A Comprehensive Exploration of Personalized Learning in Smart Education: From Student Modeling to Personalized Recommendations

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With the development of artificial intelligence, personalized learning has attracted much attention as an integral part of intelligent education. China, the United States, the European Union, and others have put forward the importance of personalized learning in recent years, emphasizing the realization of the organic combination of large-scale education and personalized training. The development of a personalized learning system oriented to learners' preferences and suited to learners' needs should be accelerated. This review provides a comprehensive analysis of the current situation of personalized learning and its key role in education. It discusses the research on personalized learning from multiple perspectives, combining definitions, goals, and related educational theories to provide an in-depth understanding of personalized learning from an educational perspective, analyzing the implications of different theories on personalized learning, and highlighting the potential of personalized learning to meet the needs of individuals and to enhance their abilities. Data applications and assessment indicators in personalized learning are described in detail, providing a solid data foundation and evaluation system for subsequent research. Meanwhile, we start from both student modeling and recommendation algorithms and deeply analyze the cognitive and non-cognitive perspectives and the contribution of personalized recommendations to personalized learning. Finally, we explore the challenges and future trajectories of personalized learning. This review provides a multidimensional analysis of personalized learning through a more comprehensive study, providing academics and practitioners with cutting-edge explorations to promote continuous progress in the field of personalized learning.

Additional Key Words and Phrases: Personalized Learning, Learning Analytics, Personalized Recommendation, Cognitive Diagnosis, Educational Theory

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1 INTRODUCTION

Throughout history, education has evolved over the course of history, and in the present digital age, it is undergoing profound transformations. Personalized learning has emerged as a key strategy to address the distinctive needs and objectives of individual learners. Beginning with early educational research that focused on individual differences [22] and evolving into the era of computer-assisted instruction [183], personalized learning gradually integrated into intelligent educational systems, introducing recommender systems and learning analytics [26, 181]. With the rise of big data technologies, personalized learning has successfully transitioned to a data-driven stage, offering more profound personalized support for education[16].

Personalized learning, based on the individual's learning level, ability, and progress arrangement, aims to achieve the teaching effect of "individualized teaching, no class." It seeks to meet the unique needs of each learner by integrating advanced technology and a deep understanding of the learning process, providing a more flexible and targeted learning experience. Personalized learning not only proves effective in traditional classrooms but also demonstrates significant potential in online learning[242, 225], training[28], and career development[207].

The significance of personalized learning is evident in its capacity to effectively address individual differences, enhance learning outcomes, and cultivate a keen interest in learning[130]. Traditional one-size-fits-all teaching methods often struggle to accommodate the diverse learning speeds and styles of students. Truong[198] argued that presenting identical content to students with varying learning interests, styles, and characteristics falls short of meeting their educational needs. In contrast, personalized learning excels in adapting to individual students' learning processes by dynamically adjusting both the content and delivery of instruction. Firstly, personalized learning elevates learning outcomes by considering each student's unique needs, and learning styles, tailoring the educational experience to individual differences[86]. Secondly, it can fine-tune the learning content based on students' interests and proficiency levels, thereby sparking learners' enthusiasm for learning and boosting their independent learning capabilities through personalized approaches that align with their preferred learning styles.

Personalized learning has garnered significant attention in recent years, primarily because it embodies the humanistic ideals of education. In personalized learning settings, students cease to be passive recipients; instead, they become active participants and leaders in the educational process. This learner-centric approach is more likely to kindle their motivation and enthusiasm for learning. Concurrently, personalized learning yields positive academic outcomes and promotes greater educational equity by precisely addressing individual student needs. It enhances academic performance, and cultivates a genuine enthusiasm for learning. Additionally, FitzGerald et al.[61] propose that personalized learning is emerging as a focal point in the realms of mass media, government agencies, and scientific research.

The exploration of personalized learning holds paramount significance in the realm of intelligent education. It is designed to address the diverse needs of students, encompassing cognitive, affective, and behavioral differences[81]. The impetus behind research on personalized learning stems from its perceived capacity to enhance student satisfaction and bolster academic competence and knowledge acquisition[71]. As the field of education evolves, it faces increasingly complex challenges such as student dropout and rapid updating of subject knowledge. Research on personalized learning serves to delve into flexible and effective instructional models that can boost student motivation, mitigate dropout rates[156], and enable education to adeptly respond to evolving societal needs.

In recent years, several researchers have delved into personalized learning across various dimensions[32, 177, 248, 193, 236, 237], yielding notable research outcomes. For instance, Chen etc.[32]

extensively explored the intricate interplay between individual differences and personalized learning, encompassing a spectrum of factors such as learning styles, preferences, and abilities. The work of [248] involved a comprehensive review of literature in the realm of personalized recommendation, with a specific focus on leveraging deep learning algorithms. Shemshack et al.[177], on the other hand, took a different perspective by concentrating on the terminology associated with personalized learning. This involved an examination of the similarities and distinctions among different terms related to personalized learning, along with the definitions of these terms. While existing literature has seen some research on personalized learning, the majority tends to be confined to specific facets or discussions revolving around the application of particular algorithms in personalized learning. There remains a need for a more comprehensive synthesis of research in the field of personalized learning. Building upon the considerations outlined above, this review strives to furnish readers with a thorough and comprehensive insight by delving into the latest research on personalized learning. Delving into various dimensions, the exploration spans from definitions and objectives to methodologies and practical implementations. It spans from educational theories to real-world applications, from student modeling (cognitive and non-cognitive) to personalized recommendations, and from data-driven approaches to algorithmic evaluations, providing readers with a comprehensive and in-depth understanding. This paper aims to foster a deeper understanding of the intrinsic motivations underpinning personalized learning, scrutinize its role within the domain of intelligent education, and deliberate on existing challenges and future trajectories.

In this paper, we conducted a comprehensive literature search spanning from January 2016 to October 2023 using various databases, including Google Scholar, Ei Compendex, IEEE Xplore, and CNKI academic search engine. Our search targeted around 150 research articles published in esteemed conferences and journals like Educational Data Mining(EDM), Computers & Education, IEEE Transactions on Learning Technologies(IEEE TLT), Association for the Advancement of Artificial Intelligence(AAAI), and International World Wide Web Conference(WWW) etc. The selected literature revolves around key concepts such as “personalized learning”, “learning analysis”, “cognitive diagnosis”, “course planning”, and “personalized recommendation” and so on. This paper presents a systematic and thorough review of this body of literature.

This review is organized as follows: Chapter 2 will examine the definition and objectives of personalized learning, highlighting its distinctions and connections with traditional education, and outlining the advantages it offers. In Chapter 3, we will explore the theoretical foundations of education related to personalized learning, and understand personalized learning from a more in-depth educational perspective. Chapter 4 will concentrate on personalized learning data, examining aspects such as an overview of frequently utilized datasets, their sources, and related topics. In Chapter 5, we will delve into a detailed discussion of how student modeling (from cognitive and non-cognitive perspectives) and recommendation algorithms form the basis for personalized support. Chapter 6 will focus on commonly used personalized assessment methods, including various types of metrics. Chapter 7 will illustrate the practical impacts of personalized learning in education and introduce related tools and platforms through specific application cases. Finally, Chapter 8 will address the challenges encountered by personalized learning and anticipate its future developmental directions. Through this structured approach, our paper aims to comprehensively analyze personalized learning, offering insights from multiple dimensions, including educational theory, algorithmic technology, and learning analytics. This exploration aims to provide academics and practitioners with a comprehensive perspective that is both deep and broad.

2 DEFINITION AND GOALS OF PERSONALIZED LEARNING

2.1 Definition of Personalized Learning

Definitions of personalized learning exhibit variation across contexts and domains, presenting a diverse and complex landscape, with no globally accepted definition [176]. Various international organizations and institutions espouse distinct interpretations of personalized learning.

The U.S. Department of Education proposed a definition of personalized learning in the U.S. National Education Technology Plan published in 2017 [51]. It emphasizes the individual differences in learning and the principle of adapting education to the needs of students. The definition characterizes personalized learning as "instruction that optimizes the pace of learning and teaching methods according to the needs of each learner." In other words, it entails supporting students' personal development and success through teaching methods and learning resources tailored to their interests, needs, and abilities.

The International Association for K-12 Online Learning (INACOL) (https://aurora-institute.org/blog/what-is-personalized-learning/) views personalized learning as the delivery of a personalized and customized learning experience by taking into account each student's strengths, needs, and interests, among other things. This covers involving students in decision-making, including determining what to learn, how to learn, when to learn, and so on.

The International Society for Technology in Education (ISTE) (https://www.iste.org/), an international organization focused on educational technology, defines personalized learning as the use of technology to enable more effective learning through customized educational strategies and resources to meet each student's unique needs and new districts.

SRI Education [52], on the other hand, emphasizes the use of personalized learning in k-12 education, illustrating the definition of personalized learning through the importance of the individual: "Personalization thus involves tailoring multiple elements of instruction, stressing the importance of understanding each learner as an individual, and matching learning experiences to his or her needs and interests."

In summary, while there is no universally standardized definition of personalized learning, it can be regarded as a comprehensive concept geared towards implementing customized educational strategies to address each student's unique individual abilities, knowledge levels, and learning needs.

2.2 Concepts in Personalized Learning

2.2.1 Cognitive diagnosis. Cognitive diagnosis involves the systematic assessment of students' cognitive processes, subject matter knowledge, learning strategies, and problem-solving skills to gain detailed insights into their learning status, needs, and individual differences. By diagnosing students' levels of knowledge acquisition, specific and targeted feedback can be provided to enhance their individual abilities. Moreover, cognitive diagnosis results can inform the development of tailored learning activities and teaching strategies. Simultaneously, the personalized learning system can allocate suitable teaching resources based on the diagnosis outcomes for each student.

2.2.2 Student learning styles. Learning styles encompass aspects of students' preferences, interests, and study habits, which can vary because individuals acquire information in different ways, each possessing a unique learning style. According to Keefe [100], learning styles are described as a relatively stable set of characteristics that characterize how the learner perceives and responds to the learning environment at cognitive, affective, and physiological levels.

Learning style theory constitutes a branch of educational psychology aiming to describe and elucidate individuals' preferences and traits during the learning process. These theories seek to comprehend the reasons behind diverse learning styles within the same learning environment and establish a framework for categorizing and elucidating these variations. The following are some of the more currently recognized concepts and models:

- VARK [62]: This model emphasizes the differences in the way students perceive and process information and suggests four main learning styles: Visual, Aural, Read/Write and Kinesthetic.
- Felder-Silverman Learning Style Model (FSLSM) [58]: This model specifically addresses the learning styles of students in engineering and science education, making it a prevalent choice in engineering education research. It classifies learning styles along two dimensions: Perception and Processing. The perception dimension gauges how students perceive information, spanning from perceptual to intuitive extremes. Meanwhile, processing delves into how students process information, encompassing sequential and global approaches.
- Kolb Learning Style Theory [102]: This theory classifies learning styles into four categories according to perceptual preferences: Concrete Experience(CE), Reflective Observation(RO), Abstract Conceptualization(AC), and Active Experimentation(AE).
- Gardner's Multiple Intelligences Theory [68]: This theory categorizes intelligence into various dimensions, including linguistic, logical-mathematical, and spatial intelligence. It posits that an individual's strengths and weaknesses in these intelligence dimensions contribute to the development of distinct learning styles.
- Honey and Mumford's Theory of Learning Styles [83]: This theory categorises four types of learning styles by emphasising students' different responses to learning tasks and experiences: the activist, the reflector, the theorist, and the pragmatist.
- Dunn proposed the Cognitive Learning Style Model [49]: This model emphasises an individual's dominant mode of perceiving information. It categorises learning styles into five sensory modes: visual, auditory, tactile, kinesthetic, and verbal.

Meanwhile, learning style theories have been categorized into different categories in the literature, the most well-known of which is the study by Coffield et al. [39], which categorized learning style theories into four main categories:

- Perceptual Modalities: This category of theories focuses on the tendencies of individuals in perceiving information, which includes visual learners, auditory learners, and kinesthetic learners, among others. Typically represented by the VARK model [62].
- Information Processing Styles: This category of theories deals with the way individuals process information and includes sequential and global learners. Sequential learners prefer to process information in a step-by-step, orderly fashion, while global learners prefer to view problems holistically.
- Cognitive Styles: This type of theory focuses on the strategies that individuals use to solve problems and learn new knowledge. These include concrete and abstract learners, active and reflective learners, etc.
- Personality Styles: These theories relate learning styles to the personality traits of the individual, e.g., Extraversion and Introversion.

The dimensions of learning styles vary from study to study and theory to theory, with different scholars and models employing diverse dimensions for categorization. However, in general, learning styles can be divided into three dimensions: perceptual, cognitive, and personality. Within the perceptual dimension, visual, auditory, tactile, kinesthetic, group, and individual styles are considered. Cognitive dimensions encompass field-dependent/field-independent and reflective/impulsive types, reflecting learning strategies. The personality dimension involves extraversion/introversion. Learning styles are often seen as combinations of multiple dimensions, encompassing perceptual styles, information processing styles, social preferences, cognitive strategies, and more, which collectively define an individual's preferences and traits in the learning process.

The landscape of learning style theories is characterized by diverse academic perspectives and varying categorizations in research, presenting challenges in practical application due to inconsistent definitions and measurements. Despite these challenges, the array of classifications and models serves as a valuable framework for learning styles theory. This theory becomes a crucial tool for educators, enabling a deeper understanding of students' learning needs and facilitating the design of more effective instructional activities. It empowers educators to provide personalized learning support tailored to individual students.

2.2.3 Sentiment analysis. Sentiment analysis , also known as opinion mining, is a process of identifying, extracting and inferring learners' subjective emotions and attitudes from textual data using technical methods such as natural speech processing and text analysis [12]. Its core goal is to identify the emotional colors expressed by learner-generated texts and to determine the learner's emotional inclination towards a particular topic or entity.

Sentiment analysis encompasses four distinct areas: sentiment polarity classification, sentiment intensity analysis, entity-level sentiment analysis, and aspect-level sentiment analysis:

- Emotional polarity categorization: This primarily refers to categorizing emotions into categories such as positive, negative, and neutral.
- Sentiment intensity analysis: It aims to measure the strength of the expressed sentiment.
- Entity-level sentiment analysis: This method of analysis scrutinizes the sentiment associated with individual entities in the text(e.g., characters or products), rather than focusing solely on the overall sentiment of the entire text.
- Aspect-level sentiment analysis: Its main use is to assess the sentiment pertaining to specific aspects or themes within the text.

Sentiment analysis in education strives to enhance comprehension of students' emotional experiences throughout the learning journey. Analyzing the multimodal data generated by students allows for the identification and understanding of their affective states. This, in turn, enables the delivery of personalized support to enhance teaching quality and facilitate student learning.

2.2.4 Student behavior analysis. Student behavior analysis is the process of collecting and analyzing student behavior, participation, and data generated during the learning process to gain insight into students' learning patterns, preferences, strengths, and weaknesses. By analyzing student behavior, we can better understand students' motivation and other aspects of information, leading to improved personalized teaching.

The analysis of student learning behavior encompasses the examination of various actions undertaken by students within an online platform or classroom setting. This includes activities such as interaction, questioning, and responding to assess the completion of tasks and trace the decisions made in their learning trajectories. Furthermore, it involves scrutinizing students' reactions to quizzes, assignments, and instructional feedback, providing insights into their comprehension levels and learning requirements. The scope of analysis extends to incorporate data reflecting students' daily lives, such as access control information, one-card expenditure records, and gateway login details retrieved from the campus platform. The examination of these real-world datasets facilitates an understanding of individual variances and the influence of the environment on student behavior.

2.2.5 Student performance/achievement predicition. Student performance/achievement prediction involves utilizing students' historical learning data, grades, and other relevant information to forecast their future performance or achievement in upcoming learning tasks through the application of data analysis, machine learning, and other methodologies [3].

Table 1. The goal of personalized learning.

Goal	Explanation
Improving academic performance	Deliver tailored academic assistance by offering customized learning experiences that address the student's subject proficiency, strengths, and weaknesses, to enhance their academic performance in specific subjects.
Stimulating interest in learning	Identifying students' interests through their learning processes and crafting learning tasks aligned with those interests. Supplying materials and activities that resonate with students' interests to kindle their enthusiasm for the subject.
Fostering self-directed learning	Empower students by offering them flexibility to choose their learning paths and resources. Encourage them to formulate personalized learning plans, fostering greater autonomy in managing their learning processes.
Adapting to students' pace of learning	Tailoring the content and complexity to accommodate diverse learning speeds and comprehension levels empowers students to progress at their learning pace, ensuring an optimal level of mastery.
Fostering Creative Thinking	Offer inspiring tasks that encourage students to showcase creative thinking throughout the learning journey, fostering the development of their innovation skills and independent thought.
Provide real-time feedback and support	Utilize computer technology to monitor student performance, track progress, deliver timely feedback, and offer tailored support and resources based on individual student needs.
Reducing the learning gap	Offer tailored instructional strategies designed to meet the diverse needs of students, ensuring comprehensive understanding and mastery of subject matter. Strive for a balanced approach that considers each student's level, minimizing learning gaps across the student body.
Promoting cooperative learning	Encourage collaborative learning by crafting tasks that foster teamwork and mutual learning among students.

In essence, predictions of future performance stem from an analysis of a student's academic history and behavior. Delving into a student's past academic performance, encompassing exams, quizzes, assignments, and various assessments, offers valuable insights into their proficiency across different subjects. Analytics can further explore student engagement and interaction within the classroom or instructional platform, shedding light on their learning preferences and activity levels. A thorough examination of student performance/achievement projections is crucial for accommodating individual differences among students.

2.3 Goals of Personalized Learning

The objectives of personalized learning encompass various dimensions, including motivation, competence, and achievement. The ultimate goals exhibit variations across different definitions of personalized learning, along with the employed methods [17]. Table 1 illustrates eight potential goals associated with personalized learning.

In summary, through the incorporation of flexible teaching methodologies and leveraging computer technology, its objectives encompass the enhancement of students' academic achievements and subject proficiency, the cultivation of intrinsic interest in learning, the nurturing of independent learning skills and creative thinking, and the provision of effective strategies to bolster their multifaceted abilities. In essence, personalized learning aims to establish a more efficient and individualized learning milieu, offering students a targeted and pertinent educational experience.

2.4 Connections and Differences

This section will discuss in detail the connections and differences between personalized learning and traditional education. Personalized learning bears resemblances to traditional education, as both are dedicated to imparting subject matter knowledge to students with the aim of fostering their learning. Concurrently, personalized learning continues to depend on classroom instruction or online platforms. Consequently, the teacher retains the responsibility of guiding students and offering support in both paradigms. Regardless of the approach—traditional or personalized—the subject matter system remains the bedrock of teaching and learning, necessitating active participation, assessment, and feedback on student performance.

Dimension	Teaching Mode	Learning Time	Learning Place	Teaching Resources	Learning Objectives	Learning Methods	Learning Pathways	Subject Content	Student Engagement	Teacher Role	Technology Application	Assessment
Tranditional Education	Unified learning in the industrial age is based on a synchronized learning model	Fixed time	Fixed locations, mostly schools	Mostly fixed teaching resources such as textbooks	Committed to delivering subject knowledge to students to enhance their learning	Face-to-face learning	Follow the same learning path and progress forward	Structured learning based on course outlines	Igniting student engagement and enthusiasm, but leaning towards passive knowledge reception	Instructors	Involves fewer new types of technological tools	Usually adopts standardized testing and assessment methods
Personalized Learning	Autonomous learning in the era of artificial intelligence adopts flexible teaching strategies based on asynchronous learning models	Flexible	Anywhere, mobile learning	In addition to fixed teaching resources, there are also virtual diversified teaching resources	Similar to traditional education	Blended learning combining face-to-face and online learning	Independent selection based on student's learning pace and needs	Adjusting subject matter based on student interests and needs, spanning multiple fields	Inspiring students' active engagement and enthusiasm, but placing greater emphasis on students' proactive involvement	Instructors, guides, and supporters	Typically relies on advanced educational technology	More emphasis on diverse assessment methods and real-time feedback

Fig. 1. Connections and differences between traditional education and personalized learning.

The difference between traditional education and personalized learning lies in several key areas. Firstly, traditional education prioritizes uniformity over individualization, facing challenges in tailoring teaching content and methods during instruction, making it challenging for educators to accommodate the diverse interests and preferences of each student. In contrast, personalized learning adopts more flexible teaching methods that dynamically adjust based on the varying learning abilities, levels, and needs of students, aiming to achieve a tailored approach catering to individual requirements. Secondly, unlike the passive reception of knowledge in traditional education, personalized learning places a greater emphasis on nurturing students' independent learning abilities. It affords students the autonomy to choose their learning paths and resources. While incorporating traditional examination and assessment methods, personalized learning leans towards diversified assessment techniques and provides real-time feedback. The most significant departure from traditional education is personalized learning's ability to leverage advanced educational and computer technologies, thus meeting individual differences and enhancing learning outcomes. This approach aids students in discovering learning methods and styles aligned with their uniqueness, providing educators with more precise teaching tools and robust data support.

We use Figure 1 to show in detail the connections and differences between traditional education and personalized learning.

3 EDUCATIONAL THEORY AND THE DEVELOPMENT OF PERSONALIZED LEARNING

3.1 The Evolution of Personalized Learning

The evolution of personalized learning has traversed several stages, spanning traditional educational theories, the ascent of individualized instruction, the advent of computer-assisted instruction, and the emergence of intelligent educational systems. It has culminated in personalized adaptive learning tailored to individual needs and characteristics.

Figure 2 delineates the comprehensive history of personalized learning, charting its course from the early 1800s to the present day, accompanied by significant historical events at each juncture.

