THE DESIGN CHARACTERISTICS OF INTELLIGENT TUTORING SYSTEMS FOR STEM EDUCATION

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Abstract:

This paper comprehensively examines intelligent tutoring systems as transformative educational technology that leverages artificial intelligence in creating autonomous adaptive digital learning environments for STEM education. The research articulates a sophisticated four-component framework design for delivering personalized instruction aligned with pedagogical principles. We analyzed advanced probabilistic approaches that enable the dynamic adaptation of learning pathways, content sequencing, and difficulty calibration based on continuous assessment of student knowledge states. Our investigation was extended to personalized feedback mechanisms that monitor problem-solving processes, identify misconceptions, and provide contextual guidance through natural language processing and affective computing techniques. The empirical evidence from diverse STEM disciplines demonstrated that well-designed intelligent tutoring systems significantly outperform traditional instructional methods regarding learning outcomes, knowledge retention, and student engagement. Through a detailed case analysis of exemplary systems, we identified critical design characteristics that contribute to educational effectiveness. The presented findings have significant implications for educational policy, curriculum design, and the development of next-generation intelligent tutoring systems that can effectively address the complex, interdisciplinary nature of contemporary STEM education.

Keywords:

Intelligent Tutoring Systems, STEM, Education.

INTRODUCTION

Personalized learning educational approaches supported by artificial intelligence (i.e., AI) techniques and technology have the potential to address the diverse needs of STEM students (i.e., Science, Technology, Engineering, and Mathematics – STEM), taking into account the interdisciplinary and transdisciplinary nature of educational contents as well as the capabilities and characteristics of individual learners [1]. Intelligent tutoring system (i.e. ITS) represents an educational technology utilized for providing targeted feedback, advice, guidance, and explanations to improve knowledge acquisition, enhance conceptual understanding, develop practical skills, and strengthen the competencies of individual students.

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ITS adaptive characteristics facilitate the dynamic adjustment of difficulty levels and complexity of tasks and materials, ensuring students are intellectually challenged at appropriate personalized levels [2]. The implementation of personalized learning in STEM education via ITS demonstrated significant potential in enhancing the degree of learning outcome achievement, increasing student engagement, and fostering self-regulated learning behaviors [3]. By providing students with customized support and guidance, ITS can effectively bridge knowledge gaps, address conceptual misconceptions, and promote a deeper understanding of the learned material. However, the effectiveness of implementing such systems in educational contexts critically depends on the quality of underlying models, the accuracy of established student profiles, the robustness of algorithms, and alignment with scientifically validated and accepted pedagogical principles [4].

2. INTELLIGENT TUTORING SYSTEMS

Intelligent tutoring systems are a significant educational technology advancement compared to learning management systems, as they utilize machine learning algorithms and AI to provide students with an autonomous, adaptive, and personalized learning environment. Through the application of AI techniques, these systems can dynamically assess students' specific knowledge and skills, provide individualized feedback, and optimize learning pathways to meet the needs of each individual [5]. One of the key advantages is the capacity to continuously assess students' knowledge and adjust instructional content accordingly. By employing machine learning algorithms and educational data mining techniques, these systems can analyze student interactions, responses, and performance patterns to create accurate models of their knowledge and skills. This assessment enables the system to identify gaps in understanding, misconceptions, and areas requiring additional support in real time [6]. Unlike traditional computer-based instruction that relies on pre-programmed feedback, ITS can generate dynamic and contextually relevant feedback tailored to students' specific needs. This feedback can take various forms, such as hints, explanations, examples, and guidelines, which are adapted to the student's current level of understanding and learning style [7]. In addition, ITS can dynamically adjust learning pathways and the sequence of instructional content based on student performance and progress. Through continuous monitoring of student interactions and adaptation of difficulty levels, pace, and the scope of educational materials, personalized learning trajectories can be created to optimize the learning experience. This adaptive sequencing ensures that students are presented with balanced challenges to maintain optimal levels of engagement and motivation [8].

