisticated personalized learning platform guarantees choice, connectedness, and the feeling of competence for the learner. To this end, the design of recommendation tools based on AI and ML methods should allow for enough alternatives, both at the micro- and macrolevels, to ensure autonomy. Moreover, the suggested learning content should be based on the learner's feedback and the results of accurate assessment to avoid inducing a feeling of incompetence in the learner. In addition, promoting network formation or establishing a link between coherent learners and intensive interaction results in connectedness. This is also in accordance with the self-efficacy theory, in the sense that by providing appropriate feedback and suitable side information, the platform increases the positive belief of a learner in his/her ability to perform well on a learning platform.

Building learning networks

A potential negative effect of personalized education, especially in an online environment, is a loss of peer interactions and of the sense of community that are usually present in traditional classrooms. Fortunately, the rise of online social networks seems to facilitate interaction and networking between teachers and learners, as does the coproduction of content both inside and outside the classroom. Learning applications and pedagogy can also be built based on online social networks to bridge formal and informal learning as well as to promote peer interactions on both curricular and extracurricular topics. Moreover, various education-related social networks have been created to facilitate collaboration, post/answer questions, and share resources; however, a formal method to build these learning networks and a deep understanding of their effectiveness are absent.

The core of learning networks is peer interaction, which has important implications for personalized education when teaching resources are limited. For example, peer review serves as an effective and scalable method for assessment and evaluation when the number of students enrolled in a course far exceeds the number of teaching assistants; however, in learning networks, effective peer review poses new challenges [23]. On the one hand, peer reviewers have different intrinsic capabilities, which are often unknown. On the other hand, peer reviewers can choose to exert different levels of effort (e.g., time and energy spent in reviewing), which is unobservable. Identifying unknown intrinsic capabilities corresponds to the adverse selection problem in game theory. A natural candidate for solving this problem is to use matching mechanisms, i.e., assign reviewers to students. Existing works on matching mechanisms focus on one-shot peer interactions and design one-shot matching rules. However, their assumptions do not hold in peer-review systems, where the review quality depends crucially on the reviewers' effort.

Motivating reviewers to exert high effort corresponds to the moral hazard problem in game theory. One way to address this problem is to use social norms, where each peer reviewer is assigned a rating that summarizes his/her past behavior and recommends a "norm" that rewards a reviewer with good ratings and punishes those with bad ratings. However, existing works on social norms assume that peer reviewers are homogeneous. This assumption does not hold in peer-review systems because different reviewers have different intrinsic capabilities. Because a peer reviewer's ultimate review quality is determined by his/her intrinsic capabilities and effort, designing effective peer-review systems in learning networks becomes significantly more challenging due to the presence of both adverse selection and moral hazards. Therefore, new peer-review system designs should simultaneously solve both problems so that peer reviewers find it in their self-interest to exert high effort and receive ratings that truly reflect their capabilities.

Another primary function of learning networks is to foster learning content coproduction and sharing. Building such learning networks is vastly different from building traditional networks (e.g., computer and transportation networks); as with learning networks, individual learners create and maintain the links. Because links permit the acquisition and dissemination of learning content, it is theoretically intriguing and practically valuable to have a deeper understanding of the networks that are more likely to be formed by self-interested learners. Game theory is a useful tool to formulate and understand the strategic behavior of learners. The formulation must capture the heterogeneity of learners in terms of goals, capabilities, costs, and self-interest nature [24]; that is, each learner intends to maximize his/her benefit from content coproduction and sharing, minus whatever the cost is to establish the links.

Our previous work [25] studies the endogenous formation of networks by strategic, self-interested agents who benefit from producing and disseminating information. The results showed that the typical network structure that emerges in equilibrium displays a core-periphery structure, with a smaller number of agents at the core of the network and a larger number of agents at the periphery of the network. Furthermore, we established that the typical networks that emerge are minimally connected and have short network diameters, which are independent of the size of the network. In other words, the theoretical results show that small diameters tend to make information dissemination efficient, and minimal connectivity leads to minimizing the total cost of constructing the network. These results are consistent with the outcome of numerous empirical investigations. Such theoretical analyses and tools are essential guides for building learning networks. Also, based on this analysis, one can create protocols to motivate selfish learners to take actions that promote systemwide utility.

Future research into learning networks hinges on understanding the knowledge flow between students via peer interaction. Such an understanding enables educators to effectively moderate peer interactions and to encourage the interactions that promote peer learning. Peer learning is especially valuable as education extends into more diverse settings, such as remote online learning during the COVID-19 pandemic. In these settings, it is difficult for instructors to moderate learning activities remotely; hence, peer learning through online course discussion forums becomes essential. It is therefore vital to understand

- interaction tendencies and students' behavior in these discussion forums [26]
- the flow of knowledge by combining discussion forum activities with grades
- the factors that enhance knowledge flow
- the design of automated strategies that moderate student activities when necessary.

Diversity, fairness, and biases

Experimental studies show that AI-driven personalization such as student assessment, feedback, and content recommendation improve overall learning outcomes; nonetheless, certain student subgroups may benefit more than other subgroups due to the biases that exist in training data [27]. This imbalance jeopardizes students who are already underserved, particularly because they often have limited access to advanced, digitized educational systems and are infrequently represented in the data sets collected by these systems [28]. As a result, it is essential to develop AI tools that promote fairness among learners with different backgrounds, thereby making education more inclusive for future generations.