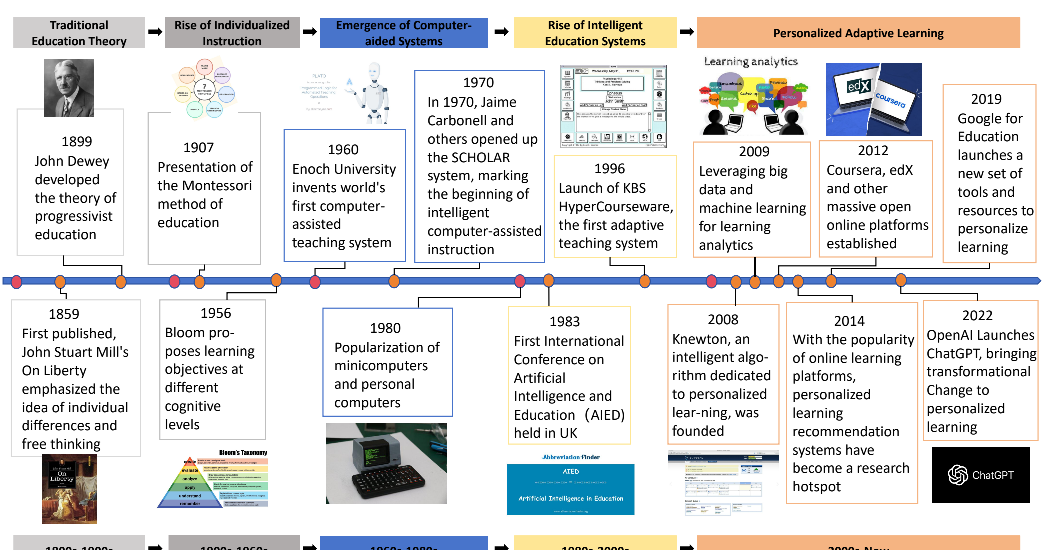

Fig. 2. The evolution of personalized learning.

The roots of personalized learning extend back to the early 19th century, an era characterized by traditional teaching methods where students were uniformly exposed to identical content and instructional pacing. However, even during this period, some educators recognized the diversity in students' learning processes, advocating for the acknowledgment of individual needs. A pivotal moment in this evolution occurred in 1859 with the publication of John Stuart Mill's "On Liberty" [151]. This influential work marked a seminal contribution to political philosophy and individual liberty, championing concepts such as freedom of speech and thought. John Dewey, a prominent figure in the progressivist education movement, underscored the significance of practical experience and active student participation, leaving an enduring impact on contemporary educational theory and practice [46].

The ascent of individualized instruction gained momentum around 1900, marked notably by the establishment of the first montessori school in rome by educator Maria Montessori. This institution served as an early manifestation of the Montessori Method, a pedagogical approach prioritizing individual variances and fostering self-directed learning [152]. Concurrently, Benjamin Bloom, an influential educational psychologist, introduced a groundbreaking educational classification system for hierarchical goals within the cognitive domains. This system delineated learning objectives into six distinct levels, furnishing a comprehensive framework for learning goals spanning various cognitive tiers [23].

Amidst the progress of computer technology, computer-assisted instruction gained prominence in the mid-twentieth century. A significant milestone was the establishment of an early computer-assisted instruction system at the University of Illinois in 1960. This pioneering system featured a series of personalized learning activities and tests, delivering a tailored educational experience for students [21]. Subsequently, the advent of SCHOLAR, a computer-assisted instruction system developed by Jaime Carbonell and his colleagues, further advanced the landscape. SCHOLAR played a foundational role in shaping the trajectory of computer-assisted education [111].

At the beginning of the 21st century, the rise of intelligent education systems ushered in a new era of personalized learning. By analyzing student data and using artificial intelligence techniques, these systems enabled personalization of the content to provide customized learning approaches [8, 160, 175].

In contemporary times, the latest phase of development is characterized by the advent of personalized adaptive learning. In 2008, Knewton was founded, a pioneering initiative committed to researching intelligent algorithms for personalized learning. Leveraging big data and adaptive learning algorithms, Knewton(https://www.knewton.com/) strives to deliver tailored educational experiences for students. Additionally, the establishment of various personalization platforms, such as Coursera, has significantly propelled the growth of online learning [5]. Within online platforms, the integration of learning analytics, personalized recommendations, and other methodologies [181, 241] enables the provision of learning resources tailored to individual needs, drawing insights from students' learning history and interests. In 2019, Google for Education (https://news.google.com) introduced a suite of innovative tools and resources aimed at personalizing the learning experience. Within the Google for Education ecosystem, notable components include Google Classroom, a robust learning management system, and Google Workspace for Education, a versatile tool empowering educators to craft and share personalized documents and presentations. Additionally, Google Meet serves as a valuable resource for facilitating distance learning and online education. Fast-forward to 2022, and OpenAI has significantly influenced the landscape of personalized learning with the introduction of ChatGPT. This platform has revolutionized personalized learning through its potent language generation capabilities, allowing for interactive conversational interactions and generative Q&A. The advent of ChatGPT has brought forth a more innovative and flexible dimension to personalized learning, expanding the possibilities within this educational paradigm.

Broadly speaking, the trajectory of personalized learning has traversed an evolutionary continuum, progressing from simplicity to complexity, from mechanization to intelligence, and from theoretical conceptualization to practical implementation. Throughout this developmental journey, personalized learning has increasingly aligned itself with the distinctive needs of diverse students. It advocates for tailored learning methodologies based on individualized progress and mastery of knowledge, with the overarching goal of fostering students' intrinsic interest in learning and, consequently, enhancing their overall learning capabilities.

3.2 Education Theory and Personalized Learning

Before entering the adaptive stage of personalization, numerous educators proposed a multitude of educational theories aimed at shaping and advancing personalized learning. The varied perspectives within these educational theories have offered crucial theoretical support and guidance for the evolution of personalized learning. In Table 2, we outline the educational theories closely associated with personalized learning, elucidating the specific connections each theory has with the concept.

Table 2. Educational theory in personalized learning.

Theory: Progressivism Theory [46, 44, 45]	
Representative Figures: Francis Wayland Parker and John Dewey	
Introduction	Progressivism is one of the most important philosophical schools of education to influence education in the West in the 20th century, also known as the "new education". The theory of progressivism was developed in opposition to the traditional schooling practices from the early 19th to the late 20th century, advocating for the reform of traditional education in response to the growing industrialization of education. The theory of progressivism emphasizes students' active participation, self-directed learning, and ability to think independently. Progressivism promotes problem-centered learning, guiding students to comprehend knowledge and enhance their learning abilities through engaging in practical problem-solving processes. Progressivism focuses on the individual differences and learning needs of students, believing that different students learn at different paces and advocating a student-centered approach to teaching and learning.

Relationship of the theory to personalized learning	The foundation of progressivism theory aligns closely with the principles of personalized learning, emphasizing individual characteristics and advocating for independent learning and problem-solving abilities. It underscores the belief that education should be tailored to each individual, aligning seamlessly with the objectives of personalized learning.
Theory: Behaviorist Theory [184, 216]	
Representative Figures: Ivan Pavlov, John Broadus Watson, Burrhus Frederic Skinner	
Introduction	Early behaviorist theory, formulated by the American psychologist Watson, conceptualized behavior as a process through which organisms establish connections between external stimuli and observable behaviors. The later neo-behaviorists, led by Tolman, sought to refine Watson's perspective, positing the existence of intermediate variables between the stimuli individuals receive and their behavioral responses, encompassing the physiological and psychological states of individuals at a given time. Another branch of neo-behaviorism, exemplified by Skinner, contends that behavior is shaped by reinforcement, with reinforcement training serving as the primary mechanism elucidating the organism's learning process. The theory focuses on the observation, measurement, and control of learner behavior and emphasizes the shaping of behavior by the environment.

Relationship of the theory to personalized learning	Behaviorist theory underscores the molding of behavior through a framework of rewards and punishments, providing a concept applicable to personalized learning paths. This involves tailoring the approach through feedback mechanisms and reward/punishment systems to cater to the diverse needs of individual learners. Additionally, the theory posits that variations exist in how distinct individuals react to stimuli, thus influencing the development of personalized learning methodologies.
Theory: Constructivism Theory [163, 206, 50]	
Representative Figures: Jean Piaget, Jerome Bruner, Lev Vygotsky, Robert Jeffrey Sternberg, Hermann Ebbinghaus	
Introduction	Constructivism theory, stemming from investigations into children's cognitive development within the cognitive psychology school, stands as a significant branch. Its influence extends deeply into educational practice. Constructivism is used to illustrate the cognitive laws of the learning process, encompassing such factors as how learning occurs, when it occurs, and how it takes shape. Constructivism posits that learners don't merely passively absorb knowledge but rather acquire it through active interaction with their environment, defining the learning environment with four key elements: "context," "collaboration," "conversation," and "meaning construction." Constructivism views learning as a process of actively engaging, thinking, experiencing, and constructing new knowledge in which learners reconfigure their cognitive structures. It also believes that different learners have different backgrounds and ways of thinking, and their construction of the new knowledge they learn is unique, so it is important to take into account the individual differences of learners.

Relationship of the theory to personalized learning	The constructivist theory promotes the idea of enabling students to build their own knowledge systems through activities like problem-solving, collaborative learning, and independent thinking, contributing to a personalized learning approach. This theory underscores the significance of individual differences and social interactions in students, aiding in the creation of learning environments tailored to learners' needs. Serving as the foundation for cognitive theory, it has heightened attention to individual variances, influencing the trajectory of personalized learning.
Theory: Cognitive Psychology [163, 25, 11, 190]	
Representative Figures: Albert Bandura, Jerome Bruner, Jean Piaget, David Ausubel	
Introduction	Cognitive theory emerged in the wake of constructivism, gradually evolving and drawing from the principles of Gestalt psychology, which centers on the processing of information and cognitive processes within the organism. Cognitive theory views learning as an active process in which the learner organizes and understands the information acquired through interaction with the environment. Cognitive theory posits that the learning process engages cognitive functions like perception, memory, and thinking. Additionally, cognitive structures such as schemas, conceptual maps, or reasoning frameworks play a crucial role in comprehending and interpreting information. Cognitive theory illustrates the importance of long-term memory by explaining that learners can comprehend and store information more easily by linking it to prior knowledge, forming meaningful structures. Cognitive theory emphasizes problem-solving as one of the important components of cognitive ability. Individuals need to think and adapt to solve the problems they face.

	Different learners have different cognitive styles, leading to some differences in learning styles, subject interests, and mastery.
Relationship of the theory to personalized learning	Cognitive theory emphasizes individual differences in learners' thinking styles, perceptual modalities, and memory abilities. It provides basic principles for personalized learning regarding the learning process and individual differences. Furthermore, cognitive theory furnishes theoretical underpinnings for crafting personalized learning trajectories, formulating learning strategies, and promoting effective problem-solving.
Theory: Sociocultural Theory [206, 205]	
Representative Figures: Lev Vygotsky	
Introduction	A theoretical framework distinct from behaviorism and cognitive psychology, proposed by Soviet psychologist Lev Vygotsky, accounts for the importance of sociocultural factors in the development of functioning in the human person. The theory highlights that human mental functions evolve and mature through the mediation of cultural artifacts, activities, and concepts. The utilization, organization, and composition of language emerge as the principal modes of mediation, enabling individuals to cultivate distinctive cognitive structures within the framework of sociocultural interactions. In this theory, the concept of the Zone of Proximal Development (ZPD) was introduced to underscore the significance of learners collaborating with others in the learning process. It emphasizes the facilitating role of social interaction in individual cognition.
Relationship of the theory to personalized learning	Sociocultural theory informs the implementation of social and collaborative learning practices. A personalized learning approach aligned with sociocultural theory may integrate concepts like social learning and collaboration, aiming to facilitate interaction and co-learning among students through the use of social tools and collaborative functions.

In summary, progressivism emphasizes students' autonomous learning, providing support for personalized learning; behaviorist theory can be utilized in the feedback system of personalized learning; constructivism focuses on students actively constructing knowledge and establishes a solid foundation for cognitive theory; cognitive theory underscores that personalized learning should address learners' cognitive needs; sociocultural theory illustrates the importance of cooperation and social environment in student development. Behaviorist theory has limitations, as it neglects cognitive processes and internal mental activities. Therefore, personalized learning tends to integrate multiple theories, including cognitive theory, constructivism theory, and sociocultural theory, to comprehensively support students' personalized needs.

These educational theories have brought profound insights and guidance to personalized learning, providing a solid theoretical foundation for creating a more flexible learning environment that aligns with individual student differences and diverse learning needs. By integrating these theoretical perspectives, personalized learning can achieve a more comprehensive and in-depth understanding of students' needs. In the evolving landscape of education, the guidance of educational theories has played a significant role in driving the development and innovation of personalized learning.

4 DATA

In personalized learning, the importance of data cannot be overlooked. By capturing information on learner behavior, preferences, attributes, and performance, personalized learning systems acquire a profound understanding of each learner's distinct needs, facilitating more targeted and effective learning support. Data serves not only as the driver for personalized recommendations and learning path planning but also forms the bedrock for sentiment analysis, performance prediction, learning analytics, and personalized assessment. Therefore, data in personalized learning not only shapes the individual learning process but also acts as the powerhouse for continuous system optimization. High-quality data can make the algorithm and system twice as effective. In this section, we traverse the relevant datasets used in the process from student modeling to recommendation, as formulated in Table 3, 4, 5. Specifically, the discussion is organized into three main sections: cognitive diagnosis, learning analytics(non-cognitive), and recommendations. Each section will independently present the most commonly used datasets in the reviewed literature.

4.1 Cognitive Diagnosis

In the realm of cognitive diagnosis, the significance of data cannot be overstated. By meticulously collecting data on students' learning processes, educators gain a more comprehensive understanding of individual students' cognitive processes, learning strategies, and areas of difficulty. The collected data may encompass personal information, preferences, and other details related to learning. Information such as student's personal details, question-answer patterns, and behavioral data serve as invaluable resources for cognitive diagnosis. In essence, these data provide profound insights into students' cognitive processes, forming the bedrock for personalized and precise analysis of their cognition. Leveraging these data to their full potential enhances the training of cognitive diagnosis models, enabling them to more accurately capture students' cognitive processes, learning strategies, and knowledge structures. Concurrently, the quality and diversity of the data directly influence the accuracy and utility of the model. Below is an introduction to some commonly used datasets in cognitive diagnosis:

- ASSISTMents: The dataset is derived from the well-known online tutoring system, ASSISTment Tutoring System [172]. Primarily, it serves as a platform for math practice targeting

Table 3. Datasets for cognitive diagnosis.

Datasets	Bibliography
ASSISTments	[209, 211, 20, 138, 232, 65, 186, 230, 118, 162, 195, 214, 88, 196, 66, 208, 147]
Junyi	[185, 211, 139, 232, 65, 146, 115, 66]
Math	[209, 243, 139, 65, 230, 118, 146, 162, 115, 195, 214, 88, 196, 208, 136, 256, 147]
Algbra	[118]
Bridge	[118]
Self-collected Dataset	[185, 36]
Simulated Dataset	[243]
FrcSub	[230, 162, 136, 147]

students in grades 1-9. The ASSIST dataset encompasses ASSISTments09-10 [1], ASSISTments12-13[2], ASSISTments15[3] etc., each collected at different times. For instance, the ASSISTments09-10 dataset compiled data for the 2009-2010 academic year. Each dataset is further categorized into skill-builder data files and non-skill-builder data files, distinguished by the type of problems and subject knowledge they entail. The skill-builder data file contains information related to a specific skill within a particular discipline, while the non-skill-builder includes information across multiple disciplines or general knowledge, making it more suitable for assessing a student's overall proficiency. In experiments, these two datasets are typically combined. The dataset comprises details such as student ID, question ID, relevant knowledge points, and time spent on each question.

- Junyi[4]: This dataset compiles log files sourced from the Junyi Academy online learning platform spanning from October 2012 to January 2015. It encompasses over 350,000 exercise-related messages from 10,000 students. The exercises included in this dataset originate from the math test database of a Chinese online platform and come annotated with comprehensive information on the relationships between all the exercises. The dataset exhibits a hierarchical structure, progressing from regions to topics to exercises. Within the exercises, each exercise involves multiple concepts and conversely, one concept is associated with multiple exercises. This dataset is characterized by the inclusion of prerequisite relationships between exercises and is therefore often used in work related to cognitive diagnosis and knowledge tracing.
- Math[5]: This dataset, obtained from the online learning platform Zhixue (https://www.zhixue.com) by iFLYTEK Co., Ltd., comprises data from a high school math final test. The exercises are categorized as subjective and objective, and further divided into Math1 and Math2. Math1 consists of 15 objective questions, 5 subjective questions, and 11 knowledge items, while Math2 includes 16 objective questions, 4 subjective questions, and 16 knowledge items. Both datasets involve approximately 4,000 users, generating around 80,000 interactions. Notably, these datasets feature expert-labeled conceptual prerequisite relations, making them widely utilized in cognitive diagnosis and related research.

[1]https://sites.google.com/site/assistmentsdata/home/2009-2010-assistment-data
[2]https://sites.google.com/site/assistmentsdata/datasets/2012-13-school-data-with-affect
[3]https://sites.google.com/site/assistmentsdata/datasets/2015-assistments-skill-builder-data
[4]https://pslcdatashop.web.cmu.edu/DatasetInfo?datasetId=1198
[5]http://staff.ustc.edu.cn/~qiliuql/data/math2015.rar

- Frcsub[6]: The dataset is primarily focused on math instruction, with a predominant emphasis on elementary school practice data for addition and subtraction. It is relatively small, comprising only 8 knowledge items, 20 exercises, and 10,720 interactions by 536 students. The data file includes expert-annotated logs and a corresponding knowledge matrix. Additionally, a Q-matrix file is stored for the 8 knowledge items.

4.2 Learning Analytics

4.2.1 Learning style analysis. Learning style analysis inevitably requires the utilization of high-quality student data. The collected student interaction data can be meticulously analyzed to discern learning preferences, behavioral patterns, and responses, enabling educators to delve deeper into each student's unique learning style. Simultaneously, learning style data can unveil how students react to various instructional strategies. This understanding empowers educators to tailor their teaching methods, adopting more effective strategies that enhance student engagement and depth of understanding. Moreover, the comprehensive utilization of learning style data provides pivotal insights for optimizing teaching strategies, aligning suitable learning resources, and ultimately enhancing learning outcomes. In essence, leveraging data in learning style analysis optimizes the teaching process, enriches the student learning experience, fosters personalized learning, and better caters to the unique learning needs of each student.

The choice of data in the literature on learning styles analysis usually depends on the researcher's research aims and questions, and below we describe common or widely used datasets in learning styles research.

- Moodel Dataset: This is student activity log data collected on Moodle[7], an online Learning Management System (LMS), which is free and open-source software designed to support the student learning process. One of the well-known datasets was collected from 127 undergraduate students in an object-oriented modeling course at a university in Austria [19, 18]. The course is hosted on Moodle and the necessary data can be extracted from its student activity log files. The dataset includes records of various student activities and behaviors on the Moodle platform, such as login information, user details, course information, online test scores, and assignment submissions.
- MOOC Dataset: This dataset comprises data collected from Massive Open Online Courses (MOOCs), including platforms like Coursera, edX, and others. One widely utilized dataset originates from Stanford University and pertains to the edX course "Statistical Learning," gathered over two academic years, winter 2015 and winter 2016. Provided by the Center for Advanced Research in Online Learning (CAROL), the dataset encompasses fundamental user details, course materials, student interactions in forums, video engagement, and comprehensive information about learners participating in various activities. Its rich data on learning behaviors, student interactions, and grades make it well-suited for research focused on learning styles.
- ILS Questionnaire Dataset: The Index of Learning Styles (ILS) questionnaire serves as a tool for evaluating students' learning styles, prompting learners to explicitly express their preferences by completing the questionnaire. Developed by Richard Felder and Barbara Soloman [59], the ILS questionnaire assesses learning styles based on the Felder-Silverman model, categorizing learners across four dimensions: The first dimension encompasses Concrete Learners and Abstract Learners (Perception); the second dimension includes Sequential Learners and Global Learners (Processing); the third dimension involves Visual Learners and Verbal Learners

[6] http://collegereadiness.collegeboard.org/psat-nmssqt-psat-10/scores/student-score-reports
[7] https://moodle.org

(Input); and the fourth dimension comprises Active Learners and Reflective Learners (Output). Upon completing the ILS questionnaire, students receive style scores in these four dimensions, providing insights into their preferences across different learning style dimensions. To ensure the reliability of the data collected, responses from students who completed the questionnaire in less than 5 minutes were typically excluded.

- Self-constructed Experimental Dataset: Given the diverse requirements of researchers in the field of learning style analysis, some opt to build their own datasets to align with the specific goals and nature of their experiments. This approach allows for enhanced control over variables and the acquisition of detailed data on students' learning styles. As in [53] the dataset records information about 1235 learners, which was obtained from the e-learning platform log files (http://www.supmanagement.ma/fc/login/index.php) from Sup Management Group (http://www.supmanagement.ma/fc). Another instance, described in [70], involved the collection of student behavior data from a Learning Management System (LMS) opened exclusively for the experiment. This dataset encompassed the activities of 100 computer science graduates, including information on content, syllabus, self-assessments, quizzes, and other relevant data. It's worth noting that much of the self-constructed data in the literature mentioned is proprietary and not publicly available.

4.2.2 *Sentiment analysis.* The significance of data in sentiment analysis resides in its capacity to delve deeper into students' emotional experiences during the learning process. Through the collection and analysis of students' sentiment data, it becomes possible to establish a more accurate sentiment analysis model. The algorithms and models for analyzing students' sentiment require substantial labeled data for effective training and validation. Simultaneously, the utilization of data in student sentiment analysis serves as crucial support for personalized learning, enhancing user experience, and facilitating adjustments in educator strategies. This section will present datasets commonly used in student sentiment analysis.

