Chapter 2
Intelligent Tutoring Systems

2.1 What Is Meant by an Intelligent Tutoring System?

Educational software with an artificial intelligence component is an intelligent tutoring or intelligent system. The software monitors student activity, modifying its comments and offering contextualized suggestions. Based on a student's performance and other cognitive and noncognitive characteristics, the software can predict strengths and shortcomings and recommend extra practice (Shute and Zapata-Rivera 2010).

In the early 1970s, Hartley and Sleeman (Hartley and Sleeman 1973) presented requirements brief for intelligent systems. Figure 2.1 provides a conceptual view of ITS components.

- Knowledge of the learner (student model).
- Knowledge of the domain (expert model).
- Knowledge of teaching strategies (pedagogical model).

Now, we will take a quick look at the three components of an intelligent system: the student, expert, and pedagogical models. While there have been improvements in all three categories, it is interesting that this simple list has remained unchanged for decades. There has been a dramatic transition from early, knowledge-free, computer-assisted instructional methods to those that rely on all computer-resident knowledge. Also, unlike simulations, intelligent computer-based systems can accurately identify where students are doing wrong and adjust their lessons accordingly. Intelligent systems are also congruent with the characteristics and objectives of formative assessment.

An intelligent system's primary method of imparting knowledge to a student is through the learner's application of that knowledge to solve carefully chosen or custom-tailored challenges. The student model is a repository for and source of up-to-date information on the student. First, the algorithm might see how much the

M. Kurni et al., *A Beginner's Guide to Introduce Artificial Intelligence in Teaching and Learning*, https://doi.org/10.1007/978-3-031-32653-0_2

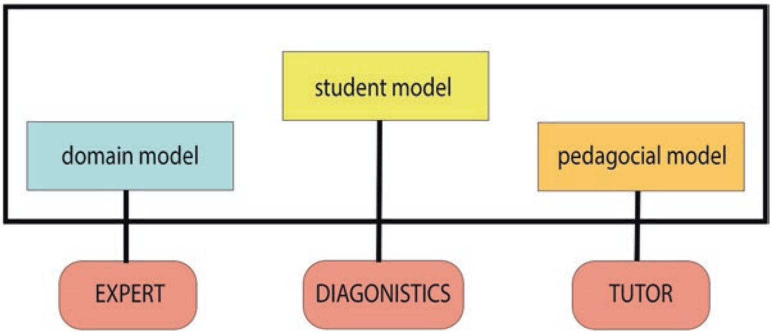

Fig. 2.1 ITS components. (Source: EduTech Wiki (2010))

student already understands. The system should take into account the student's specific learning objectives. The domain-expert model is a representation of this knowledge. The last step is for the system to choose the next unit of information to provide and the method through which it will be presented (e.g., an assessment task or an instructional element). The pedagogical model is what makes this possible (or tutor).

After considering all these factors, the system chooses or develops a problem, either figuring out a solution (using the domain-expert model) or retrieving a premade answer. The intelligent system analyzes the student's model and compares the results to its solution to arrive at a diagnosis.

The system provides input depending on several factors, including how long it has been since the student received feedback, whether or not the student has already received the same or similar advice, and so on. The program selects or generates a new problem, and the process begins again with the student's model being updated.

Brief History of ITSs Intelligent tutoring systems (ITSs) can be traced back to the 1960s and 1970s, namely, to the advent of Intelligent Computer-Assisted Learning (ICAI) in 1970 (Roybi Robot _ Medium 2020). Since then, the effectiveness of these systems has steadily risen, and their widespread adoption across the industry has soared. The name "Intelligent Tutoring Systems" gained traction in the academic community in 1982, 12 years later (Roybi Robot _ Medium 2020). The first ITS conference was conducted in 1988, and since then, many research institutions have been researching ITS (Iii et al. 2020).

Traditional Intelligent Systems The primary purpose of assessments is to better instruction and education for students. A key goal of formative assessment is to facilitate student learning by establishing the learner as an integral, resourceful, and self-reflective member of the educational community. Individualized instruction and real-world practice are commonplace in formative assessment-based classrooms.

The lack of standardization and less rigorous approach to formative assessment than summative assessment is a fundamental flaw in this paradigm (Shute and Zapata-Rivera 2010). As a result, the quality of the evaluation resources and results may suffer. Given that a student's diagnostic accuracy depends on the validity and reliability of the assessment data and that the diagnosis informs instructional support, a weak link in the chain (i.e., valid and reliable assessment data) would negatively impact the effectiveness of that support. That is to say, the quality of the data used to build the student model is crucial to how well an intelligent system performs its task (i.e., the inferences about what the student knows and can do).