2.1. GOOD PRACTICE EXAMPLES

Research findings demonstrate that the implementation of ITS as educational technology is effective in improving the achievement level of learning outcomes [9], and that they outperform traditional instruction and other derived forms of computer-based instruction (e.g., blended learning) in terms of learning progress and efficiency [10]. These systems show significant positive effects on students' academic achievement across various domains, including STEM [11]. Educational technology integration into various school subjects opened new possibilities for personalized and adaptive learning experiences. In the domain of physics education, the *Andes* ITS provides an interactive learning environment where students solve problems and receive immediate feedback and further guidance. *Andes* uses a Bayesian network to model students' knowledge states and adapts feedback and problem selection based on their individual needs [12]. The *Rimac* is a sophisticated adaptive tutoring platform designed to address persistent challenges in physics education through the implementation of knowledge construction dialogues (i.e., KCDs) [13] integrating an advanced student modeling component that dynamically assesses knowledge based on pretest responses and dialogue interactions. The *ORCCA* intelligent tutor leverages the *CTAT* [14] rule engine to deliver an adaptive chemistry homework experience through a paper-like free-form workspace coupled with dynamic feedback mechanisms [15]. This system provides students with personalized guidance during problem-solving while offering teachers valuable insights into learning challenges, representing a significant advancement over traditional digital assessment methods in chemistry education. *MetaTutor* can be used as a hypermedia-based ITS for learning biology that employs pedagogical agents to deliver adaptive scaffolding through strategic prompts and feedback in the experimental condition while allowing unrestricted exploration without guidance in the control condition [16]. Its technical architecture integrates three resource categories: content materials, experimental protocol parameters, and condition-specific workflows. *StuDiAsE* is an ITS that leverages AI to assess comprehension, evaluate prior knowledge, and deliver personalized educational assistance based on individual learner profiles [17]. The system integrates five core subsystems (monitoring, logging, profiling, modeling, and evaluation) that work cohesively to track and enhance the learning experience in engineering education. The platform provides differentiated interfaces that allow learners to navigate educational materials with adaptive guidance while enabling educators to modify content and assess learning outcomes. *TECH8* is an effective individualized tutoring system for learning mechanical engineering, with the experimental group achieving 55.7% on summative assessments compared to 44.3% in the traditional teaching control group [18]. Its implementation resulted in measurable cognitive advancement, with 23.7% of students progressing to higher cognitive levels. *Active Math* ITS dynamically creates learning materials based on individual student preferences, knowledge levels, and learning objectives by providing interactive exercises, explanations, and examples tailored to the assessed individual needs of students, thus indicating very high efficacy in promoting self-regulated learning and enhancing mathematical problem-solving skills [19]. Based on the *Cognitive Tutor* ITS that has been successfully implemented to provide guidance and feedback to students for complex mathematical problem-solving [20], the *MATHia* ITS was developed for individual mathematics formative and summative assessment and successfully used in primary and secondary education [21]. Currently, the most popular mathematics blended learning intelligent tutoring platform is *ALEKS*. The system presents students with an individualized sequence of questions guiding them through the problem-solving process, consequently requiring very little teacher involvement in the learning process [22]. The advancements in natural language processing (i.e., NLP) and dialogue systems have enabled the development and modernization of conversational ITS that now can engage students in direct interaction using natural language, understand students' questions, provide explanations, and adaptively guide them through the problem-solving process using natural language vocal conversation. This approach enhances students' conceptual understanding and problem-solving abilities in target domains. By simulating the interactive nature of human teaching, conversational ITS creates immersive learning experiences [23] [24]. The development of ITS requires significant investment in terms of expertise, resources, and time. Creating accurate domain models, student models, and pedagogical strategies relies on close collaboration between subject teachers, instructional designers, and researchers in the field of programming, machine learning, and AI.

3. DESIGN CHARACTERISTICS

The ITS architecture constitutes a sophisticated framework comprising four principal components:

1. **Domain Model** – represents the knowledge and skills that the ITS teaches. It encompasses domain-specific expertise, including concepts, facts, procedures, and problem-solving strategies. The domain model serves as the foundation for generating instructional content, assessment elements, and formulating feedback [25]. Various knowledge representation techniques are employed to structure domain knowledge in digitally readable formats, such as ontologies, semantic networks, and rules. For instance, the domain model of mathematics education ITS incorporates mathematical concepts, theorems, problem-solving strategies, and common misconceptions. The domain model facilitates the generation of contextualized explanations and examples based on learner interactions with the application. It enables the system to evaluate student problem-solving steps, identify errors or misconceptions, and provide appropriate feedback to guide the learner toward successful mastery of the material [26].
2. **Student Model** – constitutes a critical component of ITS in education as it records current knowledge, preferences, and other relevant learner characteristics. This model represents a dynamic representation of the student's understanding and progress within the domain, enabling the system to adequately adapt instructional strategies and content delivery [27]. The student model is continuously updated based on learner interactions with the system (e.g., responses to questions, problem-solving attempts, and navigation choices). To establish a model of student knowledge, techniques such as overlay modelling, perturbation modelling, and knowledge tracing are utilized. For example, language learning ITS tracks learners' proficiency levels across different linguistic skills (grammar, vocabulary, pronunciation) and adjusts the difficulty level and content of lessons accordingly [28]. With an accurate representation of student strengths and weaknesses, the ITS can provide valid personalized recommendations, exercises, and feedback.