- IMDb Dataset: This extensive movie database encompasses diverse movie details such as titles, release dates, directors' information, actors' profiles, user ratings, and more. IMDb, widely utilized in the film industry, academic research, and data science, empowers users to rate and comment on movies they have watched, offering valuable insights into user sentiment. Frequently employed in sentiment analysis tasks, this dataset plays a crucial role in categorizing user reviews as positive or negative. Typically, the literature focuses on a subset of the database, comprising 1000 positive and 1000 negative reviews. Ratings of 3.5 and above are considered positive labels, while lower ratings are assigned to negative labels.
- MOOC Dataset: In contrast to the predominant use of MOOC datasets for recommendation algorithms, this particular dataset zeroes in on the analysis of student reviews. In contrast to the predominant use of MOOC datasets for recommendation algorithms, this particular dataset zeroes focuses on the analysis of student reviews. The literature reveals three distinct MOOC sentiment analysis datasets: Firstly, the 100k Coursera(https://www.kaggle.com/septa97/100k-courseras-course-reviews-datase) dataset, sourced from a prominent public university in the US, was gathered from the Coursera website. Comprising over 1,800 courses and 100,000 reviews, the dataset primarily consists of concise English reviews, averaging 8.36 words across 1.87 sentences. The reviews cover various aspects of the given MOOC, including instructor feedback, platform reviews, and course critiques. Secondly, a dataset encompassing randomly selected MOOCs from Class Central, a well-known public review site for MOOCs, provides essential information such as topic, cost, session, and duration. The use of crawler technology facilitates the automatic retrieval of metadata and comments for all courses associated with the selected MOOC, offering direct access to learners' opinions on course content, teachers,

platforms, etc. The third dataset involves comment data extracted from MOOC courses at Chinese universities, totaling over 19,000 entries. This dataset includes comment text and sentiment polarity for each discipline, categorizing sentiments into positive, neutral, and negative. As these datasets are collected within the MOOC platform framework, this paper categorizes them under the broader umbrella of MOOC platform datasets.

- Twitter Dataset: This category of datasets pertains to information extracted and gathered from the Twitter platform, primarily consisting of textual data encompassing tweets or user comments. These datasets are commonly utilized for training and evaluating sentiment analysis models. Due to the diversity of research domains and specific inquiries, researchers employ varied keywords for data collection on Twitter. For instance, datasets like SentiTEXT and eduSERE, comprised of user comments, are built on Twitter-mined keywords related to teachers, exams, tasks, programming, etc. [14]. Another example is the TASS corpus, employed in training the OM classifier [159]. This corpus, utilized in the Spanish Sentiment Analysis Workshop, incorporates around seven thousand Twitter messages, each labeled with sentiment polarity indicating the expressed sentiment in the text. Conversely, for an exploration of public perceptions regarding the use of ChatGPT in education [199], a tweet corpus from 1 February 2023 to 12 February 2023 was assembled using keywords like "ChatGPT AND education," "Teaching AND ChatGPT," and others on Twitter. Extraction was conducted using Python and the Twitter API, focusing on english tweets while prioritizing relevant content.
- Self-constructed Experimental Dataset: Sentiment analysis tasks often necessitate the creation of bespoke experimental datasets due to their capacity to cater to specific research requirements, offering more accurate labeling and nuanced sentiment categories. Moreover, concerns regarding privacy may arise when utilizing data from social media or other public platforms. Self-constructed datasets address these concerns by providing better control over data privacy issues and ensuring research compliance. As none of the sentiment analysis datasets examined in the literature are publicly accessible, this section refrains from providing further details.

4.2.3 Behavior analysis. Student behavior data serves as an essential foundation for behavior analysis, acting as the cornerstone of learning analytics and offering a wealth of insights into student learning activities. By collecting and analyzing data related to student engagement with learning platforms, a profound understanding of student performance, learning requirements, and overall engagement can be obtained. These datasets not only aid in identifying patterns and trends in student learning but also facilitate personalized support, the adjustment of teaching strategies, and the optimization of instructional design. The accuracy and reliability of student behavior analysis are directly influenced by the quality and diversity of the data. In summary, the utilization of data in student behavior analysis is apparent, providing crucial perspectives on academic performance, learning processes, and behavioral patterns.

In the reviewed references, there were no publicly available datasets common across a large body of literature. Mostly, researchers employ self-constructed experimental datasets because they allow for better control over information, such as experimental conditions, instructional variables, and student characteristics. This control enhances the internal validity of the study and lends greater credibility to the results. Simultaneously, self-constructed datasets offer the flexibility to conduct experiments tailored to specific research questions and hypotheses, meeting the diverse needs of researchers. Monitoring and adjusting the data collection process ensures the quality and accuracy of the data. Given that different research questions may require distinct behavioral analyses, researchers building their datasets can better reflect the actual situation in specific areas.

Moreover, in student behavioral analysis, researchers often explore new educational methods, and in such cases, finding suitable existing datasets might be challenging. Therefore, researchers opt for self-constructed datasets to support their unique research objectives. The data in the literature are mainly divided into two categories. The first type is student learning data collected through teaching platforms and questionnaires [180, 30, 42, 137, 97]. The second category is the life and learning data of college students collected from the Network Information Center and the Digital System Database of colleges and universities [212, 124, 178, 13, 125].

Data collected through teaching platforms, online platforms, cloud classrooms, and questionnaires primarily constitute students' learning data. This encompasses students' online activities (such as video viewing, chapter tests, online behaviors, and the number of visits to topic forums), programming information (including students' statistical files, operational details, and code specifics), and achievement data.

The collection of student life, learning, and behavioral data on college campuses was motivated by the belief that student behavior is influenced by various factors, including individual differences, teaching and learning environments, and social factors. Therefore, the utilization of actual student data helps address these complex relationships, enhances the study's authenticity, and allows for the demonstration of the constructed model's performance in real-world applications based on genuine student data. Commonly included information in the dataset comprises students' consumption data, life data, and study data, specifically encompassing one-card consumption records, gateway login behavior records, book borrowing records, library study hours, access control records, as well as students' credits and grades.

While self-constructed datasets demand more resources and time, they afford researchers increased autonomy and control. Contributing to the progression of cutting-edge research in the realm of student behavior analysis.

Table 4. Datasets for learning analytics.

Datasets	Bibliography
Moodle Dataset	[19, 18, 54, 78, 79, 93, 40]
MOOC Dataset	[80, 174, 141, 169, 222, 154, 140, 99, 122]
ILS Questionnaire	[73, 19, 18, 70, 54]
OULAD	[107, 108]
xAPI-Edu-Data	[95, 9, 155, 64, 2]
ASSISTMents	[6]
IMDb Dataset	[40]
Twiter Dataset	[40, 93, 159, 199]
Self-collected Dataset	[53, 70, 109, 103, 107, 227, 203, 155, 69, 226, 245, 165, 224, 180, 212, 30, 42, 124, 178, 13, 125, 27, 137, 97, 14, 142, 153, 158, 164, 182, 235, 34, 29, 170, 60]

4.2.4 Predictions of student performance/achievement. The significance of data in forecasting student performance and accomplishments cannot be emphasized enough. By comprehensively documenting students' academic journeys, behavioral patterns, and engagement activities, data serve as the foundational information needed for constructing effective predictive models. Firstly, through the collection and analysis of student learning data, we can predict and assess student performance with greater efficacy. Secondly, by identifying early indicators of learning difficulties or potential issues, timely interventions can be implemented, offering additional resources and support to reduce the likelihood of student dropout. For instance, data points like online activity participation, assignment submission duration, and interaction frequency can furnish more precise features for predictive modeling, thus playing a pivotal role in model construction. Concurrently, actively utilizing data to advance student performance and grade prediction contributes to the development of more accurate and reliable prediction models. In summary, the crucial role of data for student performance and achievement prediction is that it provides insights into students' academic characteristics, supports the continuous optimization and adjustment of models, and provides a solid foundation for developing accurate modeling strategies. The datasets commonly used in student performance and achievement prediction are described in detail below.

- Open University Learning Analytics Dataset (OULAD): This publicly available dataset[110], provided by Open University in the UK, serves as a standardized dataset for academic research. It primarily comprises student activity records from various Open University courses in the social sciences, technology, and mathematics spanning from 2013 to 2014, encompassing data from over 32,000 students. The dataset includes essential information such as Open University course details, students' psychological stress levels, emotional states, exam outcomes, and other pertinent data during the assessment period. In the context of predicting student performance and grades, the OULAD dataset utilized consists solely of student demographic characteristics, information on clickstream patterns from alternative connections gathered during student interaction with the Virtual Learning Environment (VLE), and characteristics of student activity logs.
- xAPI-Edu-Data: Open-source data sourced from the Kaggle repository (https://www.kaggle.com /aljarah/xAPI-Edu-Data) stands out as one of the prevalent datasets in the realm of online education. Comprising 480 students (305 males and 175 females), this dataset encompasses 17 attribute features, each representing distinct performance indicators of the students. These characteristics are categorized into three primary groups: personal, academic, and social. Personal features delve into students' individual details, including gender, nationality, and place of birth. Academic features encompass metrics such as the utilization of digital resources, test scores, and more. Social features capture elements like the guardians responsible for the student, parents' assessments of the school, and educational levels.
- Self-constructed Experimental Dataset: Experimental datasets constructed by researchers offer enhanced control over various experimental conditions, encompassing the teaching environment, course design, and student characteristics. These self-constructed datasets are prevalent in references related to predicting student performance and achievement. They provide a unique opportunity for experimental design, enabling researchers to tailor conditions based on specific hypotheses and evaluate their potential impact on student outcomes. Moreover, self-constructed datasets, when made publicly available, contribute significantly to advancing academic research in the field. This discussion highlights two such datasets derived from cited references that are now accessible to the public. The first dataset involves performance data from 1854 students enrolled in a Turkish language program during the 2019-2020 academic year, collected by [227] from a state university in Turkey. This dataset includes information such as midterm exam results, final exams, and departmental details, and has been publicly released as an attachment. In another example, literature [69] introduced the SETAP (Software Engineering Teamwork Assessment Data) program, designed to record data on learners' learning abilities and application of software engineering processes in a teamwork environment. This self-collected and publicly released educational dataset is available from the Machine Learning Repository[7]. Originating from software engineering courses at San Francisco State University (USA), Fulda University (Germany), and Florida

Atlantic University (USA), the dataset spans seven semesters from 2012 to 2015. It involves over 383 learners organized into 74 groups with 3-7 members each, resulting in a total of more than 30,000 entries stored in 11 different file groups.

4.3 Personalized Recommendation Algorithms

Data-driven personalized learning relies on recommender systems that analyze learners' historical data, such as past learning performance and preferences, to recommend personalized learning materials, courses, exercises, and more. This data serves as the power source for these recommender systems, enabling continuous optimization and adjustment of their strategies to enhance learner satisfaction and learning effectiveness. The following section introduces the datasets commonly used in personalized recommendation, as summarized in this paper:

- XueTangX: This dataset is sourced from XueTangX[8], the largest MOOC learning platform in China. Various studies have gathered data from the platform at different points in time, resulting in varying amounts of information and pre-processed user and course counts. One widely utilized dataset is the user data collected by Zhang and others [241] on the platform from 1 October 2016 to 31 March 2018. Users who took less than or equal to 2 courses were excluded. The data includes information such as user ID, course ID, knowledge points, and the duration of video viewing. The final dataset obtained comprises 1,302 courses, 82,535 users, and 458,454 user-course pairs.
- MOOCCourse[9]: This dataset is from XueTangX. It contains 1302 courses with 82,535 registered user information and 458,453 user interactions with courses. The dataset contains data information such as student ID, enrollment time, course ID, and course name.
- MOOCCube[234]: Data was collected from the XueTangX platform during the academic years 2017-2019. The dataset comprises 55,203 registered users, 706 courses, 38,181 instructional videos, and 114,563 concepts, with a total of 354,541 interactions between users and courses. MOOCCube consists of two main parts: the primary repository, MOOCCube, and the individual course repository, MOOCCube_DS, the former of which has been widely cited in the literature. MOOCCube focuses on three main dimensions: concepts, courses, and student behaviors. It encompasses a substantial amount of data, including entity files (course, concept, user, etc.), relationship files (course-concept, user-course, etc.), and supplementary files (concept_information, etc.).
- MovieLens[10]:This is a popular movie rating dataset widely employed in recommendation systems and machine learning research. The dataset encompasses user ratings and metadata information about movies. MovieLens is available in several versions, with MovieLens 100K, MovieLens 1M, and MovieLens 10M being the most commonly used ones. The distinction among these datasets lies in their size, reflecting varying amounts of ratings and movie information, suitable for different scales of research. In the related literature, this dataset is typically used in conjunction with another educational dataset. This dataset is used in order to demonstrate the effectiveness of the proposed recommendation algorithm in dealing with sparse data as well as the scalability of the method. In other words, the proposed method can be applied not only to educational recommendations but also to datasets with similar data organization in other domains, such as movies.

The datasets highlighted in the preceding three sections are commonly employed in relevant exploratory literature. The majority of these datasets are open and readily accessible to researchers

[8]http://www.xuetangx.com
[9]http://moocdata.cn/data/course-recommendation
[10]https://grouplens.org/datasets/movielens

Table 5. Datasets for personalized recommendations.

Datasets	Bibliography
ASSISTments	[35, 117, 74, 219, 116, 173, 218]
XueTangX	[241, 96, 223, 247, 231, 75, 213, 33, 233]
MOOCCourse	[132, 134, 133]
MOOCCube	[132, 134, 133, 240, 145, 192, 112, 56, 75, 253, 233, 112, 76]
MOOPer	[114]
Junyi	[117]
EdX	[48, 239]
Algebra	[74, 219, 173]
Statics	[74, 173]
E-learning System	[92]
Coursera	[225]
Self-collected Dataset	[37, 217, 105, 215, 10, 255, 84, 31, 252, 57, 220, 210, 246, 168, 244, 143, 91, 194, 187, 189, 221, 201, 179, 188, 171, 144, 254, 47, 72, 126, 127]
Simulated Dataset	[120]
MovieLens	[215, 213, 244]
Last.FM	[244]

and developers at their respective sources. It's important to note that all presented datasets are in their raw form. Various literature adopts distinct data cleaning and preprocessing techniques for specific tasks, contributing to variations in the final training and evaluation datasets.

5 STUDENT MODELING AND PERSONALIZED RECOMMENDATION

Student modeling and personalized recommendations are pivotal elements in personalized learning, working collaboratively to enhance its effectiveness. Student modeling involves two crucial dimensions: cognitive and non-cognitive, aiming to capture personalized characteristics. Cognitive modeling delves into students' cognitive processes, often utilizing cognitive diagnostics. This approach tailors the definition of learning content to enhance students' understanding, mastery of knowledge, and overall learning capabilities. On the other hand, non-cognitive modeling emphasized through learning analytics, encompasses aspects like learning styles, affective states, and learning behaviors. This multifaceted approach provides a comprehensive understanding of individual student needs.

By meticulously modeling learners and delving into both their cognitive and non-cognitive traits, the design of personalized learning paths can be significantly refined to offer tailored learning resources that cater to student's unique needs and enhance their capabilities. Consequently, student modeling forms the fundamental groundwork for personalized recommendations. These recommendation systems leverage the outcomes of student modeling to furnish individualized suggestions, thereby augmenting the level of personalization and enhancing the overall efficacy of the learning experience.

In the next sections, we will detail the methods and related work of cognitive diagnostics, learning analytics, and personalized recommendations, and how they interact with each other to advance personalized learning.

5.1 Cognitive Diagnosis

Cognitive diagnosis, involving the measurement of psychological attributes in individuals processing information within specific fields, is in alignment to assess students' mastery of knowledge in the realm of personalized learning. The diagnostic results provide educators with valuable insights to customize downstream personalized learning materials and assignments, including course or question recommendations. In this section, we will delve into cognitive diagnosis for personalized learning, covering its task formulation, background, and a literature review of recent valuable works through a fine-grained taxonomy.

5.1.1 Task Formulation. The evolving information technology brings forth ample student learning data, offering educators valuable clues to assess their knowledge proficiency through cognitive diagnosis. This task aims to estimate students' proficiency in a specific knowledge concept, by giving them a series of test questions with their responses. Consider a student set $\mathcal{U}$ and a test question set $\mathcal{P}$. Let $r_i^u = (q_i^u, a_i^u)$ represent the i^{th} response of student $u \in \mathcal{U}$. This response comprises the answered question q_i^u and binary correctness indicator $a_i^u \in \{0, 1\}$, where $a_i^u = 1$ denotes a correct response. Given the historical responses of a student as a set $\mathcal{H}^u = \{r_1^u, r_2^u, \cdots, r_{|\mathcal{H}^u|}^u\}$, the Cognitive Diagnosis Model (CDM) captures their latent proficiency θ_u regarding the target concept. Due to the absence of explicit proficiency annotations, researchers design CDMs by estimating the probability of students answering test questions correctly based on proficiency as parameters to be learned, i.e., $p(a_i^u = 1|\theta_u, q_i^u)$. Subsequently, the cognitive diagnosis process is trained by maximizing the likelihood of the observed responses:

$$\max \prod_{u \in \mathcal{U}} \prod_{r_i^u \in \mathcal{H}^u} p(a_i^u = 1|\theta_u, q_i^u). \tag{1}$$

Given the extensive personalized learning data accumulated over decades, educators have expanded the CD task to encompass multiple knowledge concepts. The learning materials have become more diverse, assigning students questions that span various knowledge domains. This expansion necessitates the CD task to diagnose students' mastery across multiple knowledge dimensions, denoted as $\boldsymbol{\theta}_u \in \mathbb{R}^{|C|}$, where C represents the set of knowledge concepts. As one question may be associated with multiple concepts, these relationships are defined by a Q-matrix $\mathbf{Q} \in \mathbb{R}^{|P| \times |C|}$. In this matrix, a value of 1 in the i^{th} row and j^{th} column indicates that question i is related to concept j, while a value of 0 signifies no association. Then the multi-dimensional knowledge proficiency is estimated by optimizing a revised version of Equation 1:

$$\max \prod_{u \in \mathcal{U}} \prod_{r_i^u \in \mathcal{H}^u} p(a_i^u = 1|\boldsymbol{\theta}_u, q_i^u, \mathbf{Q}). \tag{2}$$

5.1.2 Background. As a means of assessing psychological attributes, researchers historically employed psychometric methods for the CD task. One prevalent method, Class Test Theory (CTT) [197], is a straightforward approach that diagnoses students with a true score T and random errors E, given the observed score X:

$$X = T + E. \tag{3}$$

Here, T represents students' knowledge mastery (i.e., θ), and E is assumed to be noise following a normal distribution, resulting from environmental factors or cognitive states. Despite its simplicity and intuitive appeal, CTT has limitations. For instance, the actual correlation between knowledge proficiency and observed score is not always linear. Moreover, some essential attributes, such as question difficulty and guessing or flipping, are not adequately considered within the framework of CTT. Hence, researchers employ another psychological methodology, known as Item Response

Theory (IRT) [55], to provide a more profound model, which is expressed as

$$p(a_i^u = 1|\theta_u, q_i^u) = c_i^u + \frac{1 - c_i^u}{1 + e^{-a_i^u(\theta_u - b_i^u)}}. \tag{4}$$

In this equation, c_i^u represents the guessing parameter, indicating to what extent students can correctly guess the answer to the question q_i^u. a_i^u and b_i^u represent the question's discrimination and difficulty, respectively. Due to its comprehensiveness, the IRT model became the cornerstone of the development of CDMs. Several subsequent methods consider it their backbone for constructing precise and reliable cognitive diagnoses.

Later, as neural network technology gained prominence, the effectiveness of CD tasks in predicting student outcomes achieved notable levels. Nevertheless, this progress also resulted in a reduction in interpretability [128]. Researchers are currently concentrating on the challenge of preserving high accuracy in forecasting student performance while simultaneously enhancing the interpretability of the models.

5.1.3 Taxonomy. In this chapter, we will categorize 26 recent and representative cognitive diagnosis papers into four groups based on two orthogonal perspectives: data-driven versus pedagogical theory-driven approaches, and the focus on enhancing model accuracy versus interpretability.

- **Data-driven methods:** The advancement of information technology has supplied ample data for cognitive diagnosis. These initiatives scrutinize challenges in cognitive diagnostic scenarios stemming from data. This kind of method proposes data-driven approaches to effectively tackle these issues. For example, Wang et al. [211] introduced a self-supervised cognitive diagnosis framework. This approach leverages self-supervised methods to support graph-based cognitive diagnosis, thereby improving the academic performance of students dealing with long-tailed data. The work [139] integrates Structural Causal Models (SCM) to capture the causal relationships among students' mastery levels of different attributes. Additionally, it enhances the Q-matrix within the methodology, utilizing an artificial Q-matrix as a prior. This allows for the inference of relationships between exercises and explicit as well as latent knowledge attributes, enabling a comprehensive assessment of students' abilities.
- **Pedagogical theory-driven methods:** These approaches extensively delve into theoretical methods in the field of education, incorporating them into CD tasks to improve the accuracy or interpretability of the model. Monotonicity assumption is a classic pedagogical theory and widely used in the field of CD, such as both CCT and IRT. It states that the better students grasp any knowledge point, the higher the probability of answering the question correctly. The work [196] leverages this assumption and introduces paired learning to CD, effectively simulating the monotonicity between item responses. Some other theory like the Neutral Set (NS) theory, is applied by Ma et al. who comprehensively assessed students' cognitive status regarding knowledge concepts based on the three characteristics of understanding, misunderstanding, and uncertainty.
- **Model accuracy-oriented methods:** Due to the lack of explicitly labeled student knowledge mastery states, predicting performance on new questions has become a key indicator for evaluating the effectiveness of CDMs. Consequently, researchers enhance the performance of CDMs by integrating machine learning techniques or educational theories. The representative work NeuralCD [208] integrates neural networks to learn intricate exercise interactions, thereby obtaining both accurate and interpretable diagnostic results.
- **Model interpetability-oriented methods:** While the maturity of deep neural network technology has led to an increase in model accuracy, it has also resulted in a decrease in interpretability. Toward this issue, some methods prioritize improving the interpretability

Table 6. The fine-grained taxonomy of 26 recent works for CD tasks.

