
A Survey of Intelligent Education and Adaptive Learning Technologies

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Abstract

Intelligent education methodologies, encompassing adaptive learning systems, intelligent tutoring systems, and computerized adaptive testing, represent a paradigm shift in educational technology by leveraging AI and data-driven insights to personalize learning experiences. This survey paper examines the significance of these technologies in transforming educational practices through personalized instruction, real-time feedback, and cognitive diagnosis. It highlights the role of adaptive algorithms in customizing educational content to individual learner needs, thereby enhancing engagement and optimizing outcomes. Key methodologies such as knowledge tracing and cognitive diagnosis are explored, demonstrating their impact on accurately assessing learner understanding and predicting future performance. The paper also addresses the challenges of implementing these technologies, including data privacy concerns, algorithmic bias, and the need for scalable solutions. Ethical considerations surrounding AI integration in education are discussed, emphasizing the importance of equitable access and the preservation of pedagogical integrity. Future research directions are proposed, focusing on enhancing model interpretability, integrating multi-modal feedback, and improving the scalability of adaptive systems. The survey concludes that while intelligent education technologies hold significant promise for improving educational outcomes, ongoing research is essential to address existing challenges and ensure their successful implementation across diverse educational contexts.

1 Introduction

1.1 Significance of Intelligent Education

Intelligent education signifies a transformative shift in traditional educational practices through the application of artificial intelligence (AI) and data-driven methodologies, facilitating personalized and adaptive learning experiences. This evolution is essential for addressing the diverse learning needs present in heterogeneous classrooms, where personalized instruction is vital for accommodating varying student abilities and interests [1]. The integration of AI within the frameworks of Education 4.0 and 5.0 highlights the necessity for adaptive learning experiences that align with the demands of modern learners [2].

Intelligent tutoring systems (ITSs) are pivotal in this transformation, enhancing interactive learning environments by fostering proactive engagement and overcoming the limitations of traditional systems [3]. These systems adapt to individual student needs, providing tailored feedback and support often lacking in conventional methods [4]. The role of AI in adaptive eLearning systems is significant, presenting both opportunities and challenges in developing personalized educational experiences [5].

The rise of personalized learning in computer-based learning environments (CBLEs) underscores the inadequacies of previous generic instructional methods [6]. Intelligent education aims to address these shortcomings by analyzing educational data to foster creativity and critical thinking skills [7]. This approach not only enriches the educational experience but also equips students with the

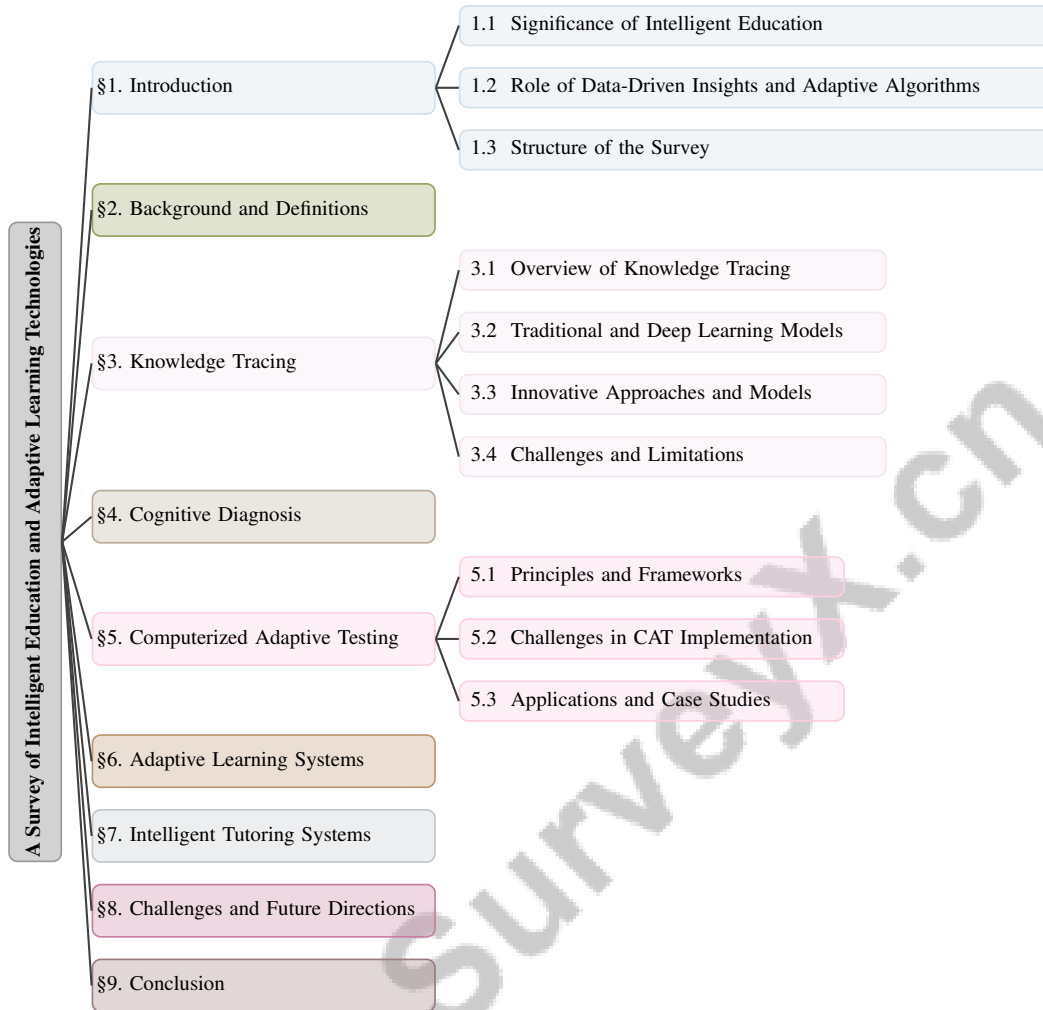


Figure 1: chapter structure

adaptability and continuous learning skills necessary for navigating the complexities of the modern world.

Moreover, AI's integration in personalized learning systems emphasizes the importance of catering to individual student needs, fundamentally transforming educational practices [8]. The focus on hint generation within intelligent tutoring systems aims to provide timely, context-specific guidance, enhancing learners' problem-solving skills and overall learning outcomes [9].

1.2 Role of Data-Driven Insights and Adaptive Algorithms

Data-driven insights and adaptive algorithms are crucial for customizing learning experiences, enabling educational platforms to dynamically respond to individual learner needs. The use of generative AI allows for the creation of tailored exercises that align with each student's unique requirements, enhancing their engagement and understanding [10]. These technologies are foundational in developing personalized learning environments and adaptive strategies essential for addressing contemporary educational challenges [2].

Incorporating AI into educational frameworks facilitates the customization of learning experiences, providing personalized opportunities and feedback through intelligent tutoring systems. These systems systematically introduce topics, offer hints, and monitor individual progress, optimizing the learning process [4]. The methodologies employed in AI to generate hints are particularly significant for delivering effective, personalized guidance to learners [9].

Adaptive algorithms, exemplified by platforms like iSTART, adjust content difficulty based on individual performance, fostering deeper engagement and comprehension [6]. This adaptability is further illustrated in e-learning environments that modify content delivery according to VARK learning styles, significantly enhancing student engagement [11].