A wealth of information about students can be mined by traditional intelligent systems using formative assessment (Shute and Zapata-Rivera 2010). All interactions between students and the system in the past and present are recorded as evidence, which can take on various forms and granularities. Thus, there are issues with effectively modeling student knowledge within such diverse environments, which is on top of the lack of standardization of methods for formative assessment in traditional intelligent systems. Regardless of the chosen measurement method, this presents several psychometric issues (e.g., modeling a wide range of learner characteristics, such as talents and aptitudes).

Enhanced Intelligent Systems Present-day intelligent systems are mostly confined to research establishments. However, the demand for accountability (e.g., standards and norm-referenced examinations) grows when these systems are brought into the classroom. Learning systems used in a controlled setting are not subject to the same stringent regulations (such as accountability requirements) as those used in a real classroom. This disconnection from actual classrooms helps explain why their designs have not focused heavily on summative assessment methods and, to some extent, why they have not been widely embraced.

Summative evaluations have the specific goal of holding students accountable. They provide an excellent example of the student's knowledge and are reliable. Schools frequently employ summative assessments because of national and international accountability mandates and interests. For instance, the No Child Left Behind (NCLB) act of 2001 was primarily responsible for the increased focus on summative examinations in the United States (Shute and Zapata-Rivera 2010). The Programme for International Student Assessment (PISA) also compares student accomplishments across countries internationally. Psychometric models (e.g., Rasch, item-response theory) developed by the measurement community offer reliable and valid assessment information, often presented as a single measure of ability at a given point in time for any individual student (Shute and Zapata-Rivera 2010). However, you cannot do much with these numbers to shape your education. Moreover, teachers often complain that the time spent on testing distracts from otherwise productive classroom activities.

First introduced recently, intelligent systems can potentially improve assessment and classroom instruction. Snow and Mandinach (1991), writing more than a decade ago, advocated for establishing guidelines to design reliable and beneficial forms of instructional-assessment systems. Systematically, these systems have (Shute and Zapata-Rivera 2010):

- Active participation of educators at every stage of development.
- Instructional and assessment interactions based on a cognitive model.
- Explicit connections to state standards and standardized state tests.

The web-based cognitive tutors that Anderson, Koedinger, and their colleagues at Carnegie Mellon University created are a great example of a successfully deployed intelligent system (Anderson et al. 1995). They developed a system that combines rigorous evaluation with instructional support; they term it an assistant, a development of the cognitive tutor model. For evaluation and education, aids use authentic (i.e., publicized) questions from the (Massachusetts comprehensive assessment system) MCAS state tests.

2.2 Need for an Intelligent Tutoring System

Why do researchers spend time and money developing intelligent computer-based tutors? Two primary drivers appear to be at play (Nwana 1990):

- *Research needs:* Learning more about the procedures that make an educational engagement successful from a purely academic standpoint is essential. ITS research is at the crossroads of cognitive psychology, artificial intelligence, and education, making it a fertile ground for testing many theories from each field. One of the main draws for John Anderson, a distinguished psychologist from Carnegie Mellon, was the opportunity to test his theories on learning at the University of Pittsburgh (Anderson 1987). As a result, developing an ITS will aid in developing more robust theories of cognition.
- *Practical needs:* On a more practical level, ITSs enable numerous outcomes that would be difficult or impossible to get with human teachers due to cost and accessibility. The ability to provide personalized instruction is a crucial benefit of ITSs. There is widespread agreement that individualized instruction is the most productive teaching method in most cases. In a study comparing private tutoring with classroom instruction of cartography and probability, Bloom (1984) showed that, despite all students spending the same amount of time learning the topics, 98% of those with private tutors outperformed the typical classroom student. When comparing the time it took for students to reach the same level of competency, Anderson et al. (1984, 1985) found that the private tutor had a four-to-one advantage. The many benefits of private tutoring have been lost as our educational systems have shifted toward group instruction. By assigning one ITS to each student in a class, a school may provide this type of tutoring while reaping the benefits of a classroom setting. The ITS could give the student real-time comments on their performance. Since tutoring is most successful when responding directly to students' needs, this personalized and timely feedback is vital.

2.3 How Are Intelligence Tutoring Systems Influencing Education?

Especially in digital settings, intelligent tutoring systems can significantly affect students' learning abilities. Digital apps give students tailored learning experiences via deep-learning algorithms, although ITSs have yet to be widely implemented in educational contexts.

