Metacognitive Tutoring Systems (MTS)

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INTRODUCTION

Intelligent Tutoring Systems (ITSs) are computational learning support systems based on the use of artificial intelligence. They incorporate computational models from the cognitive sciences, learning sciences, computational linguistics, artificial intelligence, and mathematics (Graesser et al. 2012). The term ITS was first used by Sleeman and Brown (1982) as the title of an overview on Intelligent Computer-Aided Instruction (ICAI), which at the beginning were focused mainly on the subject matter (Barr and Feigenbaum, 1982). Shute and Psotka (1994) stated that an ITS must possess knowledge of a domain, knowledge of the learner, and knowledge of teaching strategies, and that they should have accurately diagnose students' structures, skills and/or styles and then adapt instruction accordingly. ITSs were more recently defined by Graesser et al. (2018) as "computer learning environments that help students master knowledge and skills by implementing intelligent algorithms that adapt to students at a fine-grained level and that instantiate complex principles of learning" (p. 246).

According to Corbett et al. (1997) ITSs are modeled on human tutors, but the analogy should not be taken literally due to the high standard that it implies, as well as the need for students to think ITSs as tools they are employing, rather than as taskmasters, and the need for teachers to think ITSs as tools that can free their time to interact individually with students.

Cognition, affect, and metacognition are the domains on which ITSs are usually focused. The first refers to information processing, the second to emotions and feelings during the learning process, and the third to the knowledge and regulation of cognition. It is common for ITS to focus on only one of these domains, although there are systems such as Wayang Outpost that focus on all three domains (Arroyo et al., 2014).

Intelligent Tutoring Systems (ITSs) for cognitive support, i.e., support with information processing, have been notable since the 1980s under the name Cognitive Tutors (Anderson et al., 1995). Affect-oriented ITSs, i.e., emotional, and sentimental support, have gained great importance since the beginning of the 21st century under the name Affective Tutoring Systems (Sarrafzadeh et al., 2008). On the other hand, there have been studies on ITSs that focus on metacognition since the 1980s as the work of Kawamura et al. (1986), Conati (2009) referred to these systems as "intelligent tutors that scaffold metacognition". The term Metacognitive Tutoring Systems (MTS) has been used in the work of Joyner and Goel (2015), and Pelta (2015), however, this term is less popular than Cognitive Tutors or Affective Tutoring Systems.

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Since the term ITSs was coined, it was stated that control should be balanced between the student and the system (Sleeman and Brown (1982). This is analyzed from the paradigms of adaptivity and adaptability in which the former gives more control to the ITS, while the latter gives more control to the learner (Dascalu et al., 2017).

In this chapter, we introduce and discuss the meaning of metacognition, the architecture of ITSs, and how the ITSs could support metacognition, then we mention some journals and conferences about these systems, describe four successful application examples, and present some recommendations and future research directions. We also propose those systems to be grouped under the term Metacognitive Tutoring Systems (MTS).

BACKGROUND

Literature Review: Beyond Cognition, Metacognition

The term metacognition was proposed by Flavell (1976) and has a double meaning: first, it is both the knowledge we have about our own cognitive processes and, second, the active monitoring and regulation of those processes.

A cognitive process is a process of information transfer that typically takes place to connect multiple informational inputs related to perception, memory, learning, emotion, intentionality, self-representation, rationality, and decision-making (Newen, 2015). Being aware of these processes means knowing how this information is processed and which conditions and strategies are favorable or unfavorable. In this way, we can use this knowledge to our advantage, making these processes more effective. Supporting and fostering metacognition skills is important within the educational context because it allows students to become autonomous learners, to take an active role in its learning process. It also fosters their critical thinking and helps them to expand what has been learned into other contexts and different tasks.