Despite the transformative potential of AI in education, challenges persist, including uneven adoption of digital technologies and institutional hesitance to embrace AI capabilities [8]. The role of AI in content aggregation and its implications for personalized learning highlight the need for a balanced approach to integrating these technologies into educational practices [5].

The effectiveness and reliability of machine learning techniques, as demonstrated in healthcare diagnostics, suggest similar methodologies could improve educational outcomes [12]. The synergy between data-driven insights and adaptive algorithms is essential for creating educational experiences that are both personalized and responsive to learners' evolving needs, thereby enhancing the effectiveness and engagement of educational practices.

1.3 Structure of the Survey

This survey systematically explores the landscape of intelligent education and adaptive learning technologies, offering a comprehensive overview of their significance, methodologies, and applications. The introductory section establishes the transformative potential of intelligent education, emphasizing the role of data-driven insights and adaptive algorithms in personalizing learning experiences while outlining the survey's structure to guide the reader through the topics covered.

Following the introduction, a background section defines core concepts such as Intelligent Education, Knowledge Tracing, Cognitive Diagnosis, Computerized Adaptive Testing, educational technology, adaptive learning systems, and intelligent tutoring systems. This foundational understanding is crucial for appreciating subsequent discussions on methodologies and applications.

The survey then delves into specific areas of intelligent education, beginning with Knowledge Tracing, which examines methodologies and technologies for assessing learner understanding and predicting future performance, reviewing both traditional and deep learning models alongside innovative approaches and their challenges.

Next, Cognitive Diagnosis is addressed, focusing on methods that identify cognitive strengths and weaknesses, discussing various methodologies, frameworks, and innovative approaches that contribute to personalized learning.

The survey continues with Computerized Adaptive Testing, highlighting its principles, frameworks, and applications, while considering the implementation challenges supported by relevant case studies.

Adaptive Learning Systems are analyzed, emphasizing the integration of adaptive algorithms and the personalization of educational content, reviewing the frameworks and models that underpin these systems.

Intelligent Tutoring Systems are explored next, focusing on their design and implementation, discussing real-time feedback, adaptive feedback, problem generation, and various applications.

Finally, the survey identifies current challenges and future directions in intelligent education, examining the ethical implications of integrating artificial intelligence in K-12 education and identifying promising research avenues to enhance adaptive learning and tutoring systems through proactive assistance methods that anticipate students' needs based on their hint usage, thus improving overall educational outcomes [13, 14, 5]. The conclusion synthesizes the key points discussed throughout the paper, reaffirming the importance of intelligent education technologies in transforming learning experiences. The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Intelligent Education and Educational Technology

The transition to intelligent education and educational technology signifies a move from traditional methods to adaptive, personalized learning environments, largely driven by AI advancements. Intelligent tutoring systems (ITS), exemplified by the Computer Science Course-Tutor (CSCT), address

conventional teaching challenges by providing tailored learning experiences [4]. Systems like iS-TART further this trend by adjusting text difficulty based on student performance to enhance reading comprehension [6].

Educational methodologies have evolved through stages: Education 1.0 (traditional), Education 2.0 (multimedia), Education 3.0 (collaborative), Education 4.0 (AI integration), and Education 5.0 (adaptive learning) [2]. This evolution reflects an increasing focus on personalization and complexity, with modern adaptive learning systems overcoming past limitations of expert tagging and non-scalable models by employing dynamic, scalable models that adapt to individual learner profiles [15, 16].

Interactive Educational Systems (IES) underscore the significance of effective learner performance modeling through knowledge tracing, a core component of intelligent education [17]. Beyond personalized content delivery, AI integration in education facilitates intelligent question generation systems, addressing the lack of adaptive question generation in online platforms that has previously impeded tailored learning [18]. AI-driven question generation enhances assessment relevance, improving learning outcomes and engagement.

The synergy between AI techniques and educational content delivery is crucial for advancing intelligent education. Frameworks that categorize Adaptive Educational Systems (AES) highlight AI's role in refining educational content delivery [5]. Despite this progress, conventional e-learning environments often fail to accommodate diverse learning styles and preferences [11]. Addressing these challenges is essential for unlocking intelligent education's potential to transform educational practices and outcomes.

In recent years, the field of educational technology has witnessed significant advancements, particularly in the area of Knowledge Tracing (KT). This concept is crucial for understanding how learners acquire knowledge over time and how educational systems can adapt to their needs. As illustrated in Figure 2, the figure provides a structured overview of Knowledge Tracing in educational systems, categorizing its methodologies, models, innovative approaches, and challenges. It highlights the transition from traditional to deep learning models, emphasizing the role of innovative models in enhancing personalization and accuracy. Furthermore, the figure elucidates the challenges faced in interpretability and adaptability, which are critical for the effective implementation of KT in diverse educational contexts. By examining these elements, we can better appreciate the complexities and potential of Knowledge Tracing in modern educational practices.

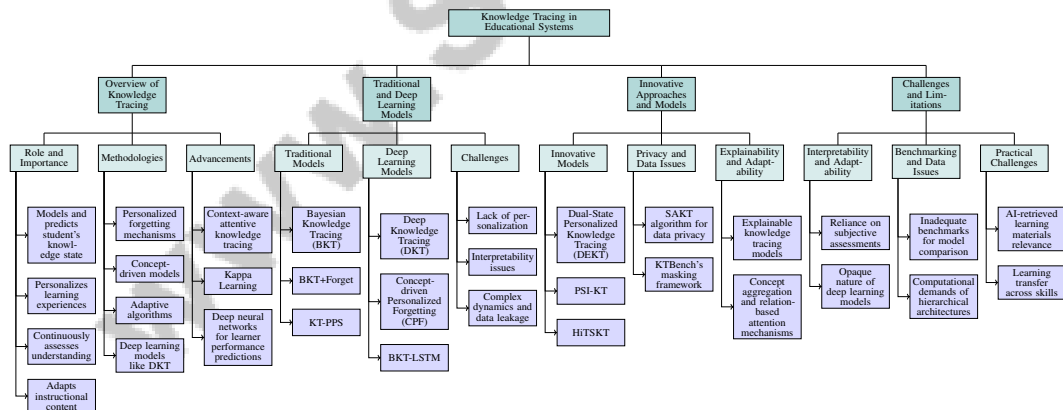


Figure 2: This figure provides a structured overview of Knowledge Tracing (KT) in educational systems, categorizing its methodologies, models, innovative approaches, and challenges. It highlights the transition from traditional to deep learning models, the role of innovative models in enhancing personalization and accuracy, and the challenges faced in interpretability and adaptability.

3 Knowledge Tracing

3.1 Overview of Knowledge Tracing

Knowledge Tracing (KT) plays a pivotal role in intelligent education systems by modeling and predicting a student's knowledge state during educational interactions. This process is essential for

personalizing learning experiences, continuously assessing understanding, and adapting instructional content to individual needs [19, 11]. KT estimates mastery levels across predefined skills by analyzing students' learning histories, which is crucial for predicting future performance and enhancing engagement.