3. **Tutoring Model** – is designed for pedagogical decision-making and implementing instructional strategies employed by the ITS. This model determines how the system interacts with the learner by selecting appropriate instructional actions based on the student's knowledge level, learning objectives, and interaction context. The tutoring model employs various pedagogical theories, strategies, and instructional design principles to optimize the learning experience, such as adaptive feedback techniques, providing hints, and selecting appropriate problems to monitor student progress and promote understanding of the learned material. The model also incorporates techniques from the domains of teaching methodology and cognitive psychology to enhance instructional efficiency, e.g., content repetition, interleaving, and retrieval practice aimed at effective knowledge transfer and long-term retention of learned material [29].
4. **User Interface** – represents the communication channel between the learner and the ITS that manages learning content, processes student inputs, and generates feedback and guidance. The user interface design should be intuitive, interactive, and visually appealing to enhance student motivation and engagement [30]. Navigation should be clear, the layout consistent, and content comprehensible and accessible to easily accommodate diverse student needs and preferences [31]. For example, the user interface of programming learning ITS must possess functions such as a code editor, debugger, and visualization tools. Feedback on potential syntax errors or logical inconsistencies must be provided in real time. The ultimate goal of a proficient user interface is to facilitate seamless interaction between the learner and the ITS, preferably enabling natural language dialogue, multimodal input, and adaptive content presentation. Advances in NLP and dialogue systems have enabled the development of conversational systems that can engage learners in interactive discussions, answer questions, and provide explanations [32].

Through the application of AI techniques and educational theories, ITS revolutionized the approach to teaching and learning in the digital age. However, their successful implementation and further development necessitate a further multidisciplinary approach, involving experts from education, psychology, and computer science, to ensure that the systems are pedagogically valid, user-friendly, and effective in achieving desired learning outcomes.

3.1. ADAPTIVE LEARNING PATHWAYS

Adaptive learning pathways constitute a pivotal characteristic of ITS that facilitates personalized instruction tailored to individual student needs. Through continuous assessment of student knowledge and performance, the system dynamically adjusts the sequence, difficulty, and pace of learning content to create an optimal learning experience. Adaptivity is fundamental in educational applications as it ensures students receive content appropriate to their current level of understanding and promotes efficient learning [33]. In the development of adaptive learning pathways, Bayesian Knowledge Tracing (i.e. BKT) is predominantly employed as a probabilistic model that evaluates student knowledge based on their performance on tasks and assessments [34]. This model represents student knowledge as a set of binary variables, indicating, for example, whether a skill has been mastered or not. The probability of skill mastery is updated following each student interaction, taking into account factors such as response accuracy and number of attempts. By inferring student knowledge states, BKT enables ITS to adapt the selection and sequence of learning tasks to optimize student knowledge and skill acquisition [35]. An alternative to the aforementioned approach is Item Response Theory (i.e. IRT), a psychometric approach that models the relationship between students' ability and their responses to assessment items [36]. The model estimates students' latent abilities based on their performance on a set of items with known difficulty and discrimination parameters, thus enabling the ITS to select items that are most informative for assessing student abilities and to adjust content difficulty based on their expertise. This adaptivity ensures that students are appropriately challenged, preventing boredom or frustration [37]. Adaptive learning pathways are implemented through various algorithms and decision rules that determine the optimal sequence and pace of instruction for each student. These algorithms consider factors such as student prior knowledge, learning objectives, cognitive abilities, and affective states. For instance, Knowledge Space Theory (i.e. KST) is an approach that represents domain knowledge as a network of prerequisites and dependencies [38]. Intelligent tutoring systems based on this theory can generate personalized learning pathways by identifying the most efficient route through the knowledge space based on the student's current knowledge and desired learning objectives [39]. Given that adaptive learning pathways are not limited solely to content selection and sequencing but also encompass the adaptation of instructional strategies and feedback, it is possible to utilize the expertise reversal effect, which suggests that instructional support effective for novices may be detrimental for more advanced students [40]. Similarly, adaptive feedback can be created based on student misconceptions, errors, and problem-solving strategies, offering personalized explanations and hints to promote understanding [41]. The efficacy of adaptive learning pathways in ITS has been demonstrated in various educational technology applications. For example, the *Cognitive Tutor Algebra* system, which utilizes BKT for skill modeling and adaptive task selection, has shown significant improvements in students' abilities to solve mathematical problems compared to traditional instruction [42]. Similarly, the *ALEKS* intelligent system employs KST to generate adaptive learning pathways, enhancing student achievement and engagement, also in mathematics [43]. One of the primary challenges in the broader ITS implementation is the necessity of defining precise and comprehensive domain models that encompass complex relationships between skills and concepts and achieving an appropriate balance between system control and student autonomy in adaptive learning pathways. Although the system can optimize the learning experience based on data-driven decisions, it is important to consider student preferences as well as self-regulated learning goals and strategies. Providing students with a degree of control over their learning pathways and enabling exploratory learning enhances student motivation and engagement [44].