Paris et al. (1984) highlighted the importance of two fundamental aspects of metacognition that follow the same line as Flavell (1976): knowledge about cognition and self-directed thinking. The first aspect includes declarative knowledge (propositional knowledge that refers to "knowing what"), procedural knowledge (refers to knowing how to carry out various actions) and conditional knowledge (involves knowing when and why different strategies can be used to achieve different purposes). The second aspect was also called executive function, which is made tangible through the activities of evaluation (measured against a standard such as effort or ease), planning (allocation of time and effort to optimize the solution of the task), and regulation (follow one's chosen plan and to monitor its effectiveness).

Two major metacognitive components were then distinguished, in accordance with the two aspects pointed out by Paris et al. (1984). The first one was knowledge about cognition and the second one was regulation of cognition (Brown, 1987; Jacobs & Paris, 1987). Schraw (1994) described the first component as stable information about the learner's strengths and weaknesses, knowledge about strategies and about when and where to use them, which goes hand in hand with the declarative, procedural, and conditional knowledge of Paris et al. (1984). The second component was linked to the actions of planning, monitoring, and correcting one's own performance.

Subsequently, Schraw and Moshman (1995) took up the model of declarative knowledge (knowledge about oneself as a learner and about what factors influence one's performance), procedural knowledge (knowledge about the execution of procedural skills) and conditional knowledge (knowing when and why to apply various cognitive actions) as subprocesses of cognition knowledge. However, with respect to the regulation of cognition, they took two subprocesses from Schraw (1994): planning (selection of appropriate strategies and allocation of resources that affect performance) and monitoring (one's awareness of comprehension and task performance) and added evaluation (assessing the products and processes of regulating one's own learning). Table 1 shows the subcomponents and subprocesses of metacognition according to Schraw and Moshman (1995).

Learning With Intelligent Tutoring Systems

The use of computers as teaching aids began in the mid-20th century, during the 1950s. These systems, known as Computer Assisted Instruction (CAI), consisted of a fixed sequence of content units that included questions that were immediately evaluated to see if they were answered correctly or not. Its main disadvantage was that it was assumed that students should not make mistakes, and consequently they should all follow the same route (Nwana, 1990).

Table 1. Subcomponents and subprocesses of metacognition according to Schraw and Moshman.

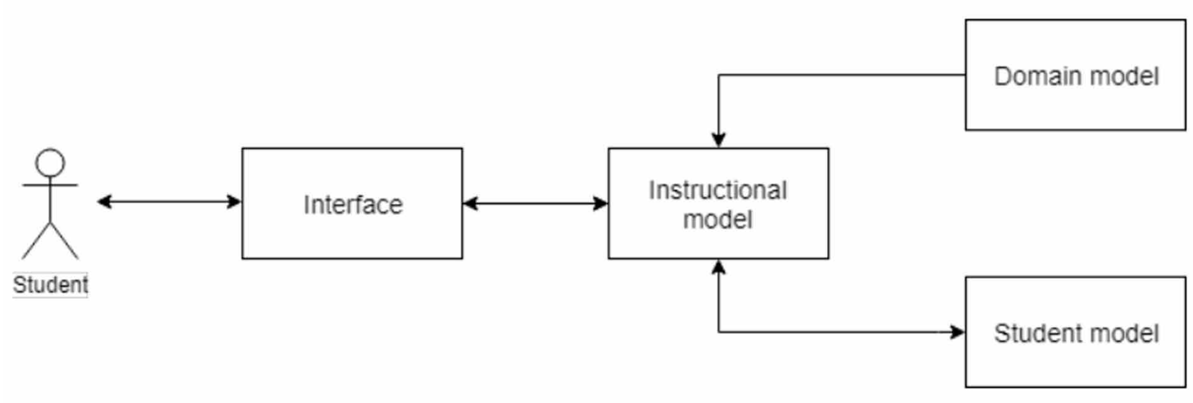
Subcomponents	Subprocesses	Description
Knowledge of cognition	Declarative knowledge	Knowledge about oneself as a learner and about what factors influence one's performance.
	Procedural knowledge	Knowledge about the execution of procedural skills.
	Conditional knowledge	Knowing when and why to apply various cognitive actions.
Regulation of cognition	Planning	Selection of appropriate strategies and allocation of resources that affect performance.
	Monitoring	One's awareness of comprehension and task performance.
	Evaluation	Appraising the products and regulatory processes of one's learning.