KT dynamically assesses students' evolving knowledge states during learning activities, a core objective of intelligent education systems. Recent methodologies, including personalized forgetting mechanisms and concept-driven models, provide a nuanced understanding of students' knowledge statuses, addressing challenges in traditional approaches [11]. Advanced methodologies employ adaptive algorithms and deep learning models, such as Deep Knowledge Tracing (DKT), to enhance interpretability and effectiveness in tracking student progress. Within Computer-Based Learning Environments (CBLEs), KT accommodates diverse skill levels and comprehension abilities, fostering an engaging educational environment [19].

As KT methodologies advance, they enhance the personalization of learning environments through tailored feedback and actionable recommendations aligned with individual characteristics, performance levels, and developmental needs. Innovations like context-aware attentive knowledge tracing and Kappa Learning leverage deep neural networks and adaptive techniques to optimize learner performance predictions, ensuring alignment with students' unique knowledge states [20, 21, 22, 23].

3.2 Traditional and Deep Learning Models

The transition from traditional KT methodologies to advanced deep learning models has significantly improved the modeling and prediction of student learning trajectories. Traditional models, such as Bayesian Knowledge Tracing (BKT), estimate mastery probabilities over specific knowledge components, with variants like BKT+Forget and KT-PPS addressing forgetting and problem-solving proficiency [24]. However, these models often struggle with the complex dynamics of student interactions and data leakage issues, leading to inaccurate evaluations [25].

Deep learning has transformed KT, with models like DKT using Recurrent Neural Networks (RNNs) to analyze temporal sequences of student interactions, enhancing prediction accuracy [19]. Despite their success, DKT models face criticism for lack of personalization and interpretability, often treating all students uniformly. Models like the Concept-driven Personalized Forgetting (CPF) model integrate personalized learning capabilities and causal relationships between knowledge concepts to improve predictive performance [26].

Innovative models, such as BKT-LSTM, enhance predictions by integrating skill mastery, learning transfer, and problem difficulty [19]. This shift towards nuanced and adaptive KT methodologies reflects a significant trend in educational technology, aiming to improve adaptability, accuracy, and personalization through advanced deep learning techniques. Studies indicate deep neural networks achieve superior predictive performance, especially with large-scale student performance datasets. Incorporating contextual factors, such as exercise relationships and student forgetfulness, enhances model effectiveness. However, interpretability challenges persist, complicating practical applications in educational settings. Addressing these issues, such as through layer-wise relevance propagation (LRP), is vital for promoting the adoption of advanced models in personalized learning environments [27, 28]. These advancements contribute significantly to developing intelligent education systems responsive to individual learning needs, promising improved educational outcomes.

3.3 Innovative Approaches and Models

Innovative approaches in knowledge tracing address traditional model limitations, enhancing personalization and accuracy in educational experiences. The Dual-State Personalized Knowledge Tracing with Emotional Incorporation (DEKT) model exemplifies this progress by integrating emotional factors into knowledge state modeling and response prediction, offering a holistic understanding of student learning dynamics [29]. Incorporating affective components alongside cognitive traits is crucial in educational contexts.

The PSI-KT model employs a hierarchical generative approach to model individual cognitive traits and the prerequisite structure of knowledge, facilitating both prediction and interpretability for accurate educational interventions [30]. Similarly, the HiTSKT model utilizes a hierarchical trans-

former framework to capture intra-session and inter-session knowledge, offering a comprehensive representation of student learning trajectories [31].

The SAKT algorithm’s application in incremental knowledge tracing across multiple schools underscores the importance of data privacy in education. By learning sequentially while preserving data privacy, SAKT presents a scalable solution for diverse educational settings [32]. Additionally, KT-Bench’s masking framework addresses data leakage issues, ensuring robust and reliable evaluations [25].

Explainable knowledge tracing models, particularly those utilizing ensemble approaches, enhance accuracy and transparency by integrating various model types. This innovation meets the demand for transparency in educational technologies, allowing educators to comprehend and trust system predictions [33]. Incorporating concept aggregation and relation-based attention mechanisms in domain-generalizable knowledge tracing models improves adaptability and effectiveness across different domains [34].

These innovative models represent significant advancements in KT, merging flexible deep neural networks with interpretable components to enhance learning experience personalization. For instance, the Context-Aware Attentive Knowledge Tracing (AKT) model employs a monotonic attention mechanism to connect learners’ future responses with their past performance, improving predictive accuracy and providing actionable feedback. Frameworks that reweight response contributions based on discrimination balance knowledge mastery with question difficulty, refining the learning process. Recent developments like Personalized Knowledge Tracing (PKT) address class imbalance issues, leading to equitable assessments of student performance. Collectively, these advancements contribute to a nuanced understanding of individual learning trajectories, facilitating tailored educational experiences that cater to diverse learner needs [20, 35, 36, 23]. As these methodologies evolve, they hold the potential to transform educational practices by providing deeper insights into student learning processes and enhancing the adaptability of educational environments.

3.4 Challenges and Limitations

Method Name	Interpretability Issues	Data and Resource Limitations	Modeling Challenges
eKG[7]	-	Computational Resources Required	Generalizability Across Contexts
HiTSKT[31]	-	Extensive Computational Resources	Sessional Structure Dynamics
DGKT[34]	Attention Mechanism	Data Scarcity	Domain Differences
BKT-LSTM[19]	Psychological Interpretability	Quality OF Data	Learning Transfer Detection
KTbench[25]	Enhanced Interpretability	Multiple Datasets Including	Data Leakage Problem

Table 1: Overview of interpretability issues, data and resource limitations, and modeling challenges associated with various Knowledge Tracing (KT) methodologies. The table details specific challenges faced by methods such as eKG, HiTSKT, DGKT, BKT-LSTM, and KTbench, highlighting the diverse obstacles in achieving effective and interpretable educational models.

KT methodologies, despite their advancements, face several challenges and limitations impacting their interpretability, adaptability, and overall effectiveness in educational contexts. A significant challenge is the reliance on subjective assessments and traditional methods, which often lack reliability and inhibit linking student behaviors to creativity patterns [7]. The opaque nature of deep learning models further complicates the interpretation of learned representations and predictions [37].

As illustrated in Figure 3, the main challenges in knowledge tracing methodologies can be categorized into three primary areas: interpretability issues, data and resource limitations, and modeling challenges. This figure highlights the complexities inherent in educational contexts, underscoring the multifaceted nature of these challenges. Table 1 provides a comprehensive comparison of the interpretability issues, data and resource limitations, and modeling challenges encountered by various Knowledge Tracing methodologies.

Existing benchmarks in KT inadequately compare deep learning and traditional models, particularly in interpretability and performance on large datasets [17]. The computational demands of hierarchical architectures and attention mechanisms further complicate the landscape, often requiring extensive resources [31]. Moreover, the Domain-Generalizable Knowledge Tracing (DGKT) method’s dependence on quality data from source domains presents practical challenges, as such data may not always be accessible [34].

The relevance and appropriateness of AI-retrieved learning materials pose challenges, particularly given the potential for inappropriate content from web resources [5]. Additionally, models like BKT and DKT struggle to effectively capture learning transfer across skills, essential for personalized education [19].