To mitigate biases and to promote fairness and equity in AI methods, currently, researchers pay significant attention to developing approaches that promote fairness, primarily in the context of predictive algorithms:

- The first major research problem studied is how to properly define fairness. Many definitions of fairness exist, including individual fairness, which requires that users with comparable feature values be treated similarly; parity in the predicted probability of each outcome across user groups (drawn using sensitive attributes); parity in the predicted probability of each outcome given actual outcomes regardless of sensitive attributes; and counterfactual fairness, which requires that the predicted outcome for each user remains mostly unchanged if the sensitive attribute changes.
- The second major research problem concerns developing methods that enforce fairness in predictive algorithms. Existing approaches include preprocessing the data to select only the fair features as inputs to algorithms, and postprocessing the output of algorithms to balance across user groups. The most promising approach is to impose regularizers and constraints while training predictive algorithms. These methods result in better fairness at the expense of sacrificing some classification accuracy; however, they are empirically shown to obtain better tradeoffs between fairness and accuracy than other fairness-promoting methods.

Promoting fairness and equity is a necessity of education that requires a comprehensive approach for it to be fulfilled: We need to not only design fair personalization algorithms but also develop systematic principles and guidelines for their application in practice. In other words, we need a set of tools to regulate the use of AI algorithms.

Finally, despite its great promise, AI-driven personalization in education can also bring risks that have to be closely monitored and controlled. Recently, there have been calls for a U.S. Food and Drug Administration-type framework for other AI applications, such as facial recognition. It is essential to establish a similar ecosystem in education with a set of regulations around the issues of data ownership, sharing, continuous performance monitoring, and validation to control every step of the process, from ensuring the diversity and quality of the collected data, developing algorithms with performance guarantees across different educational settings, to identifying misuse and implementing a fail-safe mechanism.

COVID-19 and AI-enabled personalized education

Among its several other adverse effects, the COVID-19 pandemic has disrupted or interrupted the functionality of conventional education systems around the globe. Not surprisingly, students have experienced this adverse effect to varying degrees depending on several factors, including country/region, family status, and individual characteristics. The complications differ over a wide spectrum and include reduced learning ability, depression, loss of concentration, and a decline in physical fitness. Such issues arise mainly due to spending less or no time at school, where students receive educational materials and support in learning, interact with their peers and teachers, develop incentives, and are evaluated. Furthermore, many students cannot take full advantage of replacement resources such as online materials, e.g., in the absence of an appropriate technological device/a reliable Internet connection or a suitable learning environment at home. As a consequence of its vitality, the impact of COVID-19 on education has attracted a great deal of attention. For example, in [29], the authors describe the influence of pandemic-triggered growth in online learning on students' performance and equity. Several other works, such as [30], study the domain-specific educational effects of the pandemic, evaluate available solutions, and provide suggestions for policy makers to compensate for the pandemic's negative educational consequences.

Personalized and distance education had already been trending upward in the past decade. Still, the COVID-19 pandemic has urged both public and private sectors to rapidly increase investigations into R&D in this area to earn individual and/or social profit. For instance, the pandemic has increased the use of online learning tools for signal processing education, especially at the undergraduate level. These include web-based laboratories for digital signal processing [31] and online ML education modules [32]. Although it is essential to carefully study this tremendous push toward revolutionizing education from several perspectives, in the scope of our article, we confine our attention to the role and influence of AI and ML.

As described previously, AI and ML have great potential to enhance online education in different ways, e.g., through improving the quality of learning materials, enabling fairness and diversity, generating proper tests, and allowing for the construction of knowledge networks. The latter way is a universal aspect of applying AI and ML methods in distance and asynchronous education regardless of the current pandemic; nevertheless, such methods can additionally assist in accelerating the rebuilding of education systems and in mitigating the pandemic's detrimental effects. For example, by using ML methods on the available data, policy makers can classify students based on their exposure to the educational effects of a pandemic; using this classification, one can allocate resources efficiently while satisfying fairness constraints. As another example, by taking advantage of ML methods, one can optimize a school's closure plan based on different features, such as neighborhood, size, grade, and so forth.

Summary and conclusions

Enabling personalized education is one of the most precious merits of AI, relative to education. This paradigm significantly improves the quality of education in several dimensions by adapting to the distinct characteristics and expectations of each learner, such as personality, talent, objectives, and background. Besides, online education is of the utmost value under abnormal circumstances, such as the COVID-19 outbreak or natural disasters. Indeed, conventional education requires significantly more resources than the online format with regard to education space, scheduling, and human resources, which makes it prone to failure with even a small shift in conditions. As such, emerging alternatives are inevitable. Despite having the potential of a revolutionary transformation from traditional education to modern concepts, personalized education faces several challenges. In this article, we discussed these challenges, provided a brief overview of the state-of-the-art research, and proposed some solutions. Table 2 summarizes some of the future research directions.

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Table 2. Some research directions for AI-based personalized education.

Challenge	Description	References
Content production/recommendation	Personalized and profession-oriented production, recommendation, and maintenance of contents	[13], [33]
Evaluation and assessment	Performance comparison in personalized education, testing without information loss, and accreditation	[11], [17]
Lifelong learning	Continuous education and additional qualifications for improvement and advancement in profession	[14]
Incentives	Internal and external motivation for learning, gamification, rewarding, and inducing confidence	[18], [20]
Networking and interaction	Inducing learning networks, forming coalitions for efficient learning, and imitating teacher feedback	[23], [26]
Diversity and fairness	Equal access to a quality online education and avoiding biases in platform development	[27]

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