During the 1960's, an attempt was made to solve the previous problems through the so-called "branching programs", capable of selecting subsequent content units according to the students' answers (Crowder, 1959). Another solution were the "generative systems" that allowed the automatic creation of problems in fields such as arithmetic (Uhr, 1969). The limitations that still existed were due to the computational system's lack of knowledge about the users and the subjects being taught and the barriers to the use of natural language (Nwana, 1990).

Carbonell (1970) argued that such limitations could not be solved without the use of artificial intelligence techniques. This argument led to the incorporation of AI into CAI systems during the following decades, with the result of the emergence of Intelligent Computer-Aided Instruction (ICAI) (Barr and Feigenbaum, 1982). These systems began to incorporate elements such as semantic networks (Carbonell, 1970), rule-based reasoning (Stevens & Collins, 1977), and natural language processing (Brown et al., 1982).

In the 1980s, the term Intelligent Tutor System (ITS) began to be used to designate ICAI systems based on an architecture with four main models. First, the domain, knowledge, or expert model, that contains knowledge about the subjects that must be learned. Second, the student model, which stores the student's knowledge status. Third, the instructional, teacher, or pedagogical model, that defines the teaching and tutorial strategies. Finally, the interface, that allows interaction between the user and the computational system. (Wenger, 1986). Fig. 1 shows the architecture of an ITS with its four models.

Figure 1. Architecture of an Intelligent Tutoring System.



Domain, Knowledge, or Expert Model

This module stores the system knowledge about the subject matter. One difference between CAI and ITSs is that in CAI the expertise is contained in prestored presentation blocks that are displayed to the students under certain conditions, while in ITSs the domain module contains a representation of knowledge that provides the system with a dynamic form. In most cases, the domain module in ITSs has a double function: on the one hand, it acts as the source for the knowledge to be presented, and on the other hand, it serves as a standard for evaluating the student's performance. (Wenger, 1986). The systematic review about characteristics, applications, and evaluation methods used in ITSs conducted by Mousavinasab et al. (2018) reveals that the most common field in the domain model of ITSs was computer science (37.73%), followed by health and mathematics (15.09% each). In addition, other identified fields were language (7.54%), physics (5.66%), and artificial intelligence (3.77%).

Student Model

This model includes all the aspects of the students' behavior and knowledge that have an impact on their performance and learning. Another difference between CAI and ITSs is that the student model in ITSs can include a distinct evaluation of the mastery of each element of the knowledge to be acquired, in contrast with the overall measures of performance used in CAI (Wenger, 1986). According to Mousavinasab et al. (2018) the most common component in student models is knowledge level (62.26%), while the second one is learning performance (52.83%), and the third one is behavior in the learning path (41.50%). The rest of the characteristics that were identified include learning preferences (15.09%), learning styles (9.43%), cognitive factors (5.66%), emotional factors (3.77%), cultural factors (1.88%), and intelligence level (1.88%). It is worth mentioning that these characteristics are mainly in the cognitive domain and that the metacognitive domain is not mentioned at all.

Instructional, Teacher, or Pedagogical Model

This model decides which pedagogical knowledge is made explicit, and such decisions can be derived from the interactions of specialized rules or from similar knowledge structures. Another function of this model is to determine the degrees of control possessed by the system and the learner. Some systems monitor the students very closely, adapting their actions to them, but never relinquishing control according to the adaptivity paradigm. Another approach is present in mixed-initiative dialogues, where the student and the system share the control (Wenger, 1986). As reported by Mousavinasab et al. (2018), some artificial intelligence techniques used as part of the instructional model are rule-based reasoning (33.96%), data mining techniques (22.64%), bayesian-based techniques (20.75%), intelligent agents (15.09%), fuzzy-based techniques (13.20%), natural language processing (11.32%), artificial neural networks (9.43%), and case-based reasoning (3.73%).