Taxonomy	Data-driven	Pedagogical theory-driven
Accuracy-oriented	[185, 211, 20, 138, 139, 232, 65, 186, 162, 195] [214, 209, 88, 251, 66, 208, 36, 256, 131]	[147, 118, 146, 115, 88, 196, 208, 209, 36, 136]
Intepretability-oriented	[139, 230, 88]	[146, 88, 136, 249]

of CDMs as their goal. For example, Zhou et al. [249] establishes three interpretable parameters: skill mastery, exercise difficulty, and exercise discrimination. Drawing inspiration from Bayesian networks and neural networks, they employ feature engineering to extract interpretable parameters and utilize tree-enhanced naive Bayes classifiers for prediction.

Table 6 illustrates our categorization of these 26 works. It is worth noting that certain works may belong to multiple categories, such as those simultaneously enhancing both model accuracy and interpretability.

5.2 Learning Analytics

We employ learning analytics as a pivotal non-cognitive component within the framework of student modeling. Its primary objective is to delve into learners, learning environments, and learning resources by systematically collecting, analyzing, and interpreting data generated throughout the learning process. Learning analytics manifests various levels of application, encompassing a detailed exploration of learning states and a quantitative analysis of the learning process. As depicted in Figure **??**, we will expound upon learning analysis comprehensively, covering four distinct facets: learning style analysis, student sentiment analysis, learning behavior analysis, and student performance/achievement prediction.

5.2.1 Learning style analysis. Learning style analysis aims to gain a nuanced understanding of individual learner differences. By measuring and comprehending learners' unique learning styles, the objective is to select methods that align more closely with their characteristics. Through a meticulous analysis of learning styles, the personalized learning system can precisely tailor teaching methods, offering learners more focused and effective resources to enhance knowledge mastery and elevate overall learning efficiency. Moreover, by grasping learners' learning styles, the system can personalize teaching strategies and content for individual or group needs, aligning closely with learners' cognitive preferences and learning tendencies.

Existing literature on learning style analysis covers work in several areas, including learning style definition and categorization [102, 49], learning style-based instructional design [82], technology-supported learning style analysis [19, 53, 70], and learning style prediction systems [80, 18, 174].

Illustrated in Figure **??**, we have systematically organized the gathered literature based on the employed learning style theories. Among the plethora of available learning style models, the Felder-Silverman Learning Style Model (FSLSM) is predominant in the literature [19, 80, 18, 70, 4, 103, 54, 78, 174]. Recognized for its comprehensive coverage of 8 learning styles across 4 dimensions, including perception and information processing, the FSLSM stands out as a widely adopted and valuable model for e-learning system research [81]. Numerous studies have leveraged diverse style recognition techniques to align learning objects with FSLSM learning style combinations, showcasing the efficacy of these methods in accurately capturing FSLSM learning styles.

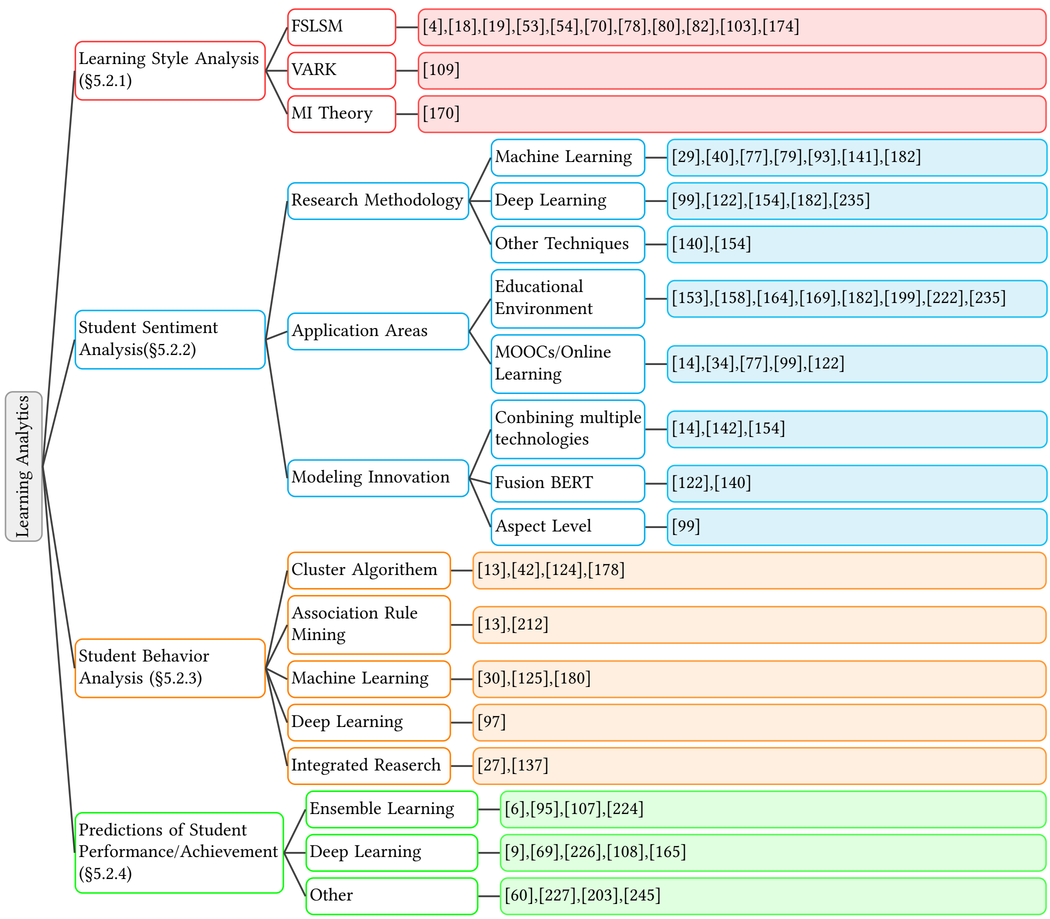

Fig. 3. Learning analytics classification maps.

Additionally, the VARK learning style[109]has found its place in some literature. Known for its simplicity and intuitive framework, VARK categorizes learning styles into visual, auditory, reading/writing, and hands-on categories. In a specific study, [170] employed two theoretical mappings—Gardner's Multiple Intelligences Theory and FSLSM Learning Styles Theory. The authors observed that existing research often neglects the multiple intelligences theory, resulting in incomplete analyses that overlook certain dimensions, particularly in studies utilizing the FSLSM model.

In contemporary research, diverse technical approaches are employed for the analysis of learning styles. Historically, the assessment of students' learning styles predominantly relied on questionnaires. This method primarily involved acquiring students' learning style information through online/offline questionnaires or survey instruments. While the questionnaire-based approach is acknowledged for its validity and reliability, it does have inherent limitations. Students' responses to the questionnaires might be erratic due to lapses in attention or prone to inaccuracies owing to personal errors. Moreover, learning styles, as gathered through questionnaires, are deemed static. However, we contend that learning styles are dynamic and subject to change over time and in response to varying environmental factors.

Therefore, to address the limitations inherent in the questionnaire format, some research methodologies employ clustering algorithms for the automatic identification of students' learning styles. This approach assists in uncovering potential associations among learners, elucidating similarities and differences by categorizing them into distinct groups. Analyzing the results of clustering groups offers insights into the needs and corresponding learning styles among diverse learner groups. Notably, clustering algorithms such as K-means and their variants find widespread application in learning style identification [54, 78]. The primary advantage lies in the algorithm's simplicity and efficiency, clustering based on the distance between samples, aligning with the measurement of learning style differences. [54] utilizes mining techniques to capture learner behaviors, converting them into sequences mapped to FSLSM categories, serving as input for the K-means algorithm. Arief et al.[78] similarly leverage student behavior results for clustering but enhance the K-means algorithm by modifying the original centroids to learning style combination vectors, subsequently remapping them to obtain new labels based on the initial centroids.

In addition to the exclusive reliance on clustering algorithms, contemporary literature introduces methods grounded in data mining and machine learning[80, 53, 109, 170] to autonomously discern students' learning styles and streamline style categorization to minimize interference. Presently, the prevailing approach involves the initial classification of learners into homogeneous groups using cluster analysis. Subsequently, machine learning algorithms are employed for style prediction based on information gleaned from learners' behaviors during the learning process. Various machine learning algorithms serve as classifiers, allowing for a comparative analysis of their effectiveness. Notably, four machine learning algorithms, namely Decision Tree, Random Forest, Naive Bayes, and Support Vector Machine (SVM) [80, 53, 109], are extensively utilized. SVM proves particularly adept as a predictor of individual learning styles, while Decision Tree excels as a predictor of combinations of learning styles [109]. Fareeha et al. [170] augment this repertoire by introducing Linear Discriminant Analysis and logistic regression for comparative evaluation. The compiled literature indicates that distinct classification algorithms exhibit varying performance across dimensions and diverse learning style models. For instance, Naive Bayes demonstrates superior accuracy in the processing dimension within the Multiple Intelligence Theory, while the Decision Tree outperforms in the perceptual dimension.

In recent years, there has been a surge in the application of advanced techniques such as deep learning and neural networks to learning style analysis. These methodologies exhibit a heightened capacity to handle intricate nonlinear relationships, thereby enhancing the modeling proficiency for accurate prediction of learners' styles. For instance, [82] conceptualized the learning style identification process as comprising six stages. Leveraging neural networks, the study tracked real-time behaviors of learners in a MOOC, implementing adaptive recommendations. Subsequently, artificial neural networks, ant colony algorithms, genetic algorithms, and hybrid methods were employed to monitor learning style performance dynamically [19]. This approach significantly augmented the accuracy of automatically identifying learning styles, with the hybrid method [80] achieving nearly 50% improvement in efficacy through a loosely coupled design. In a distinct contribution, [70] proposed a style recognition model based on an artificial neural network (ANN). Employing a deep multi-objective prediction algorithm, this model automatically and precisely identified students' learning styles through feature selection and multi-objective classification. The study [4] introduced deep learning algorithms such as CNN, Random Forest, and Long Short-Term Memory, presenting a comprehensive deep learning-based style recognition model. This model, structured by the selected deep learning algorithms, covers multiple levels and stages, accurately recognizing learners' styles based on FSLSM. Following style identification, learner-level prediction regarding course difficulty is furnished through the aid of a random forest classifier. Additionally, [103], incorporating FSLSM for learning style classification, utilized the Fuzzy Mean

(FCM) algorithm to cluster captured data into individual style categories of FSLSM. The study also introduced an enhanced version of the traditional Backpropagation Neural Network (BPNN) called the Gravitational Search-Based Backpropagation Neural Network (GSBPNN) algorithm, successfully implementing learning style classification and prediction.

Through an examination of pertinent literature in the realm of learning style analysis, it becomes evident that researchers have introduced clustering algorithms, integrated data mining and machine learning, and employed advanced computer techniques like neural networks and deep learning to surmount the limitations associated with questionnaires, marking a substantial leap forward. The incorporation of clustering algorithms not only unveils associations between learners but also distinguishes homogeneity from heterogeneity, providing a potent tool for a nuanced comprehension of learner differences. The integration of style prediction atop clustering analysis, coupled with the amalgamation of data mining and machine learning approaches, effectively mitigates interference stemming from students' personal biases. Simultaneously, recent advancements in neural networks and deep learning methodologies have introduced novel ideas and technological breakthroughs, elevating the accuracy of automatic learning style identification. The advent of these studies has injected renewed vitality into learning style analysis, opening up avenues for further research possibilities.

Despite the notable performance enhancements afforded by these methodologies, certain limitations persist. Firstly, a predominant focus on algorithmic performance improvement characterizes existing studies, with a relative absence in investigations into the theoretical underpinnings of learning style analysis, most of which hinge on the FSLSM model. Secondly, interdisciplinary and comprehensive research is lacking. Additionally, there exists a relative scarcity of studies delving into the learning styles of learners across different age groups. Future research endeavors should strive to construct a more comprehensive theoretical model of learning styles encompassing multi-age groups, integrating a broader spectrum of knowledge from psychology and education.

5.2.2 Sentiment analysis. In the field of learning analytics, sentiment analysis is gaining attention as an important research direction. It plays an important role in improving the learning experience, increasing engagement, and enabling early intervention. By providing insights into students' affective experiences during the learning process, learning analytics provides more comprehensive and subjective student-dimensional data, which provides key clues for personalized learning. Focusing on the existing literature on sentiment analysis, this section explores the analysis of student sentiment during learning tasks and the existing approaches to sentiment analysis. By analyzing existing research findings, we will reveal the importance of sentiment analysis in learning analytics and provide insights for future research.

We conducted an exhaustive literature review in this section, systematically organizing 22 pertinent papers and categorizing them into three essential dimensions: research methodology, application domain, and model innovation. These dimensions synergistically contribute to constructing a comprehensive research framework for student sentiment analysis.

From a research methodology standpoint, our analysis categorizes the relevant literature into three main groups: traditional machine learning methods, deep learning methods, and studies combining deep learning with other techniques. Traditional machine learning approaches [40, 77, 79, 93, 141, 159, 29] encompass diverse methodologies, including probabilistic models such as Latent Dirichlet Allocation (LDA) [40], as well as various supervised machine learning algorithms like SVM, naive Bayes, logistic regression, and random forests [77, 29]. These are often coupled with multifactor analytics, providing a comprehensive exploration of student sentiment.

In the domain of traditional machine learning, studies have leveraged naive Bayes, and SVM, and incorporated big data frameworks such as Hadoop [93]. For instance, Liu et al. proposed an innovative approach that employs the particle swarm optimization method to select affective features, reducing the spatial dimensionality of the feature space, resulting in a discriminative feature set and the construction of an effective emotion recognition model[141].

Another set of studies [182, 235, 154, 122] focuses on deep learning methodologies, utilizing techniques such as CNN [235, 99], LSTM [182, 154], and BERT[122] to enhance sentiment analysis accuracy. The integration of deep learning has enabled the extraction of more intricate information from text. In one instance [235], SVM and CNN were employed to identify sentiment information from students' self-evaluations, contributing to the prediction of students' performance. The introduction of the LSTM model facilitated the extraction of students' feedback and detection of sentiment polarity, providing an effective solution for addressing uncertainties in sentiment analysis [182, 154].

Furthermore, deep learning has been coupled with various techniques in sentiment analysis, such as Bayesian neural networks [154], capsule networks, and attention mechanisms[140], thereby further enhancing the accuracy of sentiment analysis. This categorization underscores the effectiveness of different research methods, where traditional machine learning serves as the foundation, and deep learning elevates our understanding of complex emotions. Additionally, the integration of deep learning with other techniques amplifies the overall performance of sentiment analysis algorithms.

Secondly, a predominant trend observed in existing literature on sentiment analysis is its concentrated application in educational settings, with a specific focus on MOOCs and online learning. To encapsulate the diverse educational contexts and learning styles, we have categorized the literature into two main groups—traditional educational settings and MOOCs/online learning. This categorization acknowledges that student sentiment analysis is a multifaceted challenge, necessitating an understanding of varying educational scenarios. Within traditional educational settings, analyses are conducted by examining multi-channel data sources such as course information [164, 182, 222, 235], tweets[199], forums[153, 222], and teacher evaluation websites [158]. These analyses aim to unravel students' affective experiences during learning. For instance, forum activities provide insights into learners' social, emotional, and skills (3S) dimensions, as demonstrated by the 3S learning analytics approach proposed in [153], which introduces the visualization tool LAT∃S for sentiment analysis through forum comments extraction. Similarly, Xing et al. delved into Coursera MOOC forum data, manually coding emotions expressed by learners in papers to discern emotional polarity [222]. In the context of teaching evaluation, sentiment analysis methods scrutinize feedback received during the teaching process [164, 169]. By extracting students' feedback on classroom teaching and learning [182], these methods identify emotional polarity and emotion types, offering valuable guidance to teachers for enhancing their teaching methodologies. Concurrently, they evaluate students' attendance and course participation [235]. In the realm of social media, [199] explores the application of ChatGPT in education, utilizing a tweet sentiment analysis model to identify prevalent sentiments and opinions about ChatGPT. Conversely, the evolving landscape of learning styles has led to an increased focus on student sentiment analysis in online learning environments in studies such as [14, 77, 34, 99, 122]. These investigations delve into students' affective feedback towards online learning, utilizing data from MOOCs and online learning reviews. Specifically, they collect user reviews from platforms like MOOCs and Coursera, analyzing these reviews to extract machine-readable factors predicting learner satisfaction, consequently assessing learners' overall evaluations of MOOCs [77, 34, 99, 122]. Recognizing the potential shifts in factors affecting student sentiment from traditional to online learning environments, this dual categorization facilitates a nuanced understanding of sentiment analysis in these two application areas.

Finally, we categorized some of the literature according to model innovation, including sentiment analysis models combining multiple techniques [14, 142, 154], fusion BERT(utilizing BERT and other training models) [140, 122], and aspect-level sentiment analysis [99]. Sentiment analysis models that combine multiple techniques integrate machine learning, deep learning, and other techniques to obtain more comprehensive sentiment information. For example, a method that covers three techniques such as machine learning, deep learning, and EvoMSA (a multilingual sentiment classifier based on genetic programming) has achieved a performance of 93% in sentiment polarity recognition [14]. The combination of CNN and LSTM, along with the introduction of BNN, has successfully dealt with the high level of uncertainty in sentiment analysis, leading to more reliable results [154]. Using BERT and other training models this type of literature introduces a deeper level of language understanding. Researchers have made significant progress on sentiment analysis tasks by integrating BERT and other advanced training models. For example, paper [122] used a 6-layer BERT-CNN model as a comment classifier, and by introducing a convolutional neural network and self-attention mechanism, the proposed model was made to perform even better in dealing with the task of comment sentiment analysis. A classification model based on Albert and Capsule networks and the attention mechanism is also proposed to deal with the problem of sentiment analysis of text. By addressing the difficulty of traditional analysis methods in distinguishing the meaning of the same word in different contexts, while using a combination of BiGRU and Capsule networks as well as the Albert pre-training model, a more context-aware feature representation is provided for sentiment analysis [140]. In addition, the paper [99] focuses on aspect-level sentiment analysis by identifying the aspect categories discussed in student comments through weakly-supervised annotations and deep learning models to analyze the sentiments expressed by students in their comments with more granularity.

By categorizing the aforementioned aspects, we observe the diverse application of various methods in the field of sentiment analysis. Both traditional machine learning and deep learning methods exhibit their unique strengths. In the current landscape, encompassing both traditional education scenarios and online learning, different sentiment analysis methods showcase a rich diversity. Simultaneously, the section on model innovation underscores researchers' endeavors to integrate multiple techniques, enhancing model performance. The existing literature on sentiment analysis encompasses various research orientations, such as deep learning, sentiment phrase matching, and models combining multiple techniques. These studies excel in processing intricate textual information, achieving heightened accuracy, and demonstrating robust generalization capabilities. Furthermore, models amalgamating multiple technologies address the limitations inherent in single models, thereby enhancing the comprehensiveness and diversity of sentiment analysis. Despite the progress, present research encounters certain challenges. Firstly, the acquisition of labels for learned sentiment often relies on manual annotation, posing a significant constraint on the feasibility of the application. Secondly, there is a notable dearth of research on generalization across different domains and text types. Additionally, some models grapple with comprehension difficulties when handling unstructured free text using simplistic machine-learning methods. Future research endeavors can focus on the development of more adaptive and generalized student sentiment analysis models catering to diverse disciplines and genres. Exploring unsupervised or weakly-supervised learning-based approaches could alleviate the time-consuming and labor-intensive challenges associated with data labeling. Attention should also be directed toward understanding the varied affective changes of learners in different educational environments and the nuances in expressing emotions. This holistic approach would contribute to a more nuanced exploration of the factors influencing learners' emotions during the learning process.

5.2.3 Behavior analysis. Embedded within learning analytics, the analysis of student behavior constitutes a fundamental component of personalized learning. Through the collection, processing, and examination of student behavioral data within the learning environment, profound insights into student behaviors can be gleaned, fostering a heightened comprehension of individual learner needs. The acquisition of information about students' online activities, learning history, interaction patterns, learning progress, and contextual data empowers personalized instruction to furnish real-time feedback and refine the utilization of personalized learning models. Concurrently, the goals of real-time feedback, anticipation of learning challenges, enhancement of instructional design, and resource optimization are all attainable through the prism of student behavior analysis. This data-driven approach stands as a potent instrument for advancing learning outcomes, refining resource utilization, and elevating educational methodologies.

As shown in Figure 3, we categorized the collected literature based on the analysis methods used, such as association rule mining, machine learning methods, and deep learning techniques. First, the research based on the clustering algorithm is mostly reflected in the literature of 2021, [178] used the K-means algorithm to cluster students' behaviors according to different data categories from the collected campus data, such as study, life, Internet time, and the number of times of going into the library, etc., respectively. The study behavior habits of students were comprehensively analyzed to get the characteristics of each category of students. [124] proposed an unsupervised ensemble clustering framework, which combines the algorithms of DBSCAN and K-means, for exploring the relationship between student behavior and grade point average (GPA). It's important to perform a ladder going of key features from student behavioral data and obtain the clustering results through statistical and entropy analysis. Bao et al. [13] used different clustering algorithms K-medoids algorithm in their study for clustering students' behavioral data. An unsupervised clustering technique based on Self-Organizing Map (SOM) was proposed in the analysis of student behaviors at Universidad Internacional de La Rioja (UNIR), which accurately and diversely portrayed the behavioral patterns of the students through the SOM distances of the two phases, which provided a better perspective for an in-depth understanding of the student's online learning behaviors.

Furthermore, association rule mining has emerged as a pivotal facet of student behavior analysis. Delving into the utilization of association rules in the analysis of student behavioral data, [212] delineated a comprehensive four-layer association architecture, a three-step mining process, and an integrated research trajectory spanning from data preprocessing to knowledge acquisition. In a parallel vein, [13] employed the Eclat association rule algorithm alongside a clustering algorithm to scrutinize the associations among diverse student data categories sourced from information centers and grades, thereby elucidating the primary factors influencing academic performance.

In addition, machine learning-based research covers a variety of classification algorithms for student behavior analysis [180]. [30] conducted an in-depth study on the blended learning model of learners through improved forest optimization algorithms and machine learning classifiers (Naive Bayes, Decision Tree, Random Forest). Li et al. [125] also used the information collected by the campus information management platform as the data source, but it combined neural network, naive Bayes, and decision tree algorithms, and built a Spark-based behavioral analysis and prediction platform.