Using machine learning algorithms to model student learning empowers educators to create AI-free digital curricula (Roybi Robot _ Medium 2020). This technology's value lies in the fact that it can be tailored to meet the needs of any individual user, from the most seasoned professor to the youngest student. If this is achieved, ITSs will make great strides toward adoption in the K-12 and higher education settings.

Humans are complex and call for individualized approaches to learning, which is a significant obstacle in educating children of all ages. This is at odds with the standardized testing and one-size-fits-all philosophy that underpins many educational institutions today (Roybi Robot _ Medium 2020). Because of the existing model's inability to identify and highlight learners' unique strengths, some students have been left behind. Many of the issues plaguing the education system today might be alleviated with the help of ITSs, which have the potential to play a pivotal role in the sector's future.

Artificial intelligence (AI) and related systems, such as intelligent tutoring systems (ITSs), directly respond to this problem by fostering an educational setting where students' unique strengths and interests are emphasized more. ITSs are only one example of the revolutionary new tools based on AI technology that will soon be a standard feature in today's classrooms and online learning spaces. Many countries are transitioning in this direction because experts agree it is the best approach to education (Roybi Robot _ Medium 2020).

2.4 Benefits of Intelligent Tutoring Systems

Intelligent tutoring systems can have the following benefits (Briggs 2014):

- Available at all hours, including late at night, the night before a test.
- Help teachers and programmers improve their methods by giving them access to real-time.
- Reduce the dependence on human resources.
- Enable students to demonstrate their understanding by having them describe what they already know and then respond appropriately based on their level of comprehension.
- Facilitate the development of tailored curricula by teachers.

- Produce better results on standardized tests than more conventional methods, especially for students who are learning English as a second language, who are from low-income families, or who have specific educational needs.
- Allow for instantaneous yes/no feedback, individualized task selection, on-demand hints, and reinforcement of mastery learning.

2.5 Examples of Intelligent Tutoring Systems

In academia, there is no shortage of intelligent tutoring systems. There is no way to compile a complete list, but some of the more significant ones (Briggs 2014) (Walsh 2019) are included below:

- *The Cognitive Tutor:* The Cognitive Tutor was developed at Carnegie Mellon University and is now used in a wide range of mathematics and science classes across the United States, from high school geometry and algebra to the university's Genetics Cognitive Tutor, which helps students gain a better grasp of gene interaction and regulation.
- *The Andes Physics Tutor and Writing Pal:* Designed by academics at Arizona State University, these tools help students succeed in beginning physics courses and improve their writing skills. Essay writing practice, game-based practice sessions, and feedback to encourage developing writers are all included in Writing Pal, which has undergone thorough testing with secondary students.
- *ASSISTments:* Worcester Polytechnic Institute has created a free online tutoring program called ASSISTments.
- *Knewton:* Knewton is a privately produced platform that offers intelligent instructors for the GMAT, LSAT, and SAT, as well as individualized support for grades K-12 and above. The platform means instantaneous responses for students, while for teachers and curriculum developers, it means access to valuable analytics.
- *Mathematics Tutor:* Using fractions, decimals, and percentages, the Mathematics Tutor guides students through problem-solving exercises. A tutor monitors a student's success rate while working on problems and then gives them additional problems to solve that are at an acceptable difficulty level for their current level. Student ability and an expected completion time for the problem determine the next set of problems to be presented to the student.
- *eTeacher:* eTeacher is an AI-powered tutor that provides personalized e-learning assistance. Tracking how well college students do in their online classes creates personalized profiles for each one. The student's results are analyzed by eTeacher, and a unique action plan is proposed to help the student succeed academically.
- *ZOSMAT:* ZOSMAT is an innovative platform that considers every factor of a functional classroom. It is designed to be there for students at every step of their education. A student-centered ITS like this one keeps track of a learner's development and adapts to individual needs. ZOSMAT can be utilized for self-paced study or with a human instructor in a classroom setting.