Interface

The interface of an ITS processes the flow of communication in and out, i.e., it translates in both directions, between the system's internal representation and a language understandable to the student. Because this model is the final form in which a system presents itself, such qualities as ease of use and attractiveness are crucial to the acceptance of the system (Wenger, 1986). According to the results of Mousavinasab et al. (2018), ITSs translate their internal representation into adaptive feedback, hints, or recommendations (52.83%), learner's evaluation (45.28%), learning material or content (41.50%), adaptive learning path navigation (28.30%), and adaptive tests and exercises (5.66%).

INTELLIGENT TUTORING SYSTEMS AND METACOGNITION

ITSs might support metacognition to the extent that they can use the adaptive potential of their algorithms to encourage students to improve the way they plan, monitor, and self-assess their own learning. The students are then enabled to know themselves as learners and to identify which learning strategies to use and when to use them. In this regard, Intelligent Tutoring Systems could take two paths: on the one hand, ITSs can offer adaptability, allowing learners to take control of the difficulty levels and other preferences; and, on the other hand, when ITSs are focused on adaptivity, the system itself monitors the student and takes control of the learning pace (Dascalu et al., 2017). Both adaptability and a mixed approach can foster learners' metacognition, since systems closer to adaptivity leave important decisions up to the system, and although the learner may learn effectively, it does not foster knowledge and regulation of his or her cognition. According to Merril et al. (1992) students can be expected to learn more by correcting their mistakes when they can play a greater role in fixing them.

The following are four successful examples of MTSs:

MetaTutor

A hypermedia-based teaches participants about the human circulatory system. MetaTutor uses four virtual agents: Gavin the Guide, Pam the Planner, Sam the Strategizer and Mary the Monitor. Their functions are, respectively, steer participants through the environment, help students set sub-goals and activate their prior knowledge, help participants engage in cognitive learning strategies, and assist participants with their use of metacognitive monitoring processes. Such functions include tasks as judging how well they understand the content they are reading (judgment of learning), how familiar the material seems (feeling of knowing), how relevant the material is to their active sub-goal (content evaluation), and if they have read enough material to proceed to the next sub-goal (monitoring progress towards goals). It allows collecting a series of multichannel data: log files (mouse clicks, and keyboard input), eye tracking, videos of facial expressions, and electrodermal activity.

Metatutor was used to investigate students' evidence scores of emotions while they engaged in cognitive and metacognitive self-regulated learning processes. Sixty-five students majoring in Education participated in the study. During learning, the system recorded log files of all interactions including mouse clicks and keyboard entries, as well as video recordings to detect facial expressions of emotions through facial recognition software. The log files were used to investigate the sequences of engaging in cognitive and metacognitive processes during learning. Results indicated that mean evidence score of surprise negatively predicted the accuracy of making a metacognitive judgment, and mean evidence score of frustration positively predicted the accuracy of taking notes, a cognitive learning strategy. These results have implications for understanding the beneficial role of negative emotions during learning with advanced learning technologies (Taub et al., 2019).

APLUS (Artificial Peer Learning Environment Using SimStudent)

An online learning environment where students learn to solve equations by teaching an agent called SimStudent that interactively learns skills to solve problems through guided problem solving. SimStudent is a machine learning agent that interactively learns skills to solve problems through guided problem solving. APLUS includes a teacher agent called Mr. Williams that provides students with help on how to appropriately tutor SimStudent for the following five metacognitive skills of tutoring: selecting an appropriate next problem to teach to SimStudent, administering the quiz at an appropriate time, reviewing resources, providing feedback, and demonstrating a step on which SimStudent gets stuck.