Benchmarking challenges include a lack of user-friendly implementations and insufficient support for replicating various BKT model variants [24]. While the KTBench framework addresses data leakage, its approach may not universally apply to all KT models, necessitating specific adaptations not covered by the masking framework [25].

Addressing the challenges associated with KT methodologies is crucial for enhancing their effectiveness in educational contexts. Developing models that predict learner performance based on historical data while incorporating interpretable feedback mechanisms will ensure actionable insights into student learning processes. This approach facilitates personalized learning experiences tailored to individual knowledge states, ultimately improving educational outcomes. Recent advancements, such as the Context-Aware Attentive Knowledge Tracing (AKT) model, illustrate the potential for integrating attention-based neural networks with cognitive-inspired components to enhance interpretability and adaptability in real-world applications, thereby supporting diverse educational needs [20, 23].

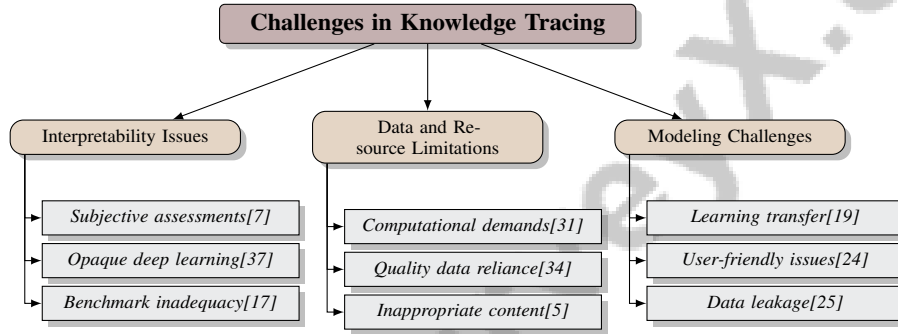


Figure 3: This figure illustrates the main challenges in knowledge tracing methodologies, categorized into interpretability issues, data and resource limitations, and modeling challenges, highlighting the complexities in educational contexts.

4 Cognitive Diagnosis

Cognitive diagnosis is critical in intelligent education systems, aiming to pinpoint individual learner strengths and weaknesses to enable personalized educational experiences. This section explores cognitive diagnosis’s foundational aspects, emphasizing its role in intelligent education systems. By understanding its principles and applications, we can recognize how cognitive diagnosis identifies learner strengths and weaknesses, guiding the creation of tailored educational interventions. The following subsection offers an overview of cognitive diagnosis, detailing its core components and methodologies employed to enhance personalized learning.

4.1 Overview of Cognitive Diagnosis

Cognitive diagnosis is a vital element of intelligent education systems, designed to identify individual learner strengths and weaknesses, thereby facilitating personalized learning. It involves analyzing students’ response patterns and learning behaviors to customize educational content and interventions, optimizing knowledge acquisition and improving educational outcomes. Accurate estimation of students’ cognitive mastery based on responses is crucial in intelligent tutoring systems, as it directly impacts the personalization of learning experiences [24].

The cognitive diagnosis model landscape is diverse, including psychometrics-based and machine learning-based frameworks predicting learner performance on various knowledge components (KCs) from past interactions. For example, BKT-LSTM methods provide psychologically meaningful interpretations and enhance prediction accuracy by capturing learning transfer, essential for personalized learning [19]. These models use insights from learner interactions to tailor educational content to individual profiles, supporting targeted educational strategies.

Innovative frameworks like the Concept-driven Personalized Forgetting (CPF) model offer significant advantages by providing personalized learning experiences and capturing causal relationships between knowledge concepts, thus improving predictive accuracy in knowledge tracing [26]. Moreover, integrating metacognitive skills in cognitive diagnosis highlights their importance in personalized learning, especially in tasks requiring deductive reasoning, as these skills enhance learners' ability to engage with and benefit from tailored educational interventions [38].

Cognitive diagnosis methodologies significantly enhance personalized learning interactions and foster adaptive educational environments by providing nuanced insights into student learning processes. These methodologies, such as Deep Item Response Theory (DIRT) and Collaborative-aware Mixed Exercise Sampling (CMES), leverage advanced data mining techniques and deep learning to analyze student performance and proficiency across various knowledge concepts. By integrating information from both interacted and un-interacted exercises, these approaches enable a comprehensive understanding of student capabilities, leading to more tailored educational experiences. Systems like eDia utilize technology to deliver regular diagnostic feedback, supporting personalized teaching and learning across subjects like reading, mathematics, and science, facilitating a more effective educational framework [39, 40, 41, 42]. As these methodologies evolve, they promise to advance personalized learning experiences by offering nuanced, accurate, and meaningful assessments of learner performance and cognitive mastery.

4.2 Methodologies and Frameworks

Cognitive diagnosis methodologies and frameworks are crucial for identifying and understanding learners' cognitive strengths and weaknesses, facilitating personalized educational interventions. The oversmoothing-resistant cognitive diagnosis framework (ORCDF) stands out by enhancing existing cognitive diagnosis models (CDMs) through response signals during the learning process [43]. This approach addresses oversmoothing in cognitive diagnosis, improving assessment accuracy and reliability.

Deep learning methodologies have significantly advanced cognitive diagnosis frameworks. The Deep Item Response Theory (DIRT) model exemplifies this by integrating deep learning techniques to enhance traditional Item Response Theory (IRT), allowing for diagnosing student latent traits, question discrimination, and difficulty [41]. This integration of machine learning with psychometric approaches enhances the depth and precision of cognitive assessments, offering more nuanced insights into student learning processes.

The Path-Specific Causal Reasoning Framework (PSCRF) combines causal inference with a novel attribute-oriented predictor to achieve fairness-aware cognitive diagnosis [44]. This framework ensures diagnostic processes are accurate and equitable, addressing potential biases in educational assessments and fostering fairer educational environments.

Moreover, incorporating metacognitive skills in cognitive diagnosis is emphasized through methodologies like the Nudge method, which integrates nudges with worked examples to enhance metacognitive awareness. This approach is crucial for identifying when to apply different problem-solving strategies, supporting learners in developing effective learning strategies [38].

The HiTSKT model employs a hierarchical transformer framework that captures both intra-session and inter-session knowledge, allowing for a comprehensive representation of student learning trajectories [31]. This model utilizes two main components: an acquisition consolidation modeling component and a retrieval responding modeling component, enhancing cognitive diagnosis's interpretability and effectiveness.

Recent literature's diverse methodologies and frameworks signify substantial progress in cognitive diagnosis. These advancements leverage innovative techniques such as Deep Item Response Theory (DIRT), which incorporates semantic representations from question texts, and the Collaborative-aware Mixed Exercise Sampling (CMES) framework, utilizing un-interacted exercises to enhance assessment accuracy. Additionally, the Oversmoothing-Resistant Cognitive Diagnosis Framework (ORCDF) addresses oversmoothing challenges in student mastery levels by integrating response signals into the learning process. Collectively, these approaches offer more precise, equitable, and interpretable assessments of student learning processes, facilitating personalized educational strategies and interventions [45, 41, 39, 43]. As these methodologies evolve, they promise to enhance

educational experiences' personalization, ensuring educational environments are responsive to each learner's unique needs.