- *REALP:* To improve students' reading comprehension, REALP provides reader-specific lexical practice and personalized practice with relevant, authentic reading resources from around the Internet. When a learner uses the system, a personalized model of their data is immediately created. The reading is followed by exercises designed to help the student practice the new vocabulary words he or she has just learned.
- *CIRCSlM Tutor:* At the Illinois Institute of Technology, first-year medical students employ an innovative tutoring technology called CIRCSIM Tutor. It teaches students how to control their blood pressure through Socratic dialogue based on real-world scenarios.
- *Why2-Atlas:* Why2-Atlas is an Intelligent Tutoring System (ITS) that evaluates how well students explain fundamental physics concepts. The algorithm can infer their opinions and turn their explanations into a proof by reading the students' explanatory paragraphs. By doing so, misconceptions and gaps in understanding are brought to light. The software prompts the learner to revise their writing after pointing up errors. Before reaching a final result, the process may undergo several iterations.
- *SmartTutor:* To better assist its continuing education students, the University of Hong Kong (HKU) created a SmartTutor. By fusing Internet tools, educational research, and AI, SmartTutor can assist students. SmartTutor's goal is to meet the demand for individualized instruction identified in HKU's adult education program.
- *AutoTutor:* AutoTutor mimics a human tutor's speech patterns and pedagogical tactics to help college students learn fundamental computer skills like hardware, operating systems, and the Internet in an introductory computer literacy course. AutoTutor aims to interpret the learner's keyboard input and generate conversational motions with feedback, reminders, correction, and tips.
- *ActiveMath:* ActiveMath is an online math program that adjusts to each user's progress. The system aims to facilitate self-directed, lifelong education and enhance online education.
- *Cardiac Tutor:* To better equip medical professionals to treat cardiac patients, the Cardiac Tutor was developed. The tutor presents students with cardiac issues, and in subsequent steps, they must choose among possible treatments. Learners can tailor their experience with Cardiac Tutor's hints, audio tips, and constructive criticism. Students receive a comprehensive report after each simulation, regardless of whether they can help the patients.
- *CODES*: Try the Cooperative Music Prototype Design on the web for collaborative music prototyping. It was made to help anybody, especially those who are not music experts, create musical pieces in a prototypical way. CODES relies heavily on communication and collaboration between its composers and their collaborators. Trying out, playing with, and tweaking musical prototypes is easy.
- *Mathia:* Mathia was created at Carnegie Mellon University by cognitive scientists to help provide each student with a positive math learning experience while giving you the real-time feedback and assessments you need to know exactly where your students stand and where they are headed.

- *Alta:* Knewton's product Alta is a suite of adaptive learning tools designed specifically for higher education (knewton.com/what-is-alta/). It seeks to integrate various topics in mathematics, economics, and chemistry. In their classroom instruction, Alta uses a mastery learning strategy based on item response theory.
- *Area9 Lyceum (area9lyceum.com):* This innovative method re-creates educational content and distributes it via their platform, which incorporates "constant self-assessment" (the user's confidence in their responses is used as part of the adaptive process). This seems to be a common approach in business and professional education.
- *Toppr:* This program, developed in India, provides individualized instruction in various scholastic levels and fields of study. Toppr employs machine learning to customize the learning experience for each student by analyzing their responses to questions and adjusting the presentation's pace.
- *Adil:* As an intelligent tutoring system (ITS), Adil (Automatic Debugger in Learning System) was developed as a software system for knowledge-based automated debugging. It helps novice C programmers learn the fundamentals of debugging their code. It helps pinpoint malfunctions and provides context for the relevant software. Adil is a debugger that can identify and explain those defects in the program's logic when given a specification and a program with no syntax errors. Without any glitches, it can explain what the code does. The Conceiver, an autonomous program understanding system, served as the inspiration for Adil.
- *ADIS:* To further assist educators in imparting knowledge of data structures such as linked lists, stacks, queues, trees, and graphs, the Java-based, web-enabled intelligent tutoring system (ITS) *ADIS* (Animated Data Structure Intelligent Tutoring System) was created. Because it has been written entirely in Java, ADIS can be used independently of any specific platform and distributed via the Internet. Graphical representations of data structures can be viewed in ADIS, and the program also supports graphical modifications of the resulting data structure. Students can visually grasp data structures' fundamental algorithms (insertion, deletion, etc.) through a tutorial mode with integrated exercises.
- *BITS:* The Bayesian Intelligent Tutoring System (*BITS*) is a web-based intelligent tutoring system (WITS) for computer programming. The BITS smart system makes judgments using a Bayesian network. By analyzing the student's goals and interests, BITS can recommend learning targets and purposes and create effective learning sequences. A student, for instance, may be interested in (the adding operation), and not all of the background information that came before it. For example, if you want to learn about addition, BITS can figure out what you already know and provide the links for these concepts in the proper learning order.
- *DCG:* The primary concept behind *DCG* (Dynamic Courseware Generation), an ITS built on an ITS-shell architecture, is using artificial intelligence (AI) planning tools to establish the nature of the course material to be taught. The curriculum is created on the fly by the system. Each student's study plan is developed with specific learning objectives in mind. The primary benefit of this method is that it makes it feasible to automatically design adaptive Computer Assisted

Learning (CAL) courses aimed toward a specific learning outcome, which is not possible with the current state of the art in CAL software.