3.2. PERSONALIZED FEEDBACK AND GUIDANCE

Personalized feedback is a critical component of each ITS designed to support the development of problem-solving skills and foster a deeper understanding of instructional content. By continuously monitoring student problem-solving steps and their comparison with expert models or predefined solution pathways, the system can identify errors, misconceptions, or suboptimal strategies. This real-time analysis enables the generation of immediate feedback that highlights specific errors or challenges faced by the student. For example, programming education ITS can identify and indicate syntax errors, logical inconsistencies, or inefficient code structures in real time, guiding the student toward correct solutions [45]. ITS employs various techniques to provide personalized instructions and explanations that support students' problem-solving processes. When a student encounters difficulty while solving a specific task, the system can display steps that gradually reveal information or suggest problem-solving strategies. This scaffolded learning approach encourages students to think critically and arrive at solutions independently [16]. Additionally, the ITS can generate explanations of specific concepts and provide justifications for certain problem-solving choices or connect the current problem with previously acquired knowledge and skills. Such targeted elaborations help students develop a deeper understanding of the instructional content and enhance their metacognitive abilities [46]. NLP techniques have significantly enhanced the interactive and conversational capabilities of ITS, enabling it to “understand” and interpret student inputs (e.g., questions and explanations) in natural human language. This simulation of human tutoring conversation facilitates more natural interaction. Beyond providing feedback on problem-solving steps and conceptual understanding, ITS can adapt its feedback based on students' affective states. Affective computing allows the system to detect and respond to students' emotional states, such as frustration, confusion, or boredom, which can significantly impact learning outcomes and motivation. By analyzing students' facial expressions, eye movements, or various physiological signals, the ITS can infer their affective states and accordingly adjust the feedback. For instance, if a student appears frustrated or disinterested, the system can provide encouraging feedback, offer additional support, or suggest alternative learning strategies to maintain motivation and promote persistence [47]. Designing effective feedback and guidance in ITS requires achieving a balance between providing sufficient support and promoting student autonomy; specifically, the timing, specificity, and adaptivity of feedback must be carefully balanced to achieve learning outcomes [48]. Domain models that enable the generation of contextually relevant feedback must be precisely and comprehensively defined. For example, incorporating NLP capabilities into ITS feedback generation requires the use of advanced information technologies and linguistic knowledge, as human language is highly complex and often ambiguous.

4. CONCLUSION

Integrating ITS into existing educational systems and curricula requires careful planning, teacher training, and continuous support to ensure their effective adoption and utilization. To address these challenges and further advance the ITS field, a new direction of development involves the integration of data mining techniques and learning analytics to improve student modeling and adaptation. By utilizing the large amounts of educational data generated by ITS, data mining algorithms can reveal patterns and details that enable more precise student modeling. Learning analytics are used in visualizing and interpreting learning patterns, facilitating data-driven decision-making by teachers and researchers, and optimizing the learning experience [49]. Another alternative research direction involves incorporating Open Learner Models (i.e., OLMs) into ITS to promote metacognition and self-regulated learning. This approach provides students with access to their models, allowing them to review results, and reflect on their identified knowledge, progress, and learning strategies. By making the student model transparent and interactive, OLMs can foster self-awareness, goal-setting, and the development of self-monitoring skills. Research indicates that these models enhance student motivation, engagement, and achievement in learning environments supported by ITS [50]. A third direction is exploring the application of affective computing techniques to create “emotional” ITS, as they are focused on recognizing, interpreting, and generating emotions in human-computer interactions. This makes ITS able to detect and respond to students' emotional states, such as frustration, confusion, or boredom. Emotionally intelligent tutoring systems can provide personalized support and adaptations that consider students' affective needs, thereby improving their engagement, motivation, and learning outcome achievement [51].

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