As shown in Figure 4, this figure illustrates the hierarchical classification of cognitive diagnosis methodologies and frameworks, highlighting deep learning methods, causal and fairness frameworks, and response signal integration approaches. The example of "Cognitive Diagnosis; Methodologies and Frameworks" is effectively illustrated through two distinct studies, each offering unique insights into educational and cognitive frameworks. The first study, titled "Exploring the Adoption of ChatGPT in Educational Settings: A Multi-phase Study," delves into a structured exploration of how ChatGPT can be integrated into educational environments. This study is methodically divided into two phases: the Open phase, which encourages teachers to engage in Experience Sharing and Open Exploration, and the Guided phase, which involves more structured activities such as Model Card Evaluation and Guided Experimentation. This phased approach provides a comprehensive understanding of the potential and challenges of adopting AI technologies like ChatGPT in educational settings. The second example, "Compose des signes," presents a tabular framework that categorizes the components of a sign, offering a detailed breakdown of its significant units. This table serves as a methodological tool for understanding the semiotic elements and their educational implications. Together, these examples showcase diverse methodologies and frameworks in cognitive diagnosis, emphasizing both technological integration and semiotic analysis in educational contexts [46, 47].

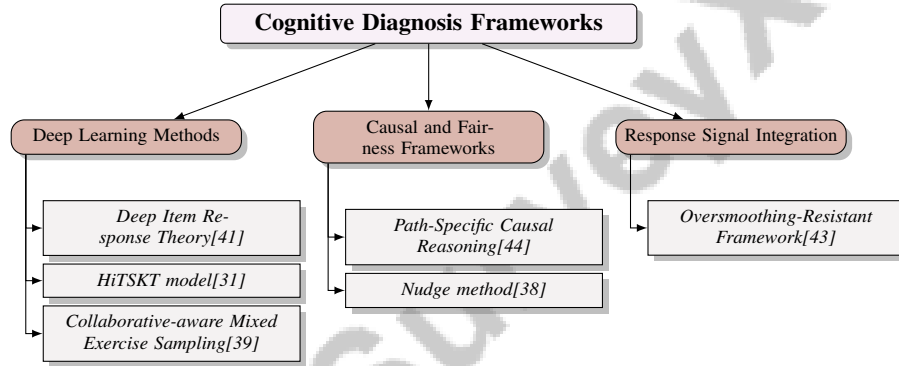


Figure 4: This figure illustrates the hierarchical classification of cognitive diagnosis methodologies and frameworks, highlighting deep learning methods, causal and fairness frameworks, and response signal integration approaches.

4.3 Innovative Approaches in Cognitive Diagnosis

Recent advancements in cognitive diagnosis have introduced innovative methodologies that significantly enhance educational assessments' precision, adaptability, and interpretability. The oversmoothing-resistant cognitive diagnosis framework (ORCDF) exemplifies these innovations by incorporating a novel response graph and a tailored response-aware graph convolution network (RGC). This approach effectively captures crucial response signals, marking a significant advancement over traditional cognitive diagnosis models (CDMs) [43]. By addressing oversmoothing, ORCDF enhances cognitive assessments' accuracy and reliability, providing more nuanced insights into student learning processes.

Deep learning methodologies continue to transform cognitive diagnosis frameworks, as demonstrated by the Deep Item Response Theory (DIRT) model. This model integrates deep learning techniques to enhance traditional Item Response Theory (IRT), offering more accurate and interpretable cognitive diagnosis results, particularly for rare questions [41]. The integration of machine learning with psychometric approaches in DIRT provides deeper insights into student learning behaviors, enabling more targeted and effective educational interventions.

Innovative instructional interventions also play a crucial role in advancing cognitive diagnosis. The study by Abdelshiheed et al. explores the effectiveness of three instructional interventions—Example, Nudge, and Presented—in teaching students effective strategy use [38]. These approaches emphasize the importance of metacognitive skills in personalized learning, particularly in tasks requiring

deductive reasoning. By enhancing learners' metacognitive awareness, these interventions support the development of effective learning strategies, thereby improving educational outcomes.

Innovative approaches in cognitive diagnosis, such as the Deep Item Response Theory (DIRT) framework and the eDia online diagnostic assessment system, highlight the ongoing evolution of educational technologies. These advancements leverage deep learning and semantic analysis to enhance traditional Item Response Theory, enabling a more nuanced understanding of student proficiency and question dynamics. Additionally, eDia offers regular diagnostic feedback across key educational domains—reading, mathematics, and science—through a comprehensive assessment framework that integrates cognitive science research. Together, these technologies provide accurate and interpretable assessments essential for fostering personalized learning experiences tailored to individual student needs [40, 41]. As these methodologies develop, they promise to further transform educational practices by providing deeper insights into student learning processes and enhancing educational environments' adaptability.

5 Computerized Adaptive Testing

5.1 Principles and Frameworks

Computerized Adaptive Testing (CAT) marks a significant leap in educational assessment through adaptive algorithms that tailor the testing experience to individual examinee abilities. At the core of CAT is Item Response Theory (IRT), which guides adaptive item selection based on an individual's ability, dynamically adjusting item difficulty to enhance assessment accuracy [48]. The evolution of CAT frameworks has led to diverse methodologies that improve adaptability and precision. For instance, the Model-Agnostic Adaptive Testing (MAAT) framework selects questions that ensure comprehensive knowledge diagnosis while balancing quality and diversity [49], enhancing both assessment effectiveness and fairness.

BOBCAT, another innovative framework, employs a bilevel optimization approach to optimize response model parameters and question selection, maximizing predictive likelihood [50]. Its refined version, C-BOBCAT, uses a constrained stochastic question selection algorithm to balance test accuracy with item security [51]. CAT research encompasses four main components: Cognitive Diagnostic Model, Selection Algorithm, Question Bank Construction, and Test Control [52]. These components work together to ensure accurate ability estimation, suitable item selection, diverse item pools, and test integrity.

Recent innovations integrate generative AI to create personalized assessments tailored to individual needs [10], enhancing engagement and diagnostic accuracy [53]. The Diffusion Cognitive States Transfer Framework (DCSR) addresses cold-start challenges by using prior diagnostic results from source domains to reconstruct abilities in the target domain [54]. Probabilistic models, including Bayesian and neural networks, further improve CAT adaptability and precision [55]. Despite these advancements, challenges such as rapid guessing patterns remain, threatening score validity and necessitating ongoing research to ensure reliability and fairness [56].

CAT's principles and frameworks, grounded in adaptive algorithms and probabilistic modeling, facilitate personalized assessments, dynamically adjusting test questions based on individual performance. Innovations like the BOBCAT framework enhance accuracy while minimizing test length. However, issues such as high item exposure and test overlap rates pose security challenges. Machine learning integration optimizes components like question bank construction and cognitive diagnosis models, striving for robust, fair, and efficient testing systems across diverse educational contexts [55, 52, 51]. These evolving methodologies promise to enhance the personalization and accuracy of educational assessments, ensuring responsiveness to learners' diverse needs.