- *DM-Tutor:* Decision-Making Tutor, or DM-Tutor, is an ITS (Intelligent Tutoring System) built into the MIS (Management Information System) used in oil palm plantation management. As such, DM-Tutor is designed to teach its customers how to put plantation analysis theory into practice. Using actual plantation conditions and operational data, DM-Tutor aims to deliver scenario-based instruction.
- *JITS:* The JITS (Java Intelligent Tutoring System) research project aims to create a programming tutor tailored to students enrolled in their first college or university-level JavaTM programming course. This work is a proof-of-concept for a future effort to model the application domain of a specific subset of the JavaTM programming language. A fully developed JavaTM intelligent tutoring system should give students a learning environment with much interaction, which should help them do better in school. The finished prototype should prove the idea.
- *KERMIT:* KERMIT (Knowledge-Based Entity Relationship Modelling Intelligent Tutoring) is an ITS that helps with entity-relationship (ER) modeling based on knowledge. The process of designing a database is not well-defined, and while there is an expected result, it is not clear how to get there. Constraint-based modeling has thus far been implemented in SQL-Tutor, a tutor for the database language, and in a system for instructing students in proper punctuation and capitalization (CAPIT). With its VB implementation, KERMIT can work with the entity-relationship data model.
- *MBITS:* MBITS, short for "Multicriteria Bayesian Intelligent Tutoring System," is a WITS (Web-based Intelligent Tutoring System) powered by Bayesian Networks (BN). The goal of MBITS was to help students have a firmer grasp of the course's overarching concept through the multicriteria approach to comparing and contrasting various data collection methods and problem-solving. It is a web app that's fun to play around with and simple to use.
- *ML-Tutor:* ML-Tutor (Machine Learning Tutor) is a web-based client-server solution incorporating Internet technology and instructional hypertext. The user interface for this system is built into the client software, which is executed in a web browser. The system's server is run only in response to a request from a client. The client records information sent to the server over the Internet. The server's machine learning component (MLC) analyzes the data and sends the results to the client.
- *NORMIT:* NORMIT (Normalization Intelligent Tutor) is the ITS students can count on when normalizing databases. NORMIT is a web-based learning management system featuring architecture and methods for managing large classes. It is written in the open-source language Allegro Common Lisp (ACL) and uses the freely available web server AllegroServe to showcase ACL's network programming as an adaptable server. With NORMIT, ICTG has created the first constraint-based tutor to instruct a procedural skill.
- *SQL-Tutor:* SQL-Tutor (Structured Query Language) Tutor is a form of ITS that focuses on teaching and studying SQL. It uses a CBM (limited) modeling strat-

egy developed by the students. The language of implementation is Allegro Common Lisp (ACL).

- *SQLT-Web:* To teach and learn the SQL query language for databases, SQLT-Web (SQL-Tutor (Structured Query Language Tutor) on the Web) is a knowledge-based, software-based intelligent tutoring system (ITS) that is independent of the original SQL-Tutor.
- *TEx-Sys:* TEx-Sys (Tutor-Expert System) is a learning management system (LMS) that provides a copyright shell for constructing an intelligent tutoring system (ITS) in a user-selected domain of expertise. It was first developed as an online system (PR) using semantic networks, frames, and production rules.
- *WITS:* A combination of an intelligent tutoring system (ITS) and an expert system (ES), WITS (Whole-Course Intelligent Tutoring System) may instruct a student in a course on solid-state electronics without the need for a human instructor. It has the potential to provide a stimulating setting for education, complete with immediate, actionable feedback to keep students engaged.

2.6 Intelligent Tutoring Systems and Online Learning

ITS has evolved from early-era physics problem-solving methods that involved human-machine communication, such as Why-2 Atlas (Vanlehn et al. 2002), which supported ITS. ITS's fast transition from the lab to practical use is unexpected and promising. Automatic Speech Recognition (ASR) and Natural Language Processing (NLP) approaches are used by downloadable software and online services like Carnegie Speech and Duolingo to identify language problems and assist users with correction (Vanlehn et al. 2002). American high schools have adopted tutoring programs like the Carnegie Cognitive Tutor to improve pupils' grasp of mathematics. Various other ITS are designed to teach subjects, including geography, circuitry, medical diagnosis, computing, programming, genetics, chemistry, and more. When a student gets stuck on a math problem, a cognitive tutor will provide helpful ideas in the style of a natural teacher. The instructor provides detailed and contextual feedback based on the sought hint and the delivered answer.