Deep learning is gaining prominence in student behavior analysis, as demonstrated in the work of [97], which explores various prediction methods, including singular value decomposition and neural network approaches. The experimentation involved the design of a straightforward three-layer regression neural network for predicting the number of errors made by students in an introductory programming course.

Moreover, some comprehensive investigations amalgamate different algorithms and methods to provide a holistic analysis of students' multifaceted behaviors. For instance, the big data framework Hadoop MapReduce integrates statistical and association rule techniques. In this context, a big data solution based on Azure HDInsight was selected to conduct a thorough analysis of student behavior, taking into account the impact of student patterns on behavior [27]. Conversely, [137] extracts patterns of students' learning behaviors in the cloud classroom through sequence analysis methods, underscoring the significance of visual presentation and human analysis.

Research on student behavior analysis spans a spectrum from clustering algorithms and association rules to neural networks and the application of deep learning. This breadth not only offers diverse methodologies for analyzing student behavior but also underscores the pressing need for the integration and comprehensive examination of data from various sources. Clustering algorithms enhance our understanding of both the commonalities and disparities among students, while association rule mining elucidates the nuanced yet pivotal connection between student behavior and academic achievement. The incorporation of machine learning algorithms further extends the scope of student behavior analysis.

The introduction of deep learning methods has elevated our capacity for a more precise and comprehensive comprehension of learner behavior. Additionally, a body of literature focuses on enhancing the accuracy of student behavior analysis by amalgamating diverse algorithms and methods. Concurrently, the utilization of big data frameworks and sequence analysis equips researchers with potent tools for handling multifaceted data.

Nevertheless, the current literature on student behavior analysis exhibits fewer references to psychological and educational theories, limited integrated application of multimodal data, and relatively shallow exploration of social factors. Future research could delve deeper into the integration of pedagogical theories, explore social interactions more thoroughly, and concentrate on longitudinal effects and trends in student behavior. Improving algorithm interpretability, as well as emphasizing validation and real-life application scenarios, should be pivotal directions for future investigations.

5.2.4 Predictions of student performance/achievement. Student performance/achievement prediction has been an important topic of great interest in personalized learning. This field aims to construct reliable prediction models through multiple data such as students' historical learning data, learning behaviors, social information, etc. By predicting students' performance and grades, we can gain insights into their learning preferences and learning patterns, and provide educators and policymakers with the means to intervene. The prediction of student performance and grades also allows for early identification of students with high dropout rates and timely instructional interventions. In addition, by accurately predicting students' academic performance, personalized learning can tailor approaches to each student's needs, weaknesses, and potential abilities to maximize mastery of current learning. Over the past few years, scholars have applied a variety of advanced techniques and methods such as machine learning algorithms and deep learning models to continuously expand the breadth and depth of student performance/achievement prediction. This chapter provides an in-depth analysis of these studies to better understand the trends and key challenges in the field of student performance prediction.

To facilitate a more organized and comprehensive understanding of the distinct research methods employed, we categorized the relevant literature into three primary groups based on research methods and similarities. These categories include performance/achievement prediction models based on ensemble learning, performance/achievement prediction models based on deep learning, and other models predicting student performance/achievement.

- Ensemble learning-based performance/achievement prediction models: Literature in this category employs ensemble learning methods to enhance the accuracy of predicting student performance/achievement. For instance, the SAPP system [107], the CatBoost model [95], and applications utilizing ensemble learning techniques [6, 224]showcase innovative approaches in this domain. he SAPP system [107]introduces a novel Student Academic Performance Prediction system, incorporating a 4-layer LSTM network, random forests, and gradient boosting techniques within an ensemble learning framework. Other studies further explore creative methods based on ensemble learning, comparing models such as LSTM+RF and LSTM+B. CatBoost [95] presents a unique approach, enhancing model transparency and prediction accuracy by categorizing reasons for improved student performance into three numerical intervals: low, medium, and high levels. Additionally, Xu et al. propose a stepwise prediction algorithm for student performance, integrating learning techniques within a two-layer structure [224]. In contrast, the PFA method [6] introduces a novel approach to ensemble learning, leveraging Random Forest(RF), AdaBoost, and XGBoost to model learners in an e-learning system, effectively elevating the accuracy of student performance prediction.

- Deep Learning-based Performance/Grade Prediction Models: This section delves into relevant literature [69, 226, 108, 165, 9] employing deep learning techniques such as deep neural networks and convolutional neural networks, with a focus on modeling intricate student behaviors for performance/grade prediction. Firstly, [69] introduces a binary classification deep neural network (DNN) framework featuring two hidden layers, emphasizing the pivotal role of deep learning in predicting team performance. Additionally, [226] explores the correlation between predicting the duration of internet usage and academic performance using decision trees and neural networks based on internet usage data, highlighting the potential effectiveness of deep learning in data processing. On another note, a two-layer ensemble learning technique that combines ensemble learning and ensemble-based asymptotic prediction has been proposed, integrating methods like KNN and random forests to introduce additional dimensions to academic achievement prediction [165]. Moreover, combining different algorithms has proven to yield superior results for grade prediction [158]. Various methods, including fuzzy C-Means, MPL, and LR random forests, have been employed for predicting student grades in the classroom. The combination of these algorithms in different configurations enhances prediction accuracy, with experiments indicating that the combination of FCM with MLP and LR yields the most accurate results.
- Other student performance/achievement prediction models: a separate category of literature that does not belong to traditional deep learning or ensemble learning, this category contains performance/achievement prediction using methods such as other machine learning, which do not belong to the above two categories, but still play an important role in the field of prediction. [60] proposes clustering of student performance through the K-means algorithm, where the k-value is determined by objective quantitative analysis, thus making the performance prediction results more convincing. At the same time, a deep learning algorithm (CNN) is introduced to train and predict the results. That is, the K-means algorithm is used for clustering analysis of student performance, and the results obtained are used as the category labels of CNN for training, which is a new idea provided by deep learning without feature labels. Meanwhile, in the task of predicting student performance/achievement, the existing literature compares different machine learning algorithms as classifiers, including decision trees random forests, support vector machines, naive Bayes, logistic regression, and so on [227, 203, 245], which will be directly used as classifiers for predicting students' academic performance.

The current research landscape on student performance/achievement prediction has witnessed significant advancements, employing techniques such as K-means clustering, SVM, and DNN to enhance prediction accuracy. The diverse array of machine learning, deep learning, and ensemble learning approaches has provided a comprehensive perspective on this critical task. Nevertheless, it is crucial to acknowledge that certain studies grapple with challenges such as data imbalance and limited model interpretability, resulting in diminished predictive performance across specific categories and complex data scenarios. Notably, approaches like the combination of BERT and other training models remain in the nascent stages of exploration and warrant further in-depth investigation. Future research endeavors can elevate the generalization capabilities of student performance/achievement prediction models by incorporating more sophisticated models, optimization algorithms, and richer data resources. Emphasis should be placed on developing interpretable methods that render model outputs more intuitive and widely accepted. Furthermore, interdisciplinary research, integrating relevant backgrounds and theories in psychology and education, holds the potential to amalgamate disciplinary knowledge in alignment with the long-term developmental trajectories of learners. This holistic approach promises a more comprehensive understanding of the multifaceted factors influencing learner performance.

5.3 Personalized Recommendation

Personalized learning recommendations for intelligent education scenarios can be subdivided into personalized learning path recommendations, personalized course recommendations, and personalized exercise recommendations according to the recommended resources. There are differences in the focus and technology of different types of personalized learning recommendation research. Among them, personalized learning path recommendation focuses on planning appropriate personalized learning paths for learners, so that learners can complete their learning goals with minimal learning costs. Personalized course recommendation provides learners with courses that meet their abilities and needs, to improve learners' learning ability and learning effect. Personalized exercise recommendation focuses on learners' lack of knowledge and provides them with targeted exercises to improve their problem-solving ability and knowledge mastery.

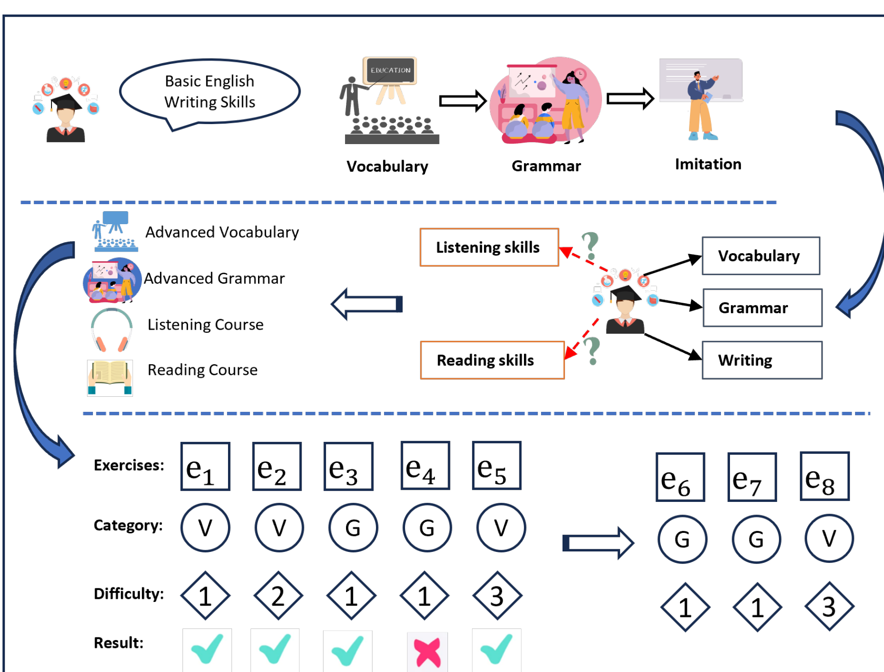

Fig. 4. Three types of personalized learning recommendations.

As shown in Figure 4, we demonstrate three different use cases of personalized learning recommendations in English learning scenarios. To satisfy the learners to improve their English writing skills, the personalized path recommendation algorithm recommends a learning path "Vocabulary course→Grammar course→Imitation Course", which is a series of courses that meet the learners' learning objectives. We can build a knowledge graph between students and course requirements based on users' learning history. Based on the knowledge graph, learners who have taken basic vocabulary, grammar, and writing courses may also be interested in improving their listening skills and reading skills. The personalized course recommendation algorithm will recommend a series of appropriate courses, including advanced vocabulary courses, advanced grammar courses, listening courses, and reading courses, based on the user's learning history and learning interests. For learners who have taken vocabulary and grammar courses, the exercises may contain questions that belong to the vocabulary or grammar category and have different difficulty levels, and the personalized exercise recommendation needs to recommend the appropriate category and difficulty level based on the user's answer history.

We summarize the articles on personalized learning recommendation from 2018 to 2023 from the perspective of personalized learning recommendation research focus and core technology, and the percentage of different types of papers is shown in the Figure 5.

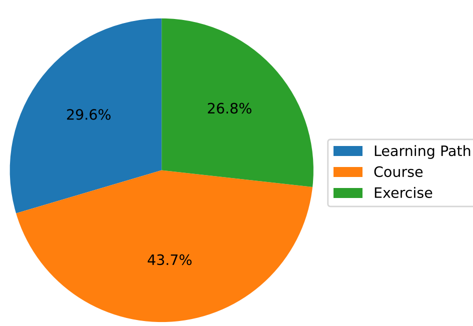

Fig. 5. Percentage distribution of personalized learning recommended papers.

5.3.1 *Personalized Learning Path Recommendation.*

Early stages of development: learning from historical similarities.

Early scholars focus on recommending learning paths for similar learners through methods such as clustering. A series of studies [252, 189, 121, 221] consider recommending learners based on their similar learning histories. A series of research efforts attempt to improve the quality of recommended learning paths. [252] takes it a step further by training an LSTM model to predict the learners' learning paths. [189] selects the most similar learning paths from the history by retrieval and then recommends them to the learners after correcting them based on their learning history. [121] considers prioritizing the recommendation of learning paths of more influential learners when providing learning paths for similar users.

However, just recommending paths for learners through the similarity of learning history is not personalized enough, but also needs to consider the adaptability of learners and the differences in their abilities [148]. The work of [201] also further emphasizes the importance of matching learning

Stage	Core Focus	Core Technical Points
2018-2019	Time limitations for learners Impact of learners Similarities of the history of learning	Cluster
2020-2021	Learner needs Learner types Learner habits Cognitive level Excellent learning paths Diverse learning paths	Cluster Knowledge graph Graph convolutional network Cognitive diagnostic Reinforcement learning
2022-2023	Learner objectives Learning styles Learning resource differentiation Implicit link between learners and resources	Knowledge graph Temporal convolutional network Graph attention network Reinforcement learning Knowledge tracing

Table 7. The Development of Personalized Learning Path Recommendations.

content and personal characteristics by using ant colony optimization and a genetic algorithm to provide learners with personalized learning paths. Since early online learning resources had learning time constraints, some research works [105, 157] considered the importance of time constraints for learning path recommendation.

Methods in this phase focus on how to calculate the similarity between learners or between learning resources to recommend learning paths. The important basis for calculating the similarity is the learners' historical records, which cannot tap into the learners' personalized learning needs, and the clustering methods cannot determine the differences in cognitive levels between different learners. Moreover, the recommended learning paths often refer to the learning paths of similar learners, and the diversity of learning paths and the quality of learning paths are relatively low.

Mid-development: the emergence of knowledge graphs and reinforcement learning techniques.

With the development of deep learning technology, personalized path recommendation methods can mine more personalized features of learners from their historical learning information [143, 148] and construct this part of personalized features into a knowledge graph, including learners' learning needs, learners' learning habits, learners' types, etc. The constructed knowledge graph is often related to the problem solved. [179] explored diverse learning paths for different learning objectives and constructed a multidimensional knowledge graph containing multiple types of learning relationships. [135] noted the poor quality of learning paths recommended by previous approaches for low-engaged users, and constructed an interaction network between courses and learners to mitigate this problem. [188] constructed a knowledge graph containing a large number of English practice questions to generate a personalized knowledge graph for each learner.

The exploratory power of reinforcement learning techniques incorporating knowledge graphs is further exemplified. [123] recognized that the learner's mastery level of the learning content is also very important for the recommendation of learning paths, analyzes the user's mastery of the learning content through a cognitive diagnostic model, and constructs a learning process with hierarchical learning techniques through a hierarchical reinforcement learning approach.

In addition, clustering-based methods are constantly being optimized. [201]clusters learners into different categories using the Fuzzy C-Mean algorithm and then recommends appropriate learning paths to different categories of learners based on prior knowledge.

Methods in this phase focus on the different learning needs of learners, but the ability of knowledge graph and reinforcement learning in personalized learning path recommendation is not fully explored.

Current stage: multi-technology convergence.

Recent research work has delved into the key role of knowledge graphs and deep reinforcement learning techniques in personalized path recommendation. Recognizing that learners may have different levels of knowledge about the same learning resources, [244] constructed a multidimensional course knowledge graph (MCCKG) and proposes a higher-order relevance modeling approach for knowledge graphs based on graph convolutional networks to more accurately capture learner's preferences, and further utilizes the features of the learning resources and the learner's features in the MCCKG to calculate the importance of the learning resources. [201] constructed a knowledge graph containing learning resource nodes and knowledge points to meet the different learning needs of learners in different learning scenarios. The study [35] combined temporal convolutional networks and graph attention networks into a knowledge tracking model to capture the dynamically changing relationship between learners and resources, and use them as an environment for the reinforcement learning model, as well as to set learning goals for the learners, and to adjust the recommendation strategy based on the state and rewards during the simulated learning process. Recognizing that previous research approaches tend to oversimplify learners' ability profiles, making recommended learning paths unsatisfactory for learners with varying levels of coverage, [120] used a new graph-based genetic algorithm (GBGA) to optimize feature alignment between learners and learning objects (LOs) to generate learning paths consisting of different LOs.

The study [117]considered the inability of previous learning methods to deal with the relationship between multiple goals and the possibility that the generated personalized learning paths may contain content unrelated to the learning goals. The role of deep reinforcement learning in the recommendation process of personalized learning paths is further explored and two types of recommenders, high-level and low-level, are constructed, where the high-level recommender is used for subgoal selection and the low-level recommender is used for constructing items for the recommended paths. In addition, a graph-based candidate selector is proposed to restrict the action space, and an internal reward mechanism based on a knowledge-tracking model is proposed.

Focusing on students' learning style characteristics, [104] designed a Moodle plugin called "Personalized Learning Guide" that determines which learning resources/activities are closer to students' learning styles to generate recommended learning paths. The plugin supports two methods for determining students' learning styles: one using the Inventory of Learning Styles (ILS) questionnaire developed by Felder and Silverman, and the other by analyzing students' past behavior patterns on Moodle.

Methods in this phase fully exploit the capabilities of knowledge graphs and deep reinforcement learning, and take the learner's learning level into account in the process of recommending personalized learning paths through knowledge-tracking models.

5.3.2 Personalized Course Recommendation.

Early stages of development: mining valuable information from large-scale data.

Early work on personalized course recommendation focused on how to mine valuable information from large-scale course data and learner data, as well as how to solve the problem of sparse interaction matrix between learners and courses. With the development of online course

Stage	Core Focus	Core Technical Points
2018-2019	Multiple interests of learners Knowledge level of learners Characteristics of courses Large and diverse data volumes	Distributed Computing Framework Multi-dimensional matrix factorization Reinforcement learning Hierarchical bandits Cluster
2020-2021	Dynamic multiple interests of learners Relevance of the course Prerequisite relationships for courses Semantic relationships for courses Sparse interaction matrix	Attention mechanism Linear discriminant analysis Cognitive diagnosis Knowledge tracking Knowledge graph Graph neural network
2022-2023	Learning styles of learners Differentiation of learners Learning experience for learners Differentiation of courses Difficulty of the course Sequential relationship of courses Multi-level learner and course characteristics	Reinforcement learning Knowledge graph Knowledge tracking Graph neural network Graph convolutional network

Table 8. The Development of Personalized Course Recommendations.

learning platforms such as Mooc, the amount of information about learners and courses increases rapidly, and traditional recommendation methods cannot be directly and efficiently applied to the platforms. [239] designed a distributed computational framework as well as a rule extraction algorithm to mine the laws of courses. [85] addressed the heterogeneity of a large-scale user base, the sequencing problem of courses, and the predictable surge in the number of courses and users by proposing the use of Hierarchical Bandits (HBs) to explore recommending the most highly rewarded courses to learners, and then logging the user feedback to further improve the performance of the recommendations to future learners.

To overcome the problem of sparsity, classified new learners into appropriate classes and recommend relevant courses by using clustering algorithm. [231] constructed a network of learners and a network of courses and utilized the HITS (Hyperlink-Induced Topic Search) algorithm to extend the user's rating matrix.

Several studies have also focused on multidimensional features of courses and multiple points of interest of learners. [191] combined the multi-dimensional Matrix Factorization (MMF) model and Collaborative Filtering (CF) algorithm to analyze the skills learned by users as well as the characteristics of the course to predict the trend of course popularity. Noting that learners may have more than one interest in learning during the learning process, [241] proposed a hierarchical reinforcement learning approach to determine whether to change the learner's interest at the current moment and which ones to change.

Early research efforts have not yet paid attention to the connections between courses, and the possible existence of prerequisite relationships between different courses that can have an impact on personalized course recommendations.

Mid-development: learner preferences and course characteristics.

Further work began to perform more in-depth data mining of learner preferences and course characteristics to further construct knowledge graphs to learn semantic correlations between courses. [247] focused on the existence of differences in knowledge backgrounds between learners, as well as the existence of significant precedence relations between both different concepts and different courses, and constructed precedence relation maps at both the concept level and the course level. [257] found that learners' learning needs may be influenced by several aspects, including individual learning interests, teachers, and peers, and proposed a graph-structured instructional evaluation network that describes students, courses, and other entities through student ratings, comment texts, ratings, and interpersonal relationships. Recognizing that traditional collaborative filtering algorithms ignore semantic correlations between courses, a knowledge graph representation learning approach [223, 145] is first employed to embed semantic information about courses into a low latitude semantic space, and then the semantic similarity between the recommended courses is calculated.

In addition to constructing correlations between courses or concepts through knowledge mapping, a part of the research work focuses on the correlated information between courses through the mechanism of attention. [192] proposed an Attention Manhattan Siamese Long Short-Term Memory (AMSLSTM) network and an autoencoder based on which course correlations are constructed from course descriptions and self-attention to adaptively differentiate the students' preference level in several aspects. A dual attention mechanism[15] is introduced in the parallel neural network recommendation model to reset the weights of preprocessed course text information. The recommendation results are categorized according to the weights of course categories to construct different types of course groups.

The learner's learning level is also initially explored in this phase. [194] dynamically updates the learner's competence by considering real-time and multi-dimensionality of competence through a knowledge tracking model, where the estimation of the learner's competence is considered as an attribute to be integrated into a collaborative filtering framework for course recommendation.

Current stage: relationship between courses and learners.

Recent work in personalized course recommendation has focused more on the relationships between courses and courses and between courses and learners. A series of work continues to mine personalized information about courses and learners and add this information to the constructed knowledge graph. [96] constructed a hierarchical map of learners and courses by integrating information from MOOCs and external knowledge bases through keywords related to learners and courses. [10] constructed a cross-learner course sequence diagram by considering the LONG-TERM and SHORT-TERM sequence relationships of courses. The representation of the web-learning course is noted through the graph, and then the learned representations are fed into GRU's sequence encoder to infer their short-term patterns and the last hidden state is the sequence-level learner embedding for learned. [33] mentioned the importance of the relationship between the user learning process and the course for course recommendation, constructed a Collaborative Sequence Graph (CSG) containing information about user interactions and course sequences, and utilized a GCN-based Knowledge Extraction Layer to display the modeled relationships. Noting the correlation between courses and the diversity of learners' intentions, knowledge graphs are constructed to describe the relationship between courses and learners, and learners' behaviors and course graphs are projected into a unified space to tap into learners' potential interests [240]. For the complex semantic information of multi-entity relationships and entity associations in the course knowledge graph, the multi-entity relationship self-symmetric meta-path (MSMP) and association relationship self-symmetric meta-graph (ASMG) are creatively constructed, and an algorithm of meta-relationship relevance (MRCor) is also designed to obtain the semantic relevance information [75]. Then, a graph embedding approach is employed to mine and fuse the potential representations of users and courses for user preferences and course features, respectively. Considering students and courses as two types of nodes, a heterogeneous information network (HIN) is constructed and personalized course recommendation (MG-CR) based on factorial memory network and graph neural network is proposed on top of the HIN [246].