The effect of metacognitive scaffolding for learning by teaching was investigated and compared against learning by being tutored. Three versions of APLUS were created for this purpose: one that provides metacognitive scaffolding, one that provides cognitive scaffolding, and another one that provides both. Two school studies were conducted with a total of 444 6th through 8th grade students. The results show that learning by teaching a teachable agent with metacognitive scaffolding on how to teach is effective for students with various levels of prior competency, and it is as effective as learning by being tutored across all levels of students' prior competency (Matsuda et al., 2020).

Amplifire

An e-learning platform that uses artificial intelligence to provide corrective and metacognitive feedback, and/or deliver self-regulatory guidance for learners. It has helped typical and non-traditional students perform better on exams, trained call-center employees to provide better customer service and helped helicopter pilots earn recertification.

Amplifire begins by asking questions in a variety of formats like multiple-choice, select-all, matching, and interactive. When answering the questions, learners indicate their confidence in their responses, making them consider the question more carefully and improving their memory for the material. After submitting a response, learners receive immediate feedback on whether their response was correct, and metacognitive feedback guides learners to understand whether they have been under- or overconfident. Corrective feedback for a given item is provided after a delay, which enhances learning. Amplifire's AI optimizes this delay by considering information collected about the learner, the content being learned, and the learner's response to that item.

Several thousand nurses were trained in Amplifire at a large healthcare system in attempting to reduce the rate of two types of hospital-acquired infection; the result was a 48% reduction in central- line-associated bloodstream infections and a 32% reduction in catheter-associated urinary-tract infections (Hays et al., 2019).

MILA-Tutoring (MILA-T)

A learning environment with five pedagogical agents (the observer, the guide, the critic, the mentor, and the interviewer) that teaches teams of students the process of inquiry-driven modeling about ecology. Through MILA-T, teams of students write their description of the phenomenon they are trying to describe; then, they propose one or more hypotheses that become one or more models of how the phenomenon might occur. Teams may also use simulations, take notes, and dismiss models they no longer wish to consider. Within the model, the students construct explanations and provide evidence about their hypothesis. On the other hand, each pedagogical agent has a specific role to support the students: the observer monitors the activity of the team and constructs assessments of the team's ability, the guide anticipates the questions that the team want to ask and provide answers, the critic provides teams with feedback on the current quality of their model, the mentor monitors for weaknesses in the team's modeling and provide the team with unsolicited feedback, and the interviewer asks the team questions that they ought to learn to ask themselves.

MILA–T was deployed in 7th grade life science classrooms and two teachers participated, each with five classes. The students were broken into teams of two or three, and for each teacher two classes were assigned to a control group and three classes were assigned to an experimental group. Fifty teams of students from the experimental group used MILA–T and they were better than the control group in either their propensity to revise their models over time or their propensity to take notes (Joyner & Goel, 2015).

It is worth mentioning that of the four examples the one that relies more heavily on the adaptability paradigm is APLUS because it is the student who teaches the ITS how to solve the problems. In the remaining three examples the ITS and the learner have a shared-control that involves a mixed approach between adaptability and adaptivity. Table 2 shows a comparison of the four MTSs described above.

Table 2. Comparison of four successful examples of MTS.

Feature	MetaTutor	APLUS	Amplifire	MILA-T
Metacognitive skills	-Learning strategies selection -Goal-setting -Self-evaluation -Self-monitoring	-Goal-setting -Planning -Self-assessment -Reflective guidance	-Self-efficacy -Self-reflection	-Group planning -Group monitoring -Help-seeking
Individual/ Collective	**Individual**	**Individual**	**Individual**	**Collective**
Collected data	-Mouse clicks -Keyboard input -Eye tracking -Facial expressions -Electrodermal activity -Performance scores -Self-reported questionnaire	-Problems tutored -Reviewed examples -Requested hints -Quiz attempts	-Degree of confidence -Time spent	-Student's model -Student's questions
Application site	**School**	**School**	**Hospital**	**School**
Adaptability/ adaptivity	Mixed approach	Adaptability	Mixed approach	Mixed approach

Journals and Conferences

There are two conferences where studies on Metacognitive Tutoring Systems are usually presented: the International Conference on Artificial Intelligence in Education (AIED) and the International Conference on Intelligent Tutoring Systems.