The use of applications in academia is expanding. SHERLOCK (Lesgold et al. 1988), an intelligent tutoring system, is currently being utilized to instruct Air Force technicians in identifying and fixing electrical system problems in aircraft. Moreover, the Information Sciences Institute at the University of Southern California has created more sophisticated avatar-based training programs to educate service members on how to interact with people from various cultural backgrounds. Individualized mastery learning and issue sequencing are made possible by new methods for personalized coaching, such as Bayesian Knowledge Tracing (Yudelson et al. 2013).

Surprisingly, MOOCs and other types of online education at all levels have taken off, with participants using resources like Wikipedia and Khan Academy and relying on learning management systems that incorporate synchronous and asynchronous education and adaptive learning technologies (Grosz et al. 2016). The Educational Testing Service and Pearson, among others, have been working on automatic NLP assessment tools to co-grade essays on standardized tests since the late 1990s. EdX, Coursera, and Udacity, three of the most prominent providers of massive open online courses (MOOCs), use natural language processing (NLP), machine learning (ML), and crowdsourcing methods to evaluate students' answers to short-answer and essay questions and coding projects. Accelerating growth is also being seen in online education infrastructures that facilitate postgraduate professional education and lifelong learning. Professionals and those switching careers benefit significantly from these systems since they reduce the necessity for personal connection. They may not be the first to adopt systems and applications bolstered by AI, but they will do so once the systems and apps have been thoroughly vetted and proven.

One may argue that artificial intelligence is the magic ingredient that has allowed professors in higher education to teach classes with student enrollment in the tens of thousands. Automated generation of questions, including those designed to assess vocabulary, wh (who/what/when/where/why) questions, and multiple choice questions using electronic resources like WordNet, Wikipedia, and online ontologies, is also possible, allowing for continuous testing of large classes of students (Grosz et al. 2016). Online education will rapidly embrace these methods as the number of available courses increases. The AI community has quickly learned a great deal, but the long-term effects of these technologies on the education system are yet unknown.

2.7 Development of an Intelligent Tutoring System

There are four iterative phases involved (Briggs 2014) in creating an intelligent tutoring system:

- Needs assessment.
- Cognitive task analysis.
- Initial tutor implementation.
- Evaluation.

Needs Assessment Step one in any instructional design is to do a learner analysis and consult with relevant subject matter experts and the teacher (s). The purpose is to define learning outcomes and create a broad curriculum framework.

- The probability that a learner will succeed in solving a particular problem.
- Time required to achieve the desired performance.
- How likely is it that the learner will make use of what they have learned.

The cost-effectiveness of the interface is another crucial factor that needs to be examined. Because both educators and students will be utilizing the system, evaluating factors such as familiarity with the subject matter at enrollment is essential.

Cognitive Task Analysis The second stage involves building a reliable computational model of the relevant expertise for solving the challenge. The main approaches to creating a domain model include the following:

- Conducting Interviews with domain experts.
- Conducting "think aloud" protocol studies with domain experts.
- Conducting "think aloud" studies with novices.
- Studying teaching and learning behavior.

By using the "think aloud" approach, instructors have students express out loud their thought processes as they work through common types of challenges. Information on solving problems can be gleaned from watching online tutoring sessions, which can be applied to developing more conversational or interactive tutoring systems.

Initial Tutor Implementation This phase involves establishing a conducive context for problem-solving, which will allow for and strengthen the student's engagement in the learning process. Evaluation tasks are carried out in the last phase of any software development process.

Evaluation

1. Feasibility tests to verify essential functionality and educational efficacy.
2. Formative evaluations of the system under development.
3. Parameter analyses that probe the usefulness of system features.
4. Summative evaluations of the tutor's impact on the student's progress in terms of their learning pace and level of achievement.

Effective intelligent tutoring systems should, in theory:

- Facilitate the student's progress toward a workable solution.
- Create a production set that represents student competence.
- Make sure you explain the reasoning behind your solution to the problem.
- Facilitate learning in the context of problem-solving.
- Improve students' ability to think abstractly about addressing problems.
- Minimize working memory load.
- Incorporate timely feedback on errors.
- Fine-tune the instruction's grain size to the student's progress.
- Help learners get closer and closer to their goal skill.

AI's Role in Developing Intelligent Tutoring Systems AI, along with other forms of disruptive technology, has been a driving force behind the development of EdTech and other intelligent learning approaches. It has recently expanded its scope to include the required field of intelligent tutoring. As their name suggests, intelligent tutoring systems are intelligent computer systems that can efficiently offer instructions to learners and provide a feedback system with minimal human participation.