A portion of the research work attempts to explore course recommendations through a reinforcement learning approach. To address the exploration-utilization trade-off in learner feature construction, a new strategy gradient approach is proposed [134]. A recurrent scheme of context-aware learning is used to utilize current knowledge, while a dynamic baseline is utilized to explore learners' future preferences. Concerned that current research methods do not distinguish well between the most relevant courses studied, an attention-based recommendation model and an archive reviser with Recurrent Reinforcement Learning (RRL) are proposed which exploits the temporal context and proposes a contextual strategy gradient with approximations for RRL [133].

Some work has attempted to improve the effectiveness of course recommendations through language models or deep knowledge tracking models. [242] focused on the role of unstructured textual data in course recommendation. First, word vectors of text are obtained from the course dataset by using the BERT pre-training model and analyzed for their semantic information in different contexts. Then, more complex representations of each word are extracted by a Long Short-Term Memory (LSTM) network, in which a multi-head attention layer adds different weights to different word vectors. Finally, a CRF layer is used to identify sentence entities, and a Sigmoid layer is used to extract relationships to accomplish personalized course resource recommendations. Concerned that the knowledge tracking task does not consider the learner's forgetting problem, [10] designed a personalized controller to augment the deep knowledge tracking model to simulate the learner's forgetting behavior, and also to simulate individual differences based on the theory of cognitive psychology.

Stage	Core Focus	Core Technical Points
2018-2019	Level of knowledge of learners Learning objectives for learners Coverage of the knowledge points	Collaborative filtering Cognitive diagnosis Knowledge graph Reinforcement learning
2020-2021	Level of knowledge of learners Difficulty of exercises Semantic relations between exercises and knowledge points	Deep knowledge tracing Cognitive diagnosis Knowledge graph Graph convolutional network Reinforcement learning
2022-2023	Level of knowledge of learners Long-term needs of learners Semantic relations between exercises and knowledge points Semantic relations between knowledge points	Deep knowledge tracing Cognitive diagnosis Knowledge graph Reinforcement learning

Table 9. The Development of Personalized Exercise Recommendations.

5.3.3 Personalized Exercise Recommendation. The work on personalized exercise recommendation is more focused in terms of research attention and research techniques compared to the work on personalized learning path recommendation and personalized course recommendation. The focus of researchers' attention tends to concentrate on learners' knowledge mastery and the connections between knowledge points, mastering students' knowledge levels through deep knowledge tracking models and cognitive diagnostic methods, and modeling the relationships between topics, between topics and knowledge points, and between knowledge points and learners through the construction of knowledge graphs.

Early stage of development: relationship between knowledge points and topics.

Early research efforts have begun to notice the relationship between knowledge points and topics, as well as the differences in learners' knowledge levels. [220] emphasized two basic requirements for personalized exercise recommendation. First, the recommended exercises must cover all knowledge points related to the learner's learning objectives. Second, the difficulty of the exercises must match the knowledge level of the target learner. [144] constructed a knowledge graph of knowledge point information, which is used to learn the dependencies between knowledge points. [47] constructed a knowledge graph containing knowledge points and exercise topics, and the final recommendation results were obtained by tree search.

Mid-development: knowledge graphs and deep knowledge tracking models.

The role of knowledge graphs in constructing relationships between knowledge points and learners has been increasingly emphasized, and the roles of deep knowledge tracking models and knowledge diagnostic models in personalized exercise recommendations have been highlighted. Noting that previous methods for constructing knowledge graphs lacked mining the semantic relationship between practice questions and knowledge points, [254, 74] constructed a knowledge graph containing a large number of practice questions and knowledge points and obtained the semantic information of the practice questions through word2vec model or graph convolutional network. [219, 250, 126]noticed that the traditional methods cannot grasp the learning status of students, so they proposed to use deep knowledge tracking model to predict the learner's mastery of the knowledge concepts and then combined with methods such as collaborative filtering or clustering to provide personalized exercise recommendations for the learners.

Current stage: knowledge graphs and deep knowledge tracking models.

Research in the last few years has continued to study personalized exercise recommendations at the level of knowledge graph construction and knowledge tracking. [74] constructed a knowledge graph containing knowledge point information, student information, and exercise topic information. [76, 173] tracked students' dynamic knowledge mastery through a deep knowledge tracking model. [228] combined the knowledge structure map, deep knowledge tracking, and constructivist learning theory to screen topics based on diversity, difficulty, innovativeness, and other characteristics. Previously constructed knowledge graphs did not consider the richness of practice topics, and by mining the information of topic personalization, the one-dimensional knowledge graph was transformed into a multidimensional knowledge graph, and the importance weight was calculated based on the novelty and popularity of topics [116]. There are also related studies that combine the teaching objectives in the teaching scenarios and propose a personalized exercise recommendation method for the teaching objectives [127], which can recommend the exercises that are highly compatible with the syllabus for the students based on their selected knowledge points and expected score ranges.

Reinforcement learning methods have been used at various stages to improve the personalization of exercise recommendations. [90] optimized multiple learning objectives in the learning process including Review & Explore, Smoothness of difficulty level, and Engagement through reinforcement learning approach. [38] added the three learning objectives of REVIEW, DIFFICULTY, and LEARN through reinforcement learning approach to the reward value setting, and the topics corresponding to the knowledge points of appropriate difficulty level are recommended to the learners. [218] focuses on the long-term learning needs of learners through the reinforcement learning approach.

6 EVALUATION

Evaluation plays a pivotal role in shaping perspectives on personalized learning, offering a variety of dependable methods to gauge the efficacy and influence of personalized learning models. This chapter will delve into a meticulous examination of evaluation metrics and model evaluation methods extensively employed in existing literature, aiming to present a thorough understanding of the effectiveness of personalized learning across various levels. The focus will be on diverse metrics employed for assessing personalized learning effectiveness, encompassing learning engagement, recommendation accuracy, and other multi-faceted evaluation criteria.

Effective evaluation metrics serve as a compass to guide researchers in comprehensively assessing the outcomes of personalized learning models. Additionally, these metrics offer valuable insights for adapting and enhancing personalized learning models. The in-depth discussion of these evaluation methods is intended to assist readers in gaining a better understanding of the complexities of personalized learning evaluation, equipping them with the tools and insights needed to leverage successes in real-world applications and research areas more effectively.

This chapter will delve into commonly employed evaluation metrics in personalized learning, examining them from three perspectives: cognitive diagnosis, learning analytics, and personalized recommendation. This exploration aims to offer comprehensive insights and robust support for both the implementation and evaluation of the effectiveness of personalized learning.

Table 10 11 12 presents the statistics of commonly employed evaluation metrics outlined in the reviewed literature. These metrics serve to gauge the performance across various personalized learning tasks, including learning analytics and personalized learning recommendations. The selection of specific evaluation metrics hinges on the task's nature; for instance, root mean square error (RMSE), mean absolute error (MAE), AUC, etc., find common use in cognitive diagnosis, while accuracy, precision, recall, F1 score, etc., may be employed in student behavior analysis. These tables offer readers a lucid overview of the evaluation metrics utilized in diverse learning analytics tasks and their application in the literature. This aids in guiding future research in learning analytics and selecting appropriate evaluation metrics for measuring model performance.

6.1 Evaluation of Cognitive Diagnosis

In order to effectively measure the performance of the cognitive diagnosis model, different metrics are often employed from a categorical and regression perspective to assess the accuracy and effectiveness of the models in correctly predicting the state of student knowledge. Table 10 shows the statistics of the corresponding evaluation indicators in the cognitive diagnosis literature.

In cognitive diagnosis tasks, the problem can be modeled as a categorization task, wherein the objective is to classify students into distinct cognitive states or levels of learning. For instance, utilizing the proposed model to forecast whether a student has attained mastery of a specific concept, by classifying it as "mastered" or "not mastered," can be viewed as a dichotomous task. The commonly employed evaluation indicators for such tasks include:

- Precision: This metric serves as an evaluator for classification models and is frequently applied in dichotomous classification scenarios. In cognitive diagnosis tasks, it gauges the model's accuracy in predicting a specific cognitive state of a student—essentially, the proportion of correctly predicted positive cases out of all correctly predicted cases.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

  where, TP is the number of samples where the model correctly predicts a positive case, and FP is the count of samples where the model incorrectly predicts a negative case as a positive case. Precision ranges from 0 to 1, with higher values signifying more precise predictions.

This metric is frequently employed alongside Recall and F1 Score to offer a more thorough performance evaluation.

- Recall: This metric is frequently employed in classification tasks to measure the model's capability to correctly identify all actual positive instances. It represents the proportion of accurately predicted positive instances relative to all actual positive instances.

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

where TP is the number of samples that the model correctly predicted as positive cases and FN is the number of samples where the model predicted positive cases as negative cases. Recall ranges from 0 to 1, with elevated values signifying the model's heightened effectiveness in capturing actual positive cases. Also recognized as Sensitivity or True Positive Rate, Recall underscores the trade-off between Precision and Recall. Striking a balance between the two is crucial in certain scenarios, and a comprehensive model evaluation can be achieved through metrics like F1 Score or other thoughtful combinations.

- F1 Score: The metric is a harmonized average of Precision and Recall, amalgamating the accuracy and comprehensiveness of the model. It is defined as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precison + Recall} \tag{7}$$

The F1 score, ranging from 0 to 1, approaches 1 when the model achieves a more optimal balance between Precision and Recall.

- Area Under the Curve(AUC) [24]: This metric is commonly applied to binary classification problems. It assesses the balance between the True Positive Rate (also known as Sensitivity or Recall) and the False Positive Rate of the classifier across various thresholds. Often utilized in conjunction with the ROC curve—a graphical representation of the trade-off between True and False Positive rates at different thresholds—and the AUC which ranges from 0 to 1 with higher values indicating better performance. The AUC is deemed more robust than alternative metrics like accuracy, making it a preferred choice, particularly in cognitive diagnosis tasks.
- Accuracy(ACC): This metric is commonly used to gauge the accuracy of model predictions. It calculates the ratio between the number of samples correctly classified by the model and the total number of samples. The use of ACC in cognitive diagnosis is primarily because the model endeavors to categorize students into different cognitive states or categories.

$$ACC = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \tag{8}$$

In this ratio, the numerator represents the count of samples accurately predicting students' cognitive status, while the denominator corresponds to the total sample size. It is essential to recognize that the applicability of the ACC metric may be compromised in situations of category imbalance, influenced by sample distribution. Consequently, literature [211] has devised a modification to this metric, calculating the mean ACC specifically for the top 50% of students with limited interaction data. This adjustment aims to emphasize the diagnosis of long-tailed students and alleviate the impact caused by the long-tailed effect.

Cognitive diagnosis can also be regarded as a regression task, where the objective is to predict the level of mastery a student has on a particular concept, yielding a continuous numerical output. Commonly used evaluation metrics are as follows:

- Root Mean Square Error(RMSE) [161]: This metric is commonly employed to gauge the model's prediction error (ranging from 0 to 1) regarding a student's cognitive state. It reflects the disparity between the probability of a correct response and the actual score. This evaluation metric is chosen due to the model's provision of a continuous prediction for a student's cognitive level score.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{9}$$

where y_i represents the true cognitive state score of a student, $\hat{y}_i$ denotes the model's predicted score for the student's cognitive state, and n represents the sample size, the RMSE considers the divergence between the actual and predicted values. This metric is particularly well-suited for regression-based cognitive diagnosis tasks, with lower RMSE values indicating enhanced model performance.

- Mean Absolute Error(MAE): Like RMSE, MAE is also a metric used to assess the prediction error of a model regarding students' cognitive state. It measures the disparity between the model's predicted values and the actual values.

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \tag{10}$$

where y_i represents the actual score of the student's cognitive state, $\hat{y}_i$ is the predicted score, and n is the number of samples, smaller MAE values signify reduced average prediction errors of the model regarding the student's cognitive state. Unlike the RMSE, the MAE does not consider the squared error, treating large and small errors equally.

In addition to classification and regression metrics employed to evaluate a model's proficiency in predicting accurate student responses, interpretability metrics play a crucial role in any cognitive diagnosis model. The prevailing literature frequently employs the degree of consistency as a metric to evaluate the interpretability of cognitive diagnosis models:

- Degree Of Consistency(DOA) [63]: This metric is commonly employed as an interpretability indicator. Specifically, if learner a's accuracy in answering questions related to knowledge concept k is higher than learner b's accuracy for the same concept k, then a's probability of mastering knowledge concept K (donoted as Θ_{ak}) should be greater than b's (denoted as Θ_{bk}),i.e., $\Theta_{ak} > \Theta_{bk}$. DOA is defined as

$$DOA(k) = \frac{\sum_{a=1}^{N}\sum_{b=1}^{N}\delta(\Theta_{ak},\Theta_{bk})\frac{\sum_{j=1}^{M} I_{jk}\wedge J(j,a,b)\wedge\delta(r_{aj},r_{bj})}{\sum_{j=1}^{M} I_{jk}\wedge J(j,a,b)\wedge[r_{aj}\neq r_{bj}]}}{Z} \tag{11}$$

where, $Z = \sum_{a=1}^{N}\sum_{b=1}^{N}\delta(\Theta_{ak},\Theta_{bk})$. $\Theta(x,y) = I(x > y)$. Θ_{ak} represents student a's proficiency in concept k, and r_{aj} denotes student a's response to exercise j. $\Theta(x,y) = 1$ for $x > y$ and 0 otherwise. I_{jk} is the (j,k) element of the q-matrix, indicating whether question j includes concept k. If it does, $I_{jk} = 1$, otherwise, it is 0. On the other hand, $J(j,a,b)$ indicates whether students a and b answered question j simultaneously, with 1 denoting they answered at the same time, and vice versa.

As depicted in Table 10, the most commonly utilized metrics in cognitive diagnosis evaluation are RMSE, ACC, and AUC. The pivotal criterion for choosing these metrics lies in conducting a comprehensive evaluation of the model's performance across various dimensions. Additionally, it is crucial to account for the specific characteristics of the task to ensure the suitability of the selected metrics for addressing cognitive diagnosis problems.

6.2 Evaluation of Learning Analytics

Learning analytics holds a pivotal role in contemporary educational research, offering valuable insights into student academic performance. This chapter aims to delve into prevalent evaluation

Table 10. Statistics on common evaluation indicators for cognitive diagnosis.

	RMSE	MAE	ACC	AUC	Precision	Recall	F1 Score	DOA
[185]	✓		✓	✓	✓	✓	✓	
[209, 232, 65, 186, 118, 146, 214, 251, 66]	✓		✓	✓				
[147]	✓		✓		✓	✓	✓	
[243, 138, 88, 136]	✓	✓						
[211]	✓		✓					
[20]			✓	✓				
[139, 115]	✓		✓	✓			✓	✓
[230, 36]	✓	✓	✓	✓				
[162]	✓			✓	✓		✓	
[195]			✓	✓				✓
[196]				✓	✓	✓	✓	✓
[208]	✓		✓	✓				✓
[256]	✓	✓	✓			✓	✓	✓

indicators within learning analytics, providing a comprehensive understanding of student's academic achievements and serving as effective tools for evaluating learning processes and outcomes. The exploration of learning analytics is segmented into key areas, including learning style analysis, student sentiment analysis, student behavior analysis, and student performance/achievement prediction. Within each of these areas, this chapter delves into a series of crucial indicators commonly employed to assess effectiveness, encompassing various levels of learning processes and outcomes.

By thoughtfully selecting and comprehending various evaluation indicators, we can gain insights into student performance, assess the effectiveness of teaching methods, and understand the impact of the learning environment. These metrics not only aid in quantifying students' academic achievements but also offer valuable insights into educational strategies. We will delve into the definitions of these metrics, their calculation methods, and their applications across different scenarios, aiming to provide robust support for both practice and research in the field of learning analytics. Table 11 summarizes widely-used evaluation metrics from the references reviewed in the field of learning analytics, specifically highlighting metrics covered in two or more papers. These metrics serve to measure the performance of diverse learning analytics tasks, including such as learning style identification and student performance prediction.

6.2.1 Learning style analysis. Commonly used evaluation metrics in research on learning style recognition vary depending on the specific task and methodology. The goal of learning style recognition is to extract features from multi-source data and classify students' learning styles, enabling the model to accurately predict students' learning preferences. Therefore, learning style recognition is mostly considered a classification problem in the reviewed literature, and classification metrics are used to quantify the performance of the model. Commonly used classification metrics include ACC, Precision, Recall, and F1 Score, which have been described in detail in Chapter 6.1. Also confusion matrices are used for classification metrics evaluation:

- Confusion Matrix: The confusion matrix serves as a pivotal tool in evaluating learning style recognition, offering a nuanced analysis of model performance, particularly in scenarios involving multiple categories. Learning styles are often diverse, encompassing categories such as visual, auditory, hands-on, etc. The confusion matrix becomes instrumental in showcasing the model's efficacy across each learning style category. Construction of the confusion matrix involves comparing the model's predictions with the true labels in four fundamental categories: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Leveraging these values, a suite of evaluation metrics, including Accuracy, Precision, and Recall, can be computed, providing a comprehensive overview of the model's performance across various learning styles. The confusion matrix vividly illustrates the model's categorization in each class, and a closer examination of its components unveils the learning styles where the model is susceptible to confusion, thereby guiding further enhancements.

In addition to classification metrics, there are a number of metrics that can also be used to assess the recognition performance of learning styles.

- Similarity(SIM) [67]: This metric, as employed in the literature, serves to gauge the effectiveness of learning style identification. It partitions the learning style dimension into three regions, exemplified by the Auditory/Reading dimension, which SIM further divides into three regions: active, reflective, and balanced. The comparison between the actual learning style (LS_{actual}) and the identified learning style (LS_{id}) is subsequently conducted based on the delineated regions.

$$SIM = \begin{cases} 1.0 & if \;\; R(LS_{id}) = R(LS_{actual}) \\ 0.5 & if \;\; R(LS_{id}) \neq R(LS_{actual}) \;\; and \\ & (R(LS_{id}) = LS_{balance} \;\; or \;\; R(LS_{actual}) = LS_{balance}) \\ 0.0 & otherwise \end{cases} \tag{12}$$

where $LS_{balance}$ is the value of the balanced region returned by R, and the R function is used to return the region of the learned style value. If the actual learning style value falls within the same region as the identified learning style value (indicating the same style), SIM is assigned a value of 1. If LS_{actual} and LS_{id} reside in adjacent regions(indicating a balance or preference), SIM is assigned a value of 0.5. Conversely, if the two are in different regions, signifying no shared style, SIM is set to 0. After calculating the SIM value for each student, the mean SIM value is computed to assess the model's performance in identifying learning styles. While the SIM metric provides specificity in evaluating the model's alignment with students' actual learning styles, accounting for the specific dimensions of learning styles segmentation, it does have a drawback. Specifically, it may yield misleading results and reduce the accuracy rate when LS_{id} or LS_{actual} is close to the threshold value.
The Learning Style Identifier(LSID) method can return a specific value to represent the learning style, so it can make up for the problem of low accuracy by measuring the difference between the result of the method and the actual style. This indicator is called ACC.
- Accuracy(ACC): The ACC here is presented by means of the LSID method, which is slightly different from the one introduced in the cognitive diagnosis section.

$$ACC = \frac{\sum_{i=1}^{n} 1 - |LS_{actual,i} - LS_{id,i}|}{n} \tag{13}$$

where n is the number of students in each dataset. $LS_{actual,i}$ is the actual style value of the ith student in the dataset, and $LS_{id,i}$ is the identification learning style value of the ith student in the dataset.
Given that both SIM and ACC metrics provide average-based evaluations, they serve as valuable tools for assessing overall performance, yet individual values may exhibit lower accuracy. In cases where a negative impact, such as the misidentification of an individual student's learning style, could lead to the provision of mismatched learning materials, the SIM and ACC metrics fall short in identifying specific errors for individual students. Hence, it becomes crucial to delve deeper into the accuracy of each student's learning style. To address this need, a new evaluation metric, %Match, has been introduced for learning style

identification, to precisely evaluate the accuracy of learning style identification for individual students.

- %Match: This metric is used to assess individual student learning style recognition, representing the percentage of students correctly identified.

$$\%Match = \frac{\sum_{i=1}^{n} \begin{cases} 0.0 & if \;\; ACC(LS_{actual,i}, LS_{id,i}) < 0.5 \\ 1.0 & otherwise \end{cases}}{n} \tag{14}$$

When the ACC result is less than 50% of the actual range of values in the dataset, the match is determined to be unreasonable and %Match is 0 and vice versa. The use of %Match provides insight into the performance of individual students and ensures that no possible deficiencies are overlooked, minimizing the negative impact on individual students.

6.2.2 Sentiment analysis. Evaluating student sentiment analysis in personalized learning is crucial for gaining a profound insight into students' emotional states throughout the learning journey. Affect analysis extends beyond positive emotions to encompass negative and neutral emotions, offering a more comprehensive understanding of personalized learning experiences. Precise analysis of students' emotions empowers personalized learning systems to finely adjust teaching strategies and offer tailored support and resources. This section will explore evaluation metrics for student sentiment analysis, providing a comprehensive assessment of performance in terms of accurately perceiving students' sentiments.