As illustrated in Figure 5, this figure illustrates the key principles and frameworks in Computerized Adaptive Testing (CAT), highlighting adaptive algorithms, innovative frameworks, and probabilistic models that enhance personalized assessments. The principles and frameworks of CAT are exemplified through various methodologies depicted in the figures. One scenario features a dynamic interaction between a student and a tutorbot, exploring cellular biology through guided dialogue, underscoring CAT's adaptive nature. Another example illustrates logical reasoning through a flowchart, showing how adaptive testing navigates logical statements and their transformations. These examples

demonstrate the versatility and efficacy of CAT frameworks in providing personalized educational experiences tailored to students' unique learning trajectories [57, 38].

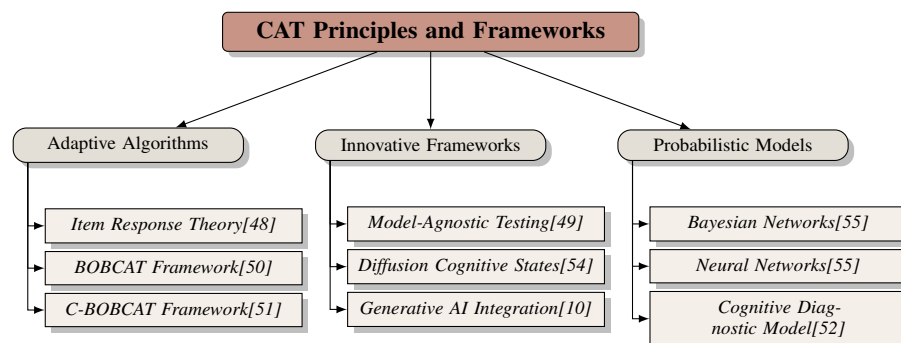


Figure 5: This figure illustrates the key principles and frameworks in Computerized Adaptive Testing (CAT), highlighting adaptive algorithms, innovative frameworks, and probabilistic models that enhance personalized assessments.

5.2 Challenges in CAT Implementation

Implementing Computerized Adaptive Testing (CAT) systems presents challenges affecting adaptability, effectiveness, and reliability. A primary concern is the static nature of existing algorithms, often tailored to specific IRT models, limiting their capacity to capture complex student-question interactions [50]. Traditional methods for mitigating high question exposure and test overlap struggle to adapt to data-driven frameworks like BOBCAT, presenting significant obstacles in transitioning to dynamic CAT environments [51]. Accurate item calibration is essential yet complicated by risks like item overexposure and the difficulty of estimating abilities for extreme performance levels [48]. Managing extensive question banks and accommodating varying examinee proficiencies are critical for maintaining test reliability and fairness [52].

Real-time decision-making complexity in CAT necessitates rapid adjustments based on student performance, further complicated by identifying low-effort responses like rapid guessing patterns, which can bias item parameters and compromise score validity [56]. The requirement for substantial initial data collection limits CAT implementation, as effective student models need significant testing data [55], highlighting the importance of robust data management strategies. Innovative approaches like the Diffusion Cognitive States Transfer Framework (DCSR) integrate diffusion models to unify cross-domain data, enhancing cold-start performance [54]. However, existing CAT systems' reliance on specific cognitive diagnosis models (CDMs) hinders adaptability and scalability when different models are employed [49].

Addressing these challenges is crucial for enhancing CAT functionality, ensuring accurate, reliable, and personalized assessments that cater to diverse learner needs. This involves overcoming issues related to item exposure and test security, integrating advanced techniques like machine learning to optimize question selection and cognitive diagnosis models. Developing flexible, model-agnostic frameworks can further improve assessment quality and diversity, leading to a more comprehensive understanding of each learner's knowledge mastery [52, 48, 51, 49].

5.3 Applications and Case Studies

Computerized Adaptive Testing (CAT) has been widely applied in educational settings, enhancing assessment efficiency and accuracy. The BOBCAT framework exemplifies this by significantly reducing test length while maintaining predictive accuracy [50], valuable in contexts where minimizing test duration without sacrificing quality is essential. The C-BOBCAT framework further enhances test integrity, addressing item exposure and fairness challenges [51]. Comparative studies show adaptive testing achieves comparable precision with fewer items than traditional methods, underscoring its value in resource-efficient educational assessments [48]. Probabilistic models refine CAT adaptability and accuracy through experimental validation [55].

The MAAT framework exemplifies a model-agnostic approach, selecting high-quality and diverse questions, outperforming traditional model-specific CAT methods. This adaptability benefits diverse educational contexts, enabling tailored assessments for varied curricula and student populations [49]. Addressing rapid guessing patterns is facilitated by hierarchical clustering frameworks that categorize examinees based on guessing behaviors, providing insights into how test design features influence such patterns, crucial for developing CAT systems accommodating diverse behaviors and upholding assessment validity [56].

The Diffusion Cognitive States Transfer Framework (DCSR) represents a cutting-edge CAT application, resolving cold-start issues by transferring prior diagnostic results to reconstruct examinees' abilities in the target domain. Experiments on real-world datasets underscore DCSR's effectiveness in enhancing CAT systems' accuracy and adaptability, highlighting its potential for online education platforms [54]. These applications and case studies illustrate CAT's transformative potential in educational assessments, optimizing to meet diverse learner needs through advanced techniques like Bilevel Optimization-Based CAT (BOBCAT) for improved question selection and reduced test length, while addressing security and item exposure challenges. Integrating machine learning into CAT enhances adaptability and provides insights into examinee behavior, such as rapid-guessing patterns, fostering a more tailored and effective testing experience that maintains integrity and efficiency [48, 50, 51, 52, 56].

6 Adaptive Learning Systems

6.1 Integration of Adaptive Algorithms

Integrating adaptive algorithms into learning platforms is pivotal for tailoring education to individual learner needs through dynamic content and feedback adjustments. These algorithms leverage real-time data to continuously refine learning pathways, ensuring responsive and effective educational experiences. The Adaptive Learning Path Navigation (ALPN) system exemplifies this by dynamically adjusting learning paths based on ongoing assessments of students' knowledge states, thereby enhancing educational outcomes [16].

Immediate feedback, as seen in technology-based assessments like eDia, aligns with learners' evolving needs, providing real-time support [40]. Predictive language models for question generation, as discussed by Srivastava et al., match question difficulty to students' knowledge states, further promoting personalized learning [18].

Behavioral analysis incorporated into adaptive algorithms enhances student engagement and performance. The ID-AILE framework allows instructors to customize learning exercises based on pedagogical insights, demonstrating the adaptability of these algorithms in educational contexts [10].

Intelligent tutoring systems, such as those using the Distributed Adaptive Control (DAC) method, tailor learning experiences based on student progress [58]. The ACSP-XAI method enhances learning by providing personalized explanations for adaptive hints, fostering deeper understanding and engagement [59].

Continuous assessment and adjustment of instructional content, as exemplified by the CSCT method, highlight the role of adaptive algorithms in personalizing educational experiences [4]. The pyBKT library modernizes Bayesian Knowledge Tracing models, offering a user-friendly interface and supporting various model extensions, facilitating the integration of adaptive algorithms in learning platforms [24].

6.2 Personalization of Educational Content

Personalizing educational content is fundamental to adaptive learning systems, allowing instructional materials to be tailored to individual learners' needs. This approach utilizes data-driven insights and adaptive algorithms to create customized learning experiences that enhance engagement and improve educational outcomes. The SRES platform exemplifies this personalization by enabling customizable data entry and analysis, aligning educational content with each learner's requirements [60].