In May 2020, researchers from Carnegie Mellon University developed a system that enables a teacher to educate computer systems with the assistance of AI and construct intelligent tutoring systems. This system also allows the instructor to create intelligent tutoring systems. Ken Koedinger, a professor of human-computer interaction psychology at CMU, is quoted in a report by the university as saying that initially, it took almost 200 h of development for each hour of tutored instruction because they programmed production rules by hand. However, later on, they used a shortcut method that reduced the number of hours to approximately 40–50. Despite this, it is a time-consuming process because there are many different kinds of difficulties and directions. The newly developed intelligent tutoring system based on AI is not slow to pick up new information and can be programmed for a 30-min session in 30 min. In work published on the same topic, it is said that to construct intelligent tutoring systems, the authors trained simulated learners using an innovative interaction design. It does this by utilizing machine learning and developing a teaching interface for machine learning applications that is simple and straightforward. Using these computer tools, educators can model multiple approaches to a problem and correct their responses if they get them wrong. Using AI and ML, the system can learn to generalize and solve problems within a domain without being explicitly taught how to do so (EG 2021).

The advent of pandemics has amplified the impact of artificial intelligence on the educational system. The capacity of intelligent tutoring systems to tailor their lessons to the specific needs of each student has garnered them much praise. The traditional education system, which operates on a one-size-fits-all premise and assumes that everyone needs the same amount of learning time and attention, will likely be disrupted by AI-powered intelligent tutoring systems. Intelligent tutoring systems are built with the understanding that every single learner is unique. It can be altered to fit the requirements of each given class. Artificial intelligence (AI)-based tutoring systems do not need to be programmed and can be easily adapted to fit different pedagogical styles.

CMU's method is helpful in various contexts, including the instruction of English grammar, chemistry, and algebra; to test its limits, the university has conducted experiments with challenges as varied as multi-column addition. In the report, Ken Koedinger explains that machine learning models often experience temporary setbacks like students. As a result, it has the potential to shed light on the relative difficulty of each method and lesson for educators. In recent years, artificial intelligence (AI) technology has come to dominate several markets, including one that is very important: education. Artificial intelligence is helping to democratize access to top-notch education by facilitating the rapid and painless creation of intelligent tutoring systems.

2.8 Limitations of Intelligent Tutoring Systems

Many critics are eager to point out the limitations of intelligent tutoring programs. Here are some of the system's blows (Briggs 2014):

- Measuring the effectiveness of ITS initiatives is challenging.
- However, frequent feedback and hint sequences do not improve students' deep learning.
- The system does not prompt children with questions that help explain their actions.
- Justifying the use of ITSs by an administrative team may prove challenging.
- Evaluating an intelligent tutoring system can be time-consuming, expensive, and complex.
- Human instructors are superior to machines in providing contextually relevant conversation and feedback.
- Currently, human instructors are better able to read and respond to their students' emotions.

The effectiveness of a sophisticated, intelligent teaching system relies on thorough testing to guarantee its claims. Either during the design and early development of the system to detect flaws and suggest improvements (formative) or after the system has been completed to support formal claims about the construction, behavior, or consequences associated with a completed system, an evaluation will be conducted (summative). Different approaches to evaluation are discussed in the published literature, but no universal standards have been established (Briggs 2014).

There have been hiccups, but efforts to improve education have moved forward. Currently, features are being developed that will enable intelligent instructors to interpret facial expressions and other signals of emotion to engage their students. Since feelings can be communicated in various ways, this presents several challenges. However, these concepts have given rise to a new subfield of ITS known as affective tutoring systems (ATS) (Briggs 2014) that aims to deal with precisely these kinds of difficulties.

Gaze Tutor (Briggs 2014) is an example of an ITS that considers students' emotions by monitoring their eye movements to ascertain if they are engaged in the material or distracted.

2.9 The Future of Intelligent Tutoring Systems

ITSs are a way to observe AIED (AI in Education) in action as a cutting-edge educational tool that has the potential to support academics. ITSs can provide a workable answer to the different barriers that students may have while trying to contact a human instructor (cost, location, time, etc.) (Cameron 2021). In certain aspects, ITSs might be a valuable addition to academic support programs that provide student accommodations. Additionally, ITSs have demonstrated efficacy in supporting students with clearly defined, solution-driven courses and in offering students unique learning opportunities that go beyond what is generally provided by conventional approaches (Cameron 2021). Teachers will still be necessary for the classroom, but ITSs will supplement them in various ways to improve instructional strategies and engage students.