In the realm of student affect analysis, researchers commonly employ categorical indicators for evaluation, aiming to delve into the nuanced emotional states articulated by students throughout the learning process. These indicators go beyond a mere focus on general emotions, encompassing more specific categories like preferences, stress, and concentration. Through the classification of students' emotions into distinct categories, evaluation metrics can offer a finer-grained perception of emotional nuances. Consequently, student sentiment analysis is frequently viewed as a categorization task, as its objective is to classify textual sentiment into discrete categories. Here are some commonly used evaluation metrics for this type of task:

- ACC, Precision, Recall, F1 Score: Unlike regression tasks, categorization tasks are more applicable to the practical needs of sentiment analysis. Student sentiment analysis typically involves categorizing students' emotions into different classes, such as positive, negative, neutral, and so on. Classification indicators assist the model in accurately determining the category to which the emotions expressed by students belong. Commonly used metrics in experimental evaluation include ACC, Precision, Recall, etc. The use of these evaluation metrics aids in quantifying and comparing the performance of the model.

In addition to evaluating categorization accuracy, for a more comprehensive understanding of the model's sentiment labeling trends, it becomes imperative to consider the sequential nature of sentiment categories and the interrelationships between various variables. To address this, sentiment analysis also incorporates a correlation evaluation metric, which allows for a nuanced examination of how sentiments unfold over a sequence of categories and how these categories relate to each other. This additional metric aids in capturing the intricate dynamics of sentiments and their sequential dependencies within the context of the analysis:

- Spearman's Rank Correlation: Also known as Spearman's rho, it is a statistical measure that assesses the strength and direction of a monotonic relationship between two variables.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}, \tag{15}$$

where d_i represents the rank difference for each pair of observations, and n is the total number of observations. The Spearman's rank correlation coefficient ranges between -1 and 1. A value of $\rho = 1$ signifies a perfect monotonic positive correlation, $\rho = -1$ denotes a perfect monotonic negative correlation, and $\rho = 0$ indicates the absence of a monotonic relationship. Unlike Pearson's correlation, Spearman's rank correlation does not assume a linear relationship between variables; instead, it evaluates how the association between variables can be characterized by a monotonic function. In student sentiment analysis, sentiment data may exhibit subjectivity, and nonlinearity, or may not conform to the assumption of a normal distribution. Spearman's correlation proves to be a more robust choice for such data. Moreover, in real student sentiment data, extreme expressions of sentiment may exist, and Spearman correlation can, to some extent, mitigate the impact of these outliers.

Sentiment analysis goes beyond evaluating the model solely on the accuracy of sentiment categories; it underscores the model's proficiency in distinguishing among sentiment categories and the consistency of their relative distributions. Simultaneously, ensuring consistency between human encoders and machine learning classifiers is crucial in sentiment analysis. Therefore, the incorporation of consistency metrics is essential:

- Cohen's Kappa: It addresses the issue of stochastic consistency by considering not only simple accuracy but also the alignment between the model and human annotations. In sentiment analysis, where there might be multiple plausible sentiment categories, relying solely on accuracy can lead to challenges. Cohen's Kappa, by capturing the consistency between the model and human annotations, circumvents such issues. In the context of student sentiment analysis, sentiments may be diverse, spanning categories like positive, negative, and neutral. Cohen's Kappa offers a more comprehensive evaluation for multi-category scenarios. Additionally, Cohen's Kappa goes beyond measuring mere agreement between the model and human labels; it corrects for consistency arising from random chance, enhancing its robustness and reducing susceptibility to data randomness.

6.2.3 Behavior analysis. This section provides a comprehensive introduction to commonly utilized indicators in the evaluation of student behavior analysis. A thorough examination of these indicators aims to enhance the evaluation of the efficiency of student behavior analysis models. This, in turn, facilitates a better understanding of student learning characteristics and the optimization of teaching strategies.

In the realm of student behavior analysis, it is essential to explore correlations between different behavioral factors and investigate associations between specific characteristics and students' behavior. Consequently, correlation analysis becomes imperative, aiding in the construction of more precise, interpretable, and pertinent models for student behavior analysis. Below are two frequently employed correlation evaluation metrics:

- x^2: The Chi-square test is a common tool for analyzing relationships between categorical variables. This is due to its capability to assess the disparity between observed and expected frequencies, thereby determining the independence of two categorical variables.

$$\mathcal{X}^2 = \sum \frac{(O_i - E_i)^2}{E_i}, \tag{16}$$

  where O_i is the observed frequency (the frequency that occurs) and E_i is the expected frequency (the frequency that is predicted based on assumptions or models). The Chi-square test is employed to determine if an association exists between two categorical variables. For instance, it can be utilized to investigate the link between a student's gender and their performance in a specific subject. Furthermore, various student behaviors during the learning process can be treated as categorical variables, and the chi-square test can analyze the relationship between these behaviors. For example, it can assess whether there are significant differences in learning behaviors for a particular subject among different student groups. The chi-square test can also compare observed and expected frequencies to evaluate whether the distribution of student behaviors aligns with expectations.

It is crucial to note that the Chi-square test has prerequisites, including the independence of observed frequencies and the avoidance of too small expected frequencies in each unit. When applying the Chi-square test, researchers must ensure these conditions are met to obtain reliable results. Additionally, the Chi-square test, as a hypothesis testing method, does not directly quantify the strength of the relationship between variables but merely indicates their independence. Therefore, in student behavior analysis, researchers typically combine other statistical methods and visualizations to gain a comprehensive understanding of the complexity of student behavior.

- Pearson Correlation Coefficient: This indicator is used to measure the interrelationship between two variables and has a value between -1 and 1.

$$r = \frac{\sum(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum(X_i - \overline{X})^2 \sum(Y_i - \overline{Y})^2}}, \tag{17}$$

where, X_i and Y_i represent the ith ovservation of variables X and Y, respectively, with $\overline{X}$ and $\overline{Y}$ denoting their means. A positive correlation yields a positive value for the correlation coefficient (r), while a negative correlation results in a negative value. If r equals zero, it signifies no linear correlation. Similar to the chi-square test, correlation analysis is employed to gauge the linear relationship among the features of learned behaviors. The calculation of the correlation coefficient enables an evaluation of the strength and direction of these behaviors, unveiling whether a positive or negative association exists. This understanding sheds light on the intricate interactions among student behaviors. Moreover, when undertaking behavioral analysis modeling, comprehending the correlation between variables aids in selecting the most pertinent ones, thereby enhancing the predictive performance of the model.

In the majority of the scrutinized learning analytics literature, the evaluation experiments were tasks defined by the researchers themselves. This is attributed to the fact that the evaluation of student behavior analysis frequently hinges on bespoke experiments designed to observe and document various student behaviors within an educational setting. These behaviors encompass engagement, interaction frequency, and learning time, contributing to the acquisition of extensive behavioral data. Through the analysis of data derived from these experiments, researchers can evaluate the efficacy of educational interventions, comprehend behavioral variations among diverse student populations, and explore the interplay between behavior and academic performance.

- Task-specific experimental analysis: It involves designing and analyzing experiments tailored to the specific requirements of student behavior analysis tasks. For instance, experiments conducted on an online platform recorded various student behaviors, including completing questions, taking tests, and watching videos. Subsequent in-depth analysis of actual data delved into the distribution, correlation, consistency, and validity of these behaviors. This approach ensures that the experimental setup and data analysis align closely with the objectives of the task at hand [30, 137, 27, 42]. An experimental perspective that illustrates the relationship between student behavioral traits allows for a better understanding of student learning characteristics across disciplines and environments. Moreover, clustering methods were employed in experiments dedicated to assessing student behavior analysis [124, 178, 13]. This involved clustering data related to students' activities and quiz scores on online learning platforms. Utilizing clustering algorithms allowed for the classification of students into distinct groups, enabling the evaluation of academic performance within these groups through behavioral data analysis. This approach aids in identifying behavioral patterns associated with either strong or weak academic performance. Additionally, cluster analysis facilitates the identification of student groups exhibiting similar academic behaviors, allowing for a comprehensive evaluation of the academic performance and engagement levels within these clusters.

Table 11. Statistics on common evaluation indicators for learning analytics.

	ACC	Precision	Recall	F1 Score	Confusion Matrix	SIM	%Math	AUC-ROC	Kappa	x^2	Pearson's Coefficient	Spearman's Rank Correlation	Case Study
[19]	✓					✓	✓						
[80, 53, 69, 6, 164, 140]					✓								
[18]	✓					✓	✓						
[70, 103, 54, 107, 95, 156, 245, 165, 9, 180, 93, 182, 235, 199, 154]	✓	✓	✓	✓									
[170]	✓	✓	✓	✓				✓					
[174, 30, 42, 124, 178, 13, 125, 27, 137, 79, 153, 169]													✓
[60, 224, 14, 40]	✓												
[227]	✓	✓	✓	✓	✓			✓					
[203]	✓	✓											
[226]												✓	✓
[108, 122]	✓			✓									
[212]										✓			
[97, 180]											✓		
[77]	✓	✓	✓	✓					✓				
[141]		✓	✓					✓					
[158]	✓			✓									
[159]	✓												✓
[222]								✓	✓				
[34]		✓	✓	✓									
[29]	✓	✓	✓	✓					✓			✓	
[99]		✓	✓	✓									

6.2.4 Predictions of student performance/achievement. Student performance/achievement prediction encompasses two types of tasks: continuous-value prediction and categorization tasks. In continuous-value prediction, the objective is to foresee a student's specific score on a particular task or exam. Here, the model's output is a real-valued value indicating the anticipated performance. Common evaluation metrics for this task include Root Mean Square Error(RMSE) and Mean Absolute Error(MAE), gauging the disparity between the model's predictions and actual performance.

For classification tasks, the aim is to classify students' performance into distinct grades or categories, such as excellent, good, passing, or failing. In this scenario, the model produces a discrete label representing the student's performance category. Evaluation metrics for this task encompass ACC, Precision, Recall, F1 Score, and area under the AUC-ROC curve, providing a comprehensive evaluation of the model's categorization performance across different performance categories.

- RMSE and MAE: These two metrics are used to measure the difference between the predicted value and the actual value, providing an overall sense of the prediction error.
- R^2: Also known as the coefficient of determination, this is a measure of how effectively the model explains changes in reality. A higher R^2 value, approaching 1, signifies a more precise representation of changes in reality by the model.
- Accuracy, Precision, Recall, F1 Score: These classification metrics are often used to evaluate the performance of binary or multivariate classification problems. In student achievement prediction, grades can be divided into different categories, and then these indicators are used to measure the model's performance in different categories.
- AUC-ROC: Utilized to evaluate the balance between true and false positive instances at various thresholds, the AUC-ROC in student performance/achievement prediction proves instrumental in appraising the model's predictive efficacy across diverse achievement levels.

The detailed mathematical formulations and meanings of these indicators have been thoroughly expounded in Section 6.1, and for brevity, they will not be reiterated in this section.

6.3 Evaluation of Personalized Recommendation

In the evaluation of personalized recommendations, metrics play a crucial role in quantitatively and qualitatively assessing the performance of recommender systems. These metrics provide researchers with a standardized means to compare the effectiveness of various algorithms or models, offering specific numerical values that reflect the system's performance. Additionally, the use of consistent evaluation metrics allows researchers to discern system performance changes under different parameter settings. This information aids in the fine-tuning and optimization of recommendation models, aligning personalized recommendations more closely with the diverse needs of students. This section provides a detailed overview of the evaluation metrics employed in the literature under review.

In personalized learning recommendations, the emphasis is typically placed on evaluating the initial recommendations rather than the entire set of suggested learning resources. Simultaneously, the focus remains on assessing the overall recommendation performance of the constructed model. This aligns with the objectives of traditional recommendation systems. Therefore, commonly employed recommendation metrics such as Hit Rate (HR) and Normalized Discounted Cumulative Gain (NDCG) are utilized in personalized learning recommendations to gauge user acceptance of the suggested learning resources.

- HR@K [43]: This metric is widely adopted for assessing recommendations, specifically as a recall-based measure that evaluates the real-time performance and hit rate of a recommender system. In essence, the metric gauges the system's success in achieving hits within the first K recommendations, providing a percentage representation of the resources (exercises/courses/concepts) effectively recommended to students.

$$HR@K = \frac{Number\ of\ Hits@K}{|GT|} \tag{18}$$

  where GT denotes the number of testsets and $|\cdot|$ is the set size. $Hits@K$ denotes that the resources belonging to the test set are also in the top-K recommendation set. This evaluation metric measures whether students find resources of interest in the recommendation list.
- NDCG@K: This metric is extensively employed in recommender systems and is accuracy-oriented. When assessing personalized learning recommendation algorithms, it aligns more closely with student needs as it considers both the relevance of items and location information.

$$\begin{aligned} NDCG@K &= \frac{DCG@K}{IDCG@K} \\ DCG@K &= \sum_{i=1}^{K} \frac{2^{rel_i} - 1}{log_2(i+1)} \\ IDCG@K &= \sum_{i=1}^{K} \frac{2^{rel_{sorted_i}} - 1}{log_2(i+1)} \end{aligned} \tag{19}$$

  rel_i is the relevance of the ith item in the recommendation list for the student, and i denotes the location of the item. rel_{sorted_i} is the relevance of the ith item to the student after sorting the items by true relevance. The NDCG@K value ranges from 0 to 1. A higher value indicates a larger proportion of cases in the recommendation list ideally sorted based on students' relevance, meaning more relevant resources are ranked higher. NDCG@K serves as a comprehensive evaluation index that considers the ranking performance of the recommender system. It is highly applicable for assessing the effectiveness of personalized learning recommendations.

The recommendation challenge in personalized learning can be conceptualized as a classification task. This is because, during the recommendation process, we frequently encounter the task of transforming a student-resource matching issue into the challenge of ranking students' preferences for specific resources. Classification metrics prove effective in evaluating a model's performance in understanding students' needs. Metrics like AUC, ACC, and Precision have been extensively discussed in the Cognitive Diagnostics section and won't be reiterated here.

Some ranking metrics are also commonly used to evaluate personalized learning recommendations.

- Mean Reciprocal Rank(MRR)(https://en.wikipedia.org/wiki/Mean_reciprocal_rank): This metric assesses the ranking of items in a recommendation list based on probability. It computes the average of the inverse rankings of correct results in a sequence.

$$MRR = \frac{1}{|U|} \sum_{i=1}^{|U|} \frac{1}{Rank_i} \tag{20}$$

  where $|U|$ represents the total number of students. $Rank_i$ denotes the rank position in the ground-truth list of the first resource interacted with in the recommendation list for the ith user. MRR concentrates on determining whether the top-ranked learning resources in the recommendation list align with those the students have actually interacted with. Consequently, it places more emphasis on the model's accuracy in ranking students' interests rather than merely classification accuracy. MRR offers a perspective that prioritizes the ranking of recommended items, making it particularly well-suited for scenarios such as course recommendations that emphasize the ranking of user interests.
- Mean Average Precision(MAP)(https://www.kaggle.com/wiki/MeanAveragePrecision): Similar to MRR, MAP centers on the precision of the model's ranking for related outcomes, with the additional aspect of evaluating the average accuracy across all correlated outcomes.

$$MAP = \frac{1}{|U|} \sum_{i=1}^{|U|} \frac{1}{Num_{rel_i}} \sum_{j=1}^{Num_{rel_i}} Precision_{j,i} \tag{21}$$

  $|U|$ represents the total number of students. Num_{rel_i} signifies the total number of learning resources that the ith student genuinely interacted with. $Precision_{j,i}$ indicates the precision of the jth genuinely interacted learning resource in the recommendation list of student i. The strength of MAP lies in its ability to amalgamate the ranking quality of all pertinent results, offering a more comprehensive evaluation of the model's performance across the entirety of the personalized learning recommendation list.

In personalized recommendation, in addition to recommendation accuracy, the novelty and diversity of the recommended learning resources can also be considered. This means that a personalized recommendation system should not only accurately match learners' semesters, but also ensure that the recommended learning resources can provide novel and diverse experiences. Therefore, these two measures can also be used as important indicators of the performance of personalized recommendation systems:

- Novelty: Novelty metrics serve to assess whether the recommended content introduces knowledge or subject matter that the learner has not previously encountered. By enhancing the novelty of recommendations, the aim is to expand the learner's current knowledge and delve into new concepts, providing them with opportunities to explore and discover additional learning dimensions.

$$Novelty(L^*) = \frac{\sum_{i=1}^{N}(1 - Jaccsim(I(q_i(k)), I(q_i^v)))}{|N|} \tag{22}$$

where, $I(q_i(k))$ denotes the set of knowledge concepts contained in exercise E_i, and $I(q_i^v)$ denotes all the concepts that target student i answered correctly in the set of knowledge concepts of the historical interaction. Jaccsim on the other hand, denotes the Jaccard similarity between to two.

- Diversity: The diversity indicator emphasizes the expansiveness of recommendations, ensuring that the suggested learning resources encompass a variety of domains, perspectives, or disciplinary forms. This approach aims to facilitate a comprehensive acquisition of knowledge, fostering a well-rounded understanding rather than solely concentrating on a singular piece of information.

$$Diversity(L^*) = \frac{2\sum_{q_i(K),q_j(K)\in L^*, i\neq j} different(q_i(K), q_j(K))}{|N|(|N|-1)} \tag{23}$$

where, $|N|$ is the length of the list, $q(K)$ denotes the recommended exercises, $different(q_i(K), q_j(K)) = 1 - sim(q_i(K), q_j(K))$, and sim is the cosin similarity. A larger value of this means that the recommended resources are more diverse.

Table 12. Statistics on common evaluation metrics for personalized recommendations.

	HR@K	NDCG@K	AUC	Recall	Precision	F1	ACC	RMSE	MAE	MAP	MRR	PP-Mismatch	Novelty	Diversity
[241, 132, 133, 10, 56, 218]	✓	✓												
[134]	✓	✓												
[240]		✓	✓	✓										
[96]		✓		✓										
[223, 242, 94, 192, 112, 242, 84, 89, 220, 112, 113, 76]				✓	✓	✓								
[217]						✓								
[105]							✓							
[215, 116, 72]			✓											
[255]	✓	✓						✓	✓					
[247]	✓	✓		✓	✓	✓								
[119, 250, 157]				✓	✓									
[252]					✓									
[202, 187]				✓	✓	✓	✓							
[48]	✓			✓										
[57]					✓					✓	✓			
[210, 157]									✓					
[75]	✓	✓	✓											
[246]		✓	✓	✓				✓						
[213]		✓			✓						✓			
[253]		✓		✓	✓									
[33]	✓	✓									✓			
[168]		✓										✓		
[233]	✓	✓	✓								✓			
[257, 171]				✓	✓	✓		✓	✓					
[244]			✓			✓								
[114]		✓		✓	✓	✓				✓	✓			
[91]					✓					✓				
[194]	✓				✓									
[231]											✓			
[191]					✓			✓						
[74]							✓						✓	
[144]					✓									✓
[254]				✓		✓	✓							✓
[219, 173]							✓						✓	✓
[90]		✓				✓								

In addition to the conventional recommendation, categorization, and sorting metrics, Ran et al. [168] introduced the Preference-Popularity Mismatch@K(PP-Mismatch@K) metric to assess the correlation between a course's popularity and student preferences. The researchers asserted that each student possesses distinct preferences; some may favor popular courses, while others prefer more niche offerings. Consequently, the popularity of a course should align with student preferences, and any misalignment can lead to a suboptimal match with students' diverse needs, resulting in an unsatisfactory user experience. This metric is evaluated based on the absolute difference between the course's popularity and students' preferences, where a larger value indicates poorer performance.

$$PP - Mismatch@K = \frac{1}{z} \sum_{a=1}^{z} \frac{1}{|K|} \sum_{c_j \in r_a} |pref(s_i) - pop(c_j)| \tag{24}$$

where z is the number of students and r_a is the list of recommendations. $pref$ for the student preferences $pref(s_i = \sum_{c_j} \in n_{s_i} pop(c_j) \frac{1}{n_{s_i}}$. In this equation, initially, we assume that students' preferences for various courses are evenly distributed. This implies that irrespective of temporal proximity, equal weight is assigned to all interacted courses in the calculation. Additionally, a higher value for this parameter suggests that students are more likely to favor courses with greater popularity. pop for the popularity of the course, $pop(c_j) = log(\frac{interactions}{semesters})$ is employed to signify the average enrollment of students in a course during the semester it is offered. A higher value indicates greater student participation in the course for that semester, signifying its popularity, and conversely.

From Table 12, it is evident that the prevalent evaluation metrics in personalized recommendation include recommendation metrics like HR and NDCG, alongside classification metrics such as AUC and Precision. The rationale behind incorporating widely used recommendation metrics lies in the similarity between personalized learning recommendations and general recommendation tasks. Both these metrics concentrate on the ranking of recommended resources and user satisfaction, providing a more accurate reflection of the recommendation model's performance in personalized learning scenarios.

Moreover, personalized learning recommendation is often construed as a classification problem. In this context, resources that a user has interacted with are labeled as positive categories (indicating potential interest), while unexplored resources are labeled as negative categories (indicating potential disinterest). The goal of the personalized learning recommendation system is consequently redefined to determine whether each learning resource falls into a positive or negative category. Within this framework, evaluation metrics designed for classification problems, such as AUC and ACC, can effectively gauge the recommender system's performance.

In general, evaluation indicators act as an important tool for evaluation, optimization, and decision-making in personalized education recommendation, which is crucial to promote the development of personalized education recommendation system and improve user experience.

7 APPLICATION CASES

In recent years, the application of personalized learning in the classroom has been quite extensive. Based on our previous categorization, these real-world application cases can be reviewed from three aspects: cognitive diagnosis, learning analysis, and recommendation, depending on the types of personalized learning technologies employed in them.

7.1 Concrete Examples

We summarize the application of personalized learning in actual teaching and learning in recent years, and the summarized table is shown in Table 13.

Examples of personalized learning approaches that focus on cognitive diagnostics and learning analysis include the following:

Bellarhmouch [15] proposes a new learner model that combines stereotyping methods, fuzzy logic, and similarity techniques to initialize and update the learner model. The model provides personalization support by analyzing the learner's interactions with the learning environment, such as page visits and mouse clicks. This analysis is used to develop personalized learning paths that help students self-regulate optimally during the learning process.