Methodologies for personalizing educational content include generating exercises based on learners' estimated knowledge states, desired vocabulary, and specified difficulty levels. This ensures that

educational materials are relevant and appropriately challenging, fostering deeper engagement and understanding [61].

Questionnaires assessing students’ learning styles inform the delivery of customized content, optimizing the learning process by adapting materials accordingly [11]. Such tailored approaches are crucial for creating responsive learning environments that improve educational outcomes.

Modern educational technologies offer personalized, adaptive learning experiences that cater to individual student needs. These systems enhance engagement and improve learning outcomes by continuously adapting content based on real-time assessments of student performance [62]. This dynamic personalization is essential for addressing varied learning needs within diverse educational settings.

The integration of adaptive learning systems signifies a profound transformation in pedagogical approaches, leveraging technologies like AI to tailor educational content to learners’ characteristics, performance metrics, and evolving needs. This shift enhances engagement and effectiveness, moving away from traditional, one-size-fits-all teaching methods to foster a more responsive educational environment [2, 63, 42, 22, 64].

As illustrated in Figure 6, the hierarchical structure of personalized educational content highlights the interplay between adaptive learning systems, various methodologies, and their impact on educational outcomes. These systems provide tailored learning experiences that improve educational outcomes and ensure responsiveness to each learner’s needs.

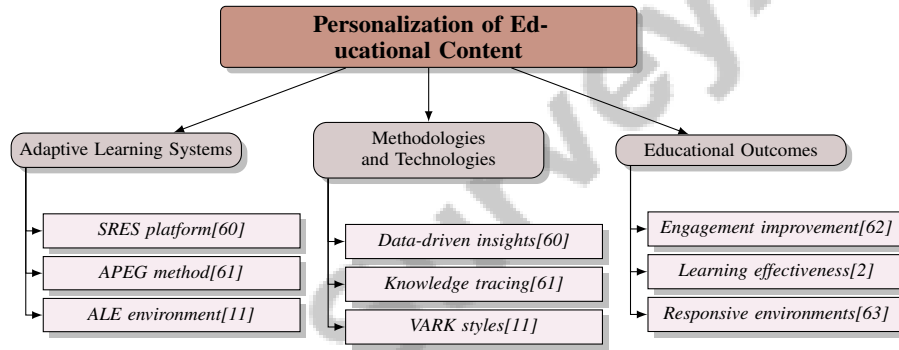


Figure 6: This figure illustrates the hierarchical structure of personalized educational content, highlighting adaptive learning systems, methodologies, and their impact on educational outcomes.

6.3 Frameworks and Models for Adaptive Learning

Benchmark	Size	Domain	Task Format	Metric
DKT-HBCU[65]	352,148	Engineering	Pass/fail Prediction	Accuracy, AUC
DRL-MI[66]	867	Metacognitive Skills	Adaptive Interventions	NLG, Post
ES-KT-24[67]	7,783,466	Educational Game-Based Learning	Knowledge Tracing	AUC, ACC
Yixue[68]	104	Education	Test Performance	Mean Gain Scores
MMA[69]	988	Mathematics	Assessment	Effect size, p-value
Korbit[70]	199	Data Science	Learning Outcomes Assessment	Learning Gains, Normalized Learning Gains
SDP[71]	20,000	Biology	Dialogue Generation	Accuracy, ROUGE
DBE-KT22[72]	167,222	Knowledge Tracing	Answer Prediction	Accuracy, F1-score

Table 2: This table presents a comprehensive overview of various benchmarks utilized in adaptive learning frameworks, detailing their size, domain, task format, and evaluation metrics. These benchmarks are crucial for assessing the performance and adaptability of educational models tailored to personalized learning experiences.

Frameworks and models for adaptive learning are essential for personalizing educational experiences by dynamically adjusting content and instructional strategies to meet individual learner needs. These frameworks leverage data-driven insights and adaptive algorithms to create responsive learning environments that enhance student engagement and performance. Timely, context-specific guidance, such as hints, significantly improves learner performance compared to distractions [58]. Table 2

provides a detailed overview of representative benchmarks used in adaptive learning frameworks, highlighting their significance in personalizing educational experiences through data-driven insights and adaptive algorithms.

Adaptive learning frameworks continuously assess learners' evolving knowledge states, ensuring content remains relevant and appropriately challenging. This dynamic adaptation is facilitated by models that incorporate real-time data analysis to tailor learning paths and instructional materials to individual needs. Systems like the Student Relationship Engagement System (SRES) enhance engagement and outcomes by leveraging data-driven insights to provide personalized feedback and support, allowing educators to adjust strategies based on real-time performance [60, 42, 73, 2].

Predictive models and machine learning enhance educational frameworks' adaptability, facilitating personalized learning experiences tailored to individual student needs. By employing AI and data mining, these frameworks analyze learners' characteristics, preferences, and past performance to optimize the educational process. This results in effective learning pathways, as systems recommend suitable content, design customized curricula, and adjust strategies in real-time based on progress and feedback. Advancements in AI and big data analysis address challenges in personalized education, such as mitigating biases and enhancing motivation, transforming the educational landscape into a dynamic environment [2, 63, 42, 74, 22].

The emphasis on personalization within adaptive learning frameworks is evident in their capacity to adjust instructional strategies to meet diverse learning styles and preferences. This adaptability is facilitated by real-time monitoring of learner characteristics and performance, enabling tailored educational experiences that evolve with each student's learning journey. By leveraging smart technologies, these frameworks accommodate varying competencies and personal development, creating flexible learning environments that enhance engagement and effectiveness [22, 64]. By aligning strategies with individual needs, these systems foster inclusive and effective educational environments supporting diverse learners.

7 Intelligent Tutoring Systems

7.1 Real-Time Feedback and Assessment

Intelligent Tutoring Systems (ITSs) are pivotal in providing real-time feedback and assessments, which are crucial for tailoring educational experiences. The VisTA system, for instance, offers immediate feedback through detailed visualizations of student interactions, enabling educators to refine instructional strategies based on performance, thereby enhancing learning outcomes [75]. The integration of metacognitive strategies within ITSs further enriches learning, with research highlighting that motivated students who are cognizant of their strategies and time management perform better across various domains [76]. This demonstrates the role of ITSs in fostering essential metacognitive skills, contributing to improved educational results.

Authoring tools streamline the design and implementation of ITSs by simplifying the creation of pedagogical and domain models for non-programmer authors, thus enhancing the responsiveness of ITSs to individual student needs [77]. Numerous studies have shown that ITSs significantly improve motivation and learning outcomes compared to traditional educational methods [78]. User satisfaction with systems such as the LP-ITS highlights the importance of user-friendly interfaces and effective learning support in improving educational experiences [79].

Despite these advancements, the effectiveness of ITSs in providing real-time feedback varies, with mixed results reported. While some studies show positive impacts on learning performance, others report no significant effects or even negative outcomes [80]. These findings underscore the need for ongoing research and refinement of ITSs to maximize their potential in enhancing educational outcomes through real-time feedback and assessment.