2.10 Conclusion

The term "intelligent tutoring system" (ITS) refers to a suite of programs designed to help students with their coursework by employing AI-based techniques. These tools aim to facilitate and enhance instruction in a particular knowledge domain while honoring each student's uniqueness. They make it possible to examine students' current knowledge and the methods employed to expand and rectify it. In this chapter, we examine intelligent tutoring systems (ITS) from the perspective of how they might be used effectively in today's educational frameworks.

References

Anderson, J. R. (1987). Production systems, learning, and tutoring. In *Self-Modifying Production Systems: Models of Learning and Development* (pp. 437–458.).

Anderson, J. R., Boyle, C. F., & Reiser, B. J. (1984). Intelligent Tutoring Systems. *Science*, *228*(4698), 456–462. https://doi.org/10.1126/science.228.4698.456

Anderson, J. R., Boyle, C. F., & Yost, G. (1985). The Geometry Tutor. *9th International Joint Conference on Artificial Intelligence*, 1–7.

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive Tutors: Lessons Learned. *Journal of the Learning Sciences*, *4*(2), 167–207. https://doi.org/10.1207/s15327809jls0402

Bloom, B. S. (1984). The 2 Sigma Problem: the search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher*, *13*(6), 4–16.

Briggs, S. (2014). *Intelligent Tutoring Systems – Can They Work For You?* InformED. https://www.opencolleges.edu.au/informed/other/intelligent-tutoring-systems/

Cameron, B. (2021). *Intelligent Tutoring Systems: Connecting AI and Education*. Crowdmark. https://crowdmark.com/intelligent-tutoring-systems-connecting-ai-and-education/

EduTech Wiki. (2010). *Intelligent tutoring system*. EduTech Wiki. https://edutechwiki.unige.ch/en/Intelligent_tutoring_system

EG, M. (2021). *Developing Intelligent Tutoring Systems and AI's Role*. Analytics Insight. https://www.analyticsinsight.net/developing-intelligent-tutoring-systems-and-ais-role/

Grosz, B. J., Altman, R., Horvitz, E., Mackworth, A., Tom Mitchell, D., & Mulligan, Y. S. (2016). *Artificial intelligence and life in 2030*.

Hartley, J. R., & Sleeman, D. H. (1973). Towards More Intelligent Teaching Systems. *International Journal of Man-Machine Studies*, *5*, 215–236.

Iii, D. W., Harpstead, E., & Koedinger, K. R. (2020). An Interaction Design for Machine Teaching to Develop AI Tutors. *CHI Conference on Human Factors in Computing Systems*, 1–11. https://doi.org/10.1145/3313831.3376226

Lesgold, A., Lajoie, S., Bunzo, M., & Eggan, G. (1988). SHERLOCK: A Coached Practice Environment for an Electronics Troubleshooting Job. In *Computer-Assisted Instruction and Intelligent Tutoring Systems: Shared Goals and Complementary Approaches* (Issue January, pp. 1–30).

Nwana, H. S. (1990). Intelligent Tutoring Systems: an overview. *Artificial Intelligence Review*, *4*, 251–277.

Roybi Robot _ Medium. (2020). *How Intelligent Tutoring Systems are Changing Education*. Medium.Com. https://medium.com/@roybirobot/how-intelligent-tutoring-systems-are-changing-education-d60327e54dfb

Shute, V. J., & Zapata-Rivera, D. (2010). Intelligent Systems. In *Third Edition of the International Encyclopedia of Education* (pp. 75–80). Elsevier.

Snow, R. E., & Mandinach, E. B. (1991). *Integrating assessment and instruction: A research and development agenda*.

Vanlehn, K., Jordan, P. W., Rosé, C. P., Bhembe, D., Böttner, M., Gaydos, A., Makatchev, M., Pappuswamy, U., Ringenberg, M. A., Roque, A., Siler, S., & Srivastava, R. (2002). The Architecture of Why2-Atlas: A Coach for Qualitative Physics Essay Writing. *6th International Conference on Intelligent Tutoring Systems*, *June*, 159–167. https://doi.org/10.1007/3-540-47987-2

Walsh, K. (2019). *Intelligent Tutoring Systems (a Decades-old Application of AI in Education)*. EmergingEdTech. https://www.emergingedtech.com/2019/12/intelligent-tutoring-systems-application-of-ai-in-education/

Yudelson, M. V., Koedinger, K. R., & Gordon, G. J. (2013). Individualized Bayesian Knowledge Tracing Models. *16th International Conference on Artificial Intelligence in Education*, 1–10.