Yang et al. [229] conducted an experiment in an undergraduate accounting information systems course with a total of 87 students, comprising 35 males and 52 females with an average age of 21. The study employed a personalized learning analytics (LA) intervention based on e-books and recommendation systems. Students used the e-book browsing system 'BookRoll' and received personalized interventions tailored to their learning progress. The study found that students who received a personalized LA-based intervention outperformed those who did not in terms of academic performance and behavioral engagement. The intervention method, which combined e-books and personalized recommender systems, was shown to be effective in enhancing students' learning outcomes.

The following examples represent the application of personalized learning in the recommendation domain:

Huang [87] conducted a study at a Taiwanese university comparing the impact of AI-enabled personalized video recommendations on student engagement, motivation, and learning outcomes in a flipped classroom setting for a systems programming course. The study included a control group and an experimental group. The results suggest noteworthy enhancements in engagement and learning outcomes, especially among students with moderate motivation levels.

Lim et al. [129] conducted a study on university students in Germany. A total of 104 students participated, and data from 98 were used for analysis. The study utilized personalized scaffolding based on real time analytics to support students' self-regulated learning (SRL). The study offered individualized support by analyzing student interactions, such as page visits, mouse clicks, and keystrokes, in the learning environment in real time. Through real time analytics and an AI-based rule-based system, the research provides a way to identify and support micro-level self-regulated learning activities in real time during learning activities.

Raj et al. [166] conducted a study at Cochin University of Science and Technology, an Indian higher education institution that offers multi-level education. The study utilized a rule-based expert system to recommend learning content, which is an adaptive learning system. It employs the Learning Object Metadata Standard (LOMS) to guide learner selection and support personalized learning.

This literature [149] discusses the development of an intelligent model for personalized learning management. The research was conducted at San Agustin University in Arequipa, Peru, and focuses on tailoring learning to individual styles in virtual environments. The model utilizes Case-Based Reasoning (CBR) and the Honey-Alonso Learning Styles Model for personalization. Educators can use these technologies to provide students with customized content that matches their learning styles, optimizing learning outcomes.

Karaoglan [98] conducted a study at a public university in Turkey with second-year students in the Department of Turkish Language Teaching. The Computer I course had 56 participants, but data were only collected from the 40 students who volunteered. The study utilized personalized recommendation and feedback methods based on learning analytics. The course employed a flipped classroom model, in which students accessed course content and materials through a learning management system (LMS). At the end of each week, the researcher, who was also the instructor of the Computer I course, provided personalized feedback to the students based on the results of the learning analytics. Students found this approach helpful in identifying learning deficits, providing opportunities for self-assessment, improving attitudes toward learning, and increasing motivation to learn.

Besides what we mentioned above, Zayet et al. [238] presents a framework for personalized e-learning in the K-12 context. The study employs a systematic review methodology and focuses on the development of personalized recommender systems for e-learning, emphasizing students' individual characteristics and learning styles. The role of educators is not explicitly detailed, but the framework suggests a need for the integration of these systems into educational practices. The paper emphasizes the significance of data-driven personalization and discusses the difficulties in precisely customizing e-learning to meet the diverse needs of students. It proposes future research and implementation directions in this area.

Recently, with the development of large language models in natural language processing, researchers have explored introducing these models into personalized learning. EduChat [41], developed by Dan, is based on open-source models and incorporates theories of psychology and pedagogy. It includes features such as open Q&A, composition correction, heuristic teaching, and emotional support. To some extent, it enhances the current generative model's ability to create from limited information and addresses the issue of delayed knowledge updates. This represents a new direction in personalized learning.

7.2 Intelligent Educational Software

Intelligent educational software is a type of software that uses modern technology, specifically artificial intelligence and data analytics, to improve the educational experience. This software provides personalized teaching and learning support based on students' learning habits, performance, and preferences. Based on our classification, intelligent education software can be categorized into six main types: adaptive learning systems, virtual education assistants, learning analytics tools, online learning platforms, learning management systems, and intelligent education games. In the following section, we will describe the features of each type of software and how they support personalized learning.

Adaptive Learning Systems (ALS) automatically adjust instruction content and difficulty by analyzing students' responses and learning progress. Knewton [200] is an example of an adaptive learning system that uses advanced algorithms to analyze students' learning behavior and performance. It provides customized learning paths for each student to ensure that the learning material matches their abilities and interests. The system can modify the instruction's content and difficulty in real time based on the student's learning progress. This ensures that students are learning at an appropriate level and maximizes learning outcomes.

Virtual Educational Assistants (VEA) are AI-based tools that interact with students to provide personalized learning resources and feedback. They assist students in solving learning problems and can be customized to their progress and preferences. Duolingo [204] is a well-known example of a VEA, which is a language-learning app that uses virtual assistants to teach various languages. It offers an enjoyable educational experience through interactive games and exercises, with personalized learning paths that adapt to the student's pace and ability.

Online Learning Platforms (OLP) offer a wide range of courses that allow students to choose learning materials based on their interests and needs. They provide flexible learning arrangements and resources to adapt to the learning pace of different students. For example, Coursera [101] is a well-known online learning platform that offers a diverse range of online courses and professional certificate programs. It enables students to select and study courses at their own pace and convenience, offering flexibility and catering to individualized learning requirements.

Learning Analytics Tools (LAT) are used to set and analyze student learning data, including engagement, grades, and progress. This provides teachers with insights to customize their teaching

Table 13. Practical Examples of The Use of Personalized Learning.

Background	Implementation	Students' Participation	Educators' Participation	Data-Driven Feedback	Challenges and Solutions
Taiwanese university, systems programming course, flipped classroom	AI-enabled personalized video recommendations	Improved engagement, motivation, and learning outcomes	Facilitation of AI-enhanced learning	AI algorithms for content recommendation	Effective integration of AI in education, addressing diverse student needs
German universities, Bachelor's and Master's students, various majors	Real time analytics-based scaffolds, online learning tools, rule-based AI	Influence on self-regulated learning activities, performance, engagement with learning strategies	Provided scaffolds, structured environment, focus on technology-driven personalization	Real time data collection and analysis, personalized feedback	Addressed technical challenges, refinement based on empirical findings and AI analysis
Broad application in e-learning, not specific to any institution	Learner modeling with learning styles, domain data, assessment data, affective data; fuzzy logic and similarity analysis	Personalized experiences based on individual characteristics, improving engagement and outcomes	Involvement in content and assessment provision, integrated into personalized system	Continuous adaptation using personal, performance, and emotional data	Addressing complexity in learner modeling, technical implementation; combination of modeling techniques
Higher education, blended learning, unspecified institution	E-book and recommendation system, personalized learning analytics	Improved academic performance and increased learning interest	Integration of personalized system into learning	Analysis of student performance for personalized feedback	Addressing complexity in personalization and technical aspects
Systematic review on K-12 e-learning, not specific to any institution	Development of a personalized recommender system for e-learning, modules for student profiling, material collection, and recommendation	Enhancement of engagement, performance, and knowledge through personalized learning materials	Provision of course materials, validation of recommended materials, monitoring, and feedback	Use of machine learning and data mining for profiling and recommendations, teacher validation	Complexity of personalized e-learning recommendations, comprehensive framework for implementation
Turkish university, flipped classroom, pre-service teachers	Learning analytics for personalized recommendation and feedback	Focus on engagement, learning outcomes, self-assessment	Facilitate personalized learning, guide students	Learning analytics for data collection, analysis, personalized feedback	Navigating personalized learning complexities, data privacy concerns
Cochin University, India, online learning	Rule-based system, Felder-Silverman Model, IEEE Standard	Enhanced engagement and learning outcomes	Guide in personalized learning process	Learner profiling, content alignment	Learner modeling, content recommendation
San Agustin University, Peru, virtual learning	CBR, Honey-Alonso Model for learning styles	Improved engagement and learning outcomes	Guiding the use of the personalized learning model	CBR for adapting learning content to styles	Adapting to diverse learning styles, efficiency in personalization

methods and personalized learning recommendations for students. IBM Watson Education [167] is a well-known example of a learning analytics tool. It analyzes student learning data, such as grades and engagement, to identify student learning patterns and needs. It predicts student performance, aiding educators in developing more effective teaching strategies.

Learning Management Systems (LMS) provide a centralized platform for creating, managing, and delivering educational content. They support personalized curriculum and learning tracking to help students learn at their own pace. Moodle [1] is one of the most representative LMSs. Moodle is an open-source online learning management system that enables educators to create personalized course content and assessment methods. Its flexibility allows for adaptation to a wide range of educational needs and facilitates online interaction and collaboration.

Educational Games(EG) combine entertainment and learning to provide an engaging and effective learning experience. These games automatically adjust difficulty based on player performance and learning speed, making the learning process more engaging and effective. Minecraft: Education Edition [106] is a representative example of an educational game that supports students in exploring and learning a variety of subjects through gaming, providing a fun and creative way to learn.

Table 14 summarizes the mainstream intelligent educational software and their characteristics, in addition to the ones listed above.

Table 14. The existing adaptive learning systems.

System	Web-site	Type	Developed by	Year	Charges	Cloud	Mobile	Local
Knewton	knewton.com	ALS	Jose Ferreira	2008	Pay	+	+	-
Smart Sparrow	smartsparrow.com	ALS	University of New South Wales	2010	Trail/Pay	+	+	-
Codecademy	codecademy.com	ALS	Zach Sims	2011	Free/Pay	+	+	-
DreamBox	dreambox.com	ALS	Lou Gray,Ben Slivka	2006	Trail/Pay	+	+	-
ALEKS	aleks.com	ALS	Jean-Claude Falmagne	1996	Pay	+	+	-
Tandem	tandem.net	VEA	Arnd Aschentrup,Tobias Dickmeis,Matthias Kleimann	2015	Free/Pay	+	+	-
Duolingo	duolingo.com	VEA	Luis von Ahn,Severin Hacker	2011	Free/Pay	+	+	+
Jill Watson		VEA	Ashok Goel	2016		+	-	-
Woebot	www.woebot.io	VEA	Alison Darcy	2017	Pay	+	+	-
IBM Watson Assistant for Education	ibm.com/watson/education/pearson	VEA		2016	Pay	+	+	-
AskAway	askaway.org	VEA			Free	+	+	-
Coursera	coursera.org	OLP	Andrew Ng,Daphne Koller	2012	Free/Pay	+	+	+
EdX	edx.org	OLP	Harvard University,MIT	2012	Free/Pay	+	+	+
Udemy	udemy.com	OLP	Eren Bali,Gagan Biyani,Oktay Caglar	2010	Pay	+	+	+

System	Web-site	Type	Developed by	Year	Charges	Cloud	Mobile	Local
Udacity	udacity.com	OLP	Sebastian Thrun,David Stavens,Mike Sokolsky	2011	Pay	+	+	-
Khan Academy	khanacademy.org	OLP	Salman Khan	2008	Free	+	+	+
Carnegie Learning	carnegielearning.com	OLP	Carnegie Mellon University	1998	Pay	+	+	-
FutureLearn	futurelearn.com	OLP	The Open University	2012	Free/Pay	+	+	-
Code.org	code.org	OLP	Hadi,Ali Partovi	2013	Free	+	+	-
Rosetta Stone	rosettastone.com	OLP	Allen Stoltzfus	1992	Pay	+	+	+
Learning Locker	www.learninglocker.net	LAT	HT2 Labs	2014	Pay	+		
Blackboard Analytics	blackboard.com	LAT	Michael Chasen,Matthew Pittingsky	1997	Pay	+	+	
Cognos Analytics for Education		LAT			Pay	+	+	
Brightspace Insights	community.d2l.com/brightspace	LAT	John Baker		Pay	+	+	-
IBM Watson Education		LAT			Pay	+	+	-
Moodle	moodle.org	LMS	Martin Dougiamas	2002	Free/Pay	+	+	+
Blackboard Learn	blackboard.com	LMS	Michael Chasen,Matthew Pittingsky	1997	Pay	+	+	+
Canvas	instruction.com/canvas	LMS	Brian Whitmer,Devlin Daley	2008	Pay	+	+	+
Schoology	schoology.com	LMS	Jeremy Friedman,Ryan Hwang,Tim Trinidad,Bill Kindler	2009	Free/Pay	+	+	-
Minecraft: Education Edition	education.minecraft.net	EG	Markus Persson,Mojang	2011	Free	+	+	+
BrainPOP	brainpop.com	EG	Avraham Kadar	1999	Pay	+	+	-
Scratch	scrap.mit.edu	EG	Mitchel Resnick	2007	Free	+	+	+
Prodigy	prodigygame.com	EG	Alex Peters,Rohan Mahimker	2011	Free/Pay	+	+	-

System	Web-site	Type	Developed by	Year	Charges	Cloud	Mobile	Local
Tinkercad	tinkercad.com	EG	Kai Backman,Mikko Mononen	2011	Free	+	-	-
Autodesk Education	autodesk.com/education	EG	John Walker	1982	Free	+	+	+

8 CHALLENGES AND FUTURE DIRECTIONS

Personalized learning, positioned as a vertical application of intelligent education and a cutting-edge research direction in education, has thrived in recent years, yielding noteworthy results. However, it still confronts a series of challenges and obstacles. These challenges emanate not only from issues related to the quality of datasets, imperfect evaluation systems, and ethical considerations but also encompass problems within existing learning analysis and personalized recommendation models. In this chapter, we delve deeply into these challenges across four key areas: dataset collection, the integration of technology and education, the assessment of personalized learning, and ethical inquiries. Additionally, we provide an outlook on future directions and explore potential innovations within the field of personalized learning. A comprehensive analysis of this domain will furnish valuable guidance for future research.

- Data: Data plays a pivotal role in the development of personalized learning, serving as the cornerstone that encapsulates information and preferences from various facets of individual learners, such as their academic history, learning behaviors, and life experiences. This wealth of data enables personalized learning systems to construct a nuanced understanding of students' knowledge states and address their distinct needs. It facilitates the modeling of students' learning styles, emotions, and behaviors, offering a dynamic power source for continuous optimization and adjustment of the learning model. However, the efficacy of personalized learning is contingent upon the availability of rich and high-quality data. The existing datasets, predominantly drawn from publicly accessible sources, may not be universally suitable for all tasks and might lack critical information essential for specific objectives. Moreover, the complexity of dataset collection poses challenges, with variations in data quality and the potential introduction of biases that can impact the model's performance in specific scenarios.
  In the realm of student behavior analysis, researchers often employ diverse and privately collected datasets that are not publicly disclosed. This practice introduces challenges related to data completeness, as individuals may not capture every detail in their self-collected data. Furthermore, these datasets are task-specific, lacking standardization, consistency, and reusability. Additionally, personalized learning systems necessitate substantial amounts of student behavioral data, raising privacy concerns when not adequately safeguarded. Hence, the intricate nature of dataset collection, coupled with privacy considerations, underscores the need for meticulous attention to data quality, standardization, and privacy protection in the development of personalized learning systems.
- Technology: The current development of personalized learning algorithms still focuses on meeting a certain related need, such as text assessment, personalized recommendation systems, etc., and there is insufficient research on generalization across different domains, which is far from the goal of fully realizing personalized learning. In the process of learning analytics facing complexity and uncertainty, how to effectively analyze student data and behavior and extract useful information from them is a challenge that needs to be solved in field of learning analytics. At the same time, all existing personalized learning technologies

lack research based on relevant psychological and educational theories, lack interdisciplinary information integration, and have not yet considered the integration and application of multimodal data. In addition, in the field of personalized learning research, the problem of model interpretability still needs to be solved urgently. Moreover, the rapid development of big language modeling poses many challenges for the future of education [150].

- Assessment: Evaluating the effectiveness of personalized learning presents a multifaceted challenge. Conventional assessment metrics fall short of capturing the comprehensive learning progress of students and the true efficacy of personalized learning systems. Common metrics like HR, NDCG, and recall, typically employed in personalized recommendation assessments, inadequately reflect the real-world impact of personalized learning applications. The reliance on traditional evaluation methods conducted offline further complicates the ability to gauge the performance of personalized learning systems within real-time and dynamic learning environments. The timely assessment of metrics poses a significant challenge, hindering the dynamic evaluation of these systems. Moreover, offline experiments cannot promptly gather user feedback, overlooking the crucial aspect that personalized learning aims to enhance the student experience and address individual needs. Certain assessment metrics also fall short in accounting for diverse learning styles, potentially limiting the generalizability of results. Additionally, indicators devised by individuals through practical experiments or personal judgments lack universal applicability and may not enjoy broad recognition. In summary, current assessment methods exhibit limitations in accurately evaluating diverse tasks, lack dynamism and timeliness, and disproportionately rely on traditional metrics at the expense of prioritizing user experience.
- Ethics: Education is socially complex, and with the rapid development of personalized learning, the quality of model frameworks and systems introduced varies, and there are certain risks. On the one hand, personal privacy may be violated as learning systems collect large amounts of student data, such as student behaviors, interests, and student personal information. On the other hand, personalized learning systems may be biased against certain groups when customizing learning content because of historical inequality and bias issues in the input training data, which will raise concerns about the fairness of the algorithms. At the same time, the feedback permission of personalized learning influences students' decision-making through student paths, which may raise ethical questions about the risk of manipulation and education, and how to balance the possible influences on personalized learning requires in-depth research and the designation of relevant ethical guidelines. In addition, the flourishing of big models, also raises a series of ethical challenges such as privacy security, bias and inequality, fairness issues with output content, and lack of interpretability. Also in generative dialogic education big models, the problem of hallucination may arise.

Despite the numerous challenges confronting personalized learning, ongoing technological advancements and deepening research are poised to provide an expansive avenue for future development. Addressing the data dilemma necessitates the implementation of effective methods, including the establishment of clear data collection protocols, transparent collection records, and a focus on privacy protection with a judicious level of disclosure for reusability. This approach aims to enhance data quality and credibility. Furthermore, heightened emphasis on the fusion and processing of multimodal data will offer a more comprehensive understanding of students' learning statuses. Interdisciplinary research should be reinforced, fostering the integration of technology with expertise in education, psychology, and related fields to construct a more holistic personalized learning model. Simultaneously, there is a pressing need to promote technological innovation, with personalized learning poised to benefit significantly from the generation and integration of new technologies. The deep integration of substantial models and education, leveraging the reasoning abilities of big models, promises to provide more refined guidance for personalized learning. Large language models have the potential to revolutionize personalized learning in the future. They can create a smarter, more interactive, and adaptive educational environment by providing highly customized learning paths and resources. This is achieved through an in-depth analysis of learner behavior, preferences, and performance. As a result, each student will receive content and challenges tailored specifically to their learning style, interests, and abilities. This includes the generation of personalized educational questions, the evaluation of programming courses, and the transformative impact of big models on education, presenting future research opportunities. A notable gap persists between academic research and industry focus, necessitating strengthened collaboration between educational enterprises and academia. Academic models and algorithms must transition from theoretical constructs to practical implementation, with collaborative efforts driving innovation and the real-world application of personalized learning technology. Additionally, the ethical dimension warrants attention, urging the establishment of more stringent regulations and ethical guidelines to ensure the balanced development of personalized learning.

In summary, although personalized learning faces challenges, it is also full of opportunities. Through continuous research and innovation, more intelligent and flexible personalized learning systems will emerge in the future, which can be adapted to different fields of knowledge and different subject backgrounds, to meet the diversified needs of students, and personalized learning will move to new heights in the future.

9 CONCLUSION

This paper conducts a comprehensive and in-depth examination of cutting-edge research in personalized learning within the realm of intelligent education. Commencing with the intricate definition of personalized learning, which lacks a universally accepted consensus, the study delves into the understanding of existing definitions. By scrutinizing the interplay between educational theories and personalized learning, the impact of diverse educational theories on personalized learning is discussed, drawing insights from pertinent educational theories. The paper elucidates the developmental history, research motivations, and objectives of personalized learning.

Subsequently, an exploration of the pivotal role of data in personalized learning is undertaken, with a meticulous exposition of commonly used datasets. This exploration encompasses three distinct facets: cognitive diagnosis, learning analytics, and personalized recommendation. In the realm of student modeling and personalized recommendation methods, the study succinctly encapsulates the prevailing core algorithms, structured around the aforementioned three components In the domain of cognitive diagnostics, the paper traces its evolution from early psychometric approaches to the contemporary focus on model accuracy and interoperability, presenting an exhaustive review of the existing literature. Addressing the learning analytics domain, the paper intricately explores four key areas: learning wind analysis, student sentiment analysis, student behavior analysis, and student performance/achievement prediction.

Delineating personalized recommendation, the paper categorizes it into three segments for detailed elucidation: course recommendation, exercise recommendation, and learning path recommendation. The study elucidates how, within the epoch of big data and machine learning, students can be modeled by deeply comprehending their cognitive processes to facilitate personalized recommendations, thereby furnishing astute learning support tailored to individual needs. Simultaneously, the paper furnishes a methodological framework for evaluating personalized learning, spanning from evaluation indicators to practical research, to enhance comprehension of the effectiveness and feasibility of existing personalized learning methods. Finally, the paper furnishes concrete evidence of the practical application of personalized learning through multiple application cases and existing platforms, tools, and software. This empirical demonstration underscores the tangible effectiveness of personalized learning across diverse educational scenarios.

Nevertheless, amidst the swift advancements in personalized learning, we confront a constellation of challenges encompassing data privacy, ethical considerations, model evaluation, and the intricacies of model interpretability. Looking ahead, we anticipate the emergence of novel technologies, with a particular focus on the synergistic integration of big models with educational dimensions, poised to usher in an era of expanded possibilities for personalized learning. This review endeavors to furnish academics and practitioners with a forward-looking exploration of personalized learning, delving into a more comprehensive and profound perspective. By amalgamating multi-dimensional investigations spanning educational theories, student modeling, personalized recommendation, data discourse, and assessment metrics, the aim is to propel sustained progress within the personalized learning domain. The aspiration is that this review will empower researchers to grasp the forefront of personalized learning research, offering a valuable reference for their inquiries. Moreover, we envisage it will stimulate contemplation and discussions, fostering an environment conducive to continuous advancements in the personalized learning sphere.

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