7.2 Adaptive Feedback and Problem Generation

Adaptive feedback and problem generation within ITSs are vital for personalizing learning experiences to meet learners' evolving needs. The use of diverse knowledge discovery techniques, such as sequential pattern mining and automatic clustering of user actions, enhances system adaptability by extracting richer problem spaces [81, 82, 83, 84, 12]. This multifaceted approach facilitates the

creation of tailored feedback and problems aligned with individual learner profiles, promoting deeper engagement and understanding.

One significant challenge is managing the uncertainty in assessing student knowledge, which complicates the dynamic adaptation of tutoring strategies based on incomplete information [78]. Developing robust algorithms to accurately infer student knowledge states is crucial for generating relevant and appropriately challenging feedback and problems.

Adaptive feedback mechanisms effectively enhance problem-solving skills by providing timely, context-specific guidance. ITSs continuously analyze learner interactions and performance data to adjust the difficulty and type of problems presented. This dynamic adaptation relies on sophisticated models that track evolving knowledge states and classify interaction sequences into groups with similar abilities. Attention mechanisms are used to quantify the relevance of exercises to specific skills, improving the interpretability of predictions. Consequently, ITSs ensure that learning experiences remain aligned with each learner's unique progress, ultimately enhancing educational outcomes [12, 73, 85]. This adaptive approach not only fosters a more engaging learning environment but also optimizes educational results by catering to each student's unique needs.

7.3 Applications in Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITSs) increasingly incorporate cognitive diagnosis methodologies to enhance personalized learning experiences. By assessing individual learner strengths and weaknesses, these systems adapt instructional content to meet specific educational needs, facilitating more accurate student modeling and decision-making capabilities essential for effective personalized education [78].

Recent advancements have explored the use of Large Language Models (LLMs) for feedback generation. While LLMs offer potential for adaptive feedback, they often lack the pedagogical rigor and structured approach inherent in traditional ITS methods. This comparison highlights the importance of maintaining pedagogical integrity while integrating new technologies for adaptive feedback [86]. The challenge lies in balancing the innovative capabilities of LLMs with the established effectiveness of traditional cognitive diagnosis methods in ITSs.

The Apprentice Tutor Builder (ATB) platform exemplifies the potential for scalable personalized education, enabling teachers to create and customize intelligent tutors regardless of technical expertise. This user-friendly platform highlights the potential of ITSs to democratize access to personalized education, facilitating the widespread implementation of cognitive diagnosis methodologies across diverse educational contexts [87].

8 Challenges and Future Directions

8.1 Challenges and Ethical Considerations

The deployment of intelligent education technologies, such as Intelligent Tutoring Systems (ITSs), presents significant challenges and ethical considerations. One major challenge is the high resource demand for developing and implementing ITSs, which can limit their widespread adoption and exacerbate educational inequalities [4]. The complexity of these systems may also hinder students' effective use, necessitating user-friendly designs and comprehensive training programs [88].

Data privacy and security remain critical concerns due to the extensive student data required for training AI models. Algorithmic bias further complicates this landscape, potentially resulting in inequitable treatment of student groups, thus calling for robust ethical and legal frameworks to guide AI implementation in education [2]. Ensuring the reliability of AI-generated educational content and filtering inappropriate material are also pressing issues that current research does not adequately address [5].

Existing methods, such as BKT-LSTM, face limitations due to their reliance on data quality and assumptions about learning transfer mechanisms, underscoring the need for high-quality data and realistic assumptions in educational technology development [19]. The use of synthetic data for evaluations further complicates capturing real-world learning complexities, presenting challenges for the implementation of intelligent education systems [24].

AI's impact on teacher-student relationships introduces additional ethical implications. The integration of AI in educational settings may alter traditional pedagogical dynamics, necessitating adjustments in educators' roles [2]. Teachers may find it challenging to incorporate AI into their practices, especially without adequate familiarity, highlighting the importance of comprehensive training programs [10].

Moreover, the difficulty of teaching metacognitive skills through conventional methods, as noted by Abdelshiheed et al., underscores the need for innovative strategies that empower students to explore diverse problem-solving approaches [38]. Addressing these challenges and ethical considerations is essential to ensure that intelligent education technologies are implemented effectively and equitably, providing personalized educational experiences that are both ethical and impactful.

8.2 Future Directions and Research Opportunities

Future research in adaptive learning and ITSs should focus on enhancing effectiveness, scalability, and adaptability. A promising research direction is the refinement of Concept-driven Personalized Forgetting (CPF) models by examining multi-concept effects and intrinsic relationships among knowledge concepts, which could enhance both scalability and accuracy [26]. Additionally, improving learning transfer detection mechanisms and integrating contextual factors influencing student performance are crucial for advancing knowledge tracing methodologies [19].

Exploring user feedback and suggestions for enhancement in systems like LP-ITS is another vital area. Longitudinal studies evaluating the long-term impacts and applicability of these systems across various subjects could provide valuable insights into their effectiveness and adaptability [79]. Furthermore, combining nudges with presentations to enhance cognitive diagnosis interventions represents an innovative approach to improving educational outcomes [38].

In AI education, developing robust filtering mechanisms and improving content retrieval accuracy are essential to address AI's ethical implications in educational contexts [5]. Future research should also examine the integration of additional personalization parameters and assess the long-term effects of adaptive e-learning on student success [11].

Exploring multi-modal hint generation and incorporating emotional and cultural factors into hint design are promising directions that could enhance ITSs' personalization and adaptability [9]. Prioritizing ethical AI practices and innovative applications is crucial, particularly in addressing the digital divide to ensure inclusivity in education.

As research progresses in adaptive learning and ITSs, these technologies are poised to transform educational practices by effectively addressing diverse learning needs. Leveraging smart learning environments and artificial intelligence can offer personalized educational experiences that adapt in real-time to individual learners' characteristics, performance, and development. This transformation aims to ensure equitable access to tailored learning pathways, thereby enhancing engagement and educational outcomes while navigating ethical challenges related to data privacy and algorithmic bias [22, 2].

9 Conclusion

Intelligent education technologies, including adaptive e-learning systems and intelligent tutoring systems (ITSs), are pivotal in transforming educational experiences by offering personalized learning environments that enhance both learning efficiency and effectiveness. The incorporation of AI techniques into educational frameworks significantly augments the adaptability and personalization of e-learning, resulting in improved learning outcomes and heightened student satisfaction. These advancements enable systems to facilitate personalized and active learning experiences, which are instrumental in boosting educational outcomes and student engagement. The deployment of multi-armed bandit algorithms within ITSs exemplifies their capability to achieve learning outcomes that are on par with or superior to those designed by experts, underscoring the transformative potential of these technologies.

However, the survey also highlights several challenges that need to be addressed to maximize the benefits of AI in education. Key issues include the development of comprehensive student models, enhancing the interpretability of AI solutions, and integrating pedagogical models to improve educational effectiveness. Additionally, ensuring equitable access to resources and addressing ethical

concerns are crucial for the successful implementation of AI and machine learning in educational settings. The exploration of adaptive learning path navigation systems, such as the ALPN system, demonstrates the advantages of personalized learning paths in optimizing educational outcomes. Furthermore, the success of systems like My Math Academy in enhancing early math skills among young children, especially those from disadvantaged backgrounds, illustrates the potential of intelligent education technologies to democratize education and create equitable learning opportunities.

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