- The AIED Conference is aimed at advancing science and engineering of intelligent human-technology ecosystems that support learning, and innovative research on AI-assisted systems and cognitive science approaches for educational computing applications. It is organized by the International AIED Society (2022).
- The International Conference on Intelligent Tutoring Systems builds the foundation for the evaluation of the use of intelligent systems in education, modeling innovative applications of technologies and the adaptation of systems to specific groups of learners. It is organized by the Institute of Intelligent Systems (2022).

A journal that often publishes papers on Metacognitive Tutoring Systems is the International Journal of Artificial Intelligence in Education (IJAIED).

- The IJAIED is the official journal of the International AIED Society, and publishes papers concerned with the application of AI to education. Its coverage extends to agent-based learning environments, architectures for AIED systems, bayesian and statistical methods, cognitive tools for learning, computer-assisted language learning, distributed learning environments, educational robotics, human factors and interface design, intelligent agents on the internet, natural language interfaces for instructional systems, real-world applications of AIED systems, tools for administration and curriculum integration, and more (Springer, 2022).

SOLUTIONS AND RECOMMENDATIONS

After reviewing four successful examples of MTS, it is important to mention some aspects that could be controversial and need to be further studied.

Competency Differences Among Learners

Matsuda et al. (2020) found that metacognitive scaffolding on how to teach is effective for students with various levels of prior competency; however, this study was conducted at the individual level, while Joyner and Goel (2015) included the social dimension by working in teams of three students. This approach creates the challenge of studying prior competency among students in the same team, as unequal competency could cause problems, just as a more advanced learner could provide scaffolding for less advanced learners.

Effects of Student Monitoring

MetaTutor (Taub et al., 2019) allows collecting multichannel data like mouse clicks, keyboard input, eye tracking, videos of facial expressions, and electrodermal activity. This makes it possible to obtain information about cognitive, metacognitive, and affective aspects about students using the system; however, students may feel uncomfortable being constantly monitored and this may alter their actions during learning. This is important mainly for the affective dimension since feeling watched by a camera or physiological sensor could generate a negative emotional response. To avoid biases regarding this aspect, it is necessary to investigate the effect that each of these data sources has on the learners.

Opinion of Decision-Makers in Workplaces

Systems such as Amplifire (Hays et al., 2019) break down the separation between using ITSs solely within academia and bringing them into the workplace. It is vital to continue with this task, and to achieve this it is necessary to question what is being done in academia to ensure that decision-makers in workplaces have a favorable opinion of using this type of technology, given that this could generate resistance to change and could even cause fear of replacing personnel with machines. In this sense, it is important to disseminate technological knowledge and take a position on artificial intelligence systems as tools that help to improve people's performance.

FUTURE RESEARCH DIRECTIONS

The following are emerging trends in MTS that could have a major impact in the future:

Teachable Agents

Since their origin, most ITSs focus on facilitating learners' tasks through adaptivity, which implies that artificial intelligence oversees the decisions to be made and the learner must make less effort and take no risks, playing a more passive role. Systems such as APLUS (Matsuda et al., 2020) imply a change in the role of ITSs, as learners become instructors of the systems. This gives learners a more active role that goes in the same direction of improving their metacognitive skills following the path of adaptability.

Social Metacognition

A trend that remains dominant in ITSs is to focus on individual learners, which has the advantage of personalizing different educational aspects, but it has the disadvantage of limiting collaborative learning. Systems such as MILA-T (Joyner & Goel, 2015) make it possible to approach metacognition from a social approach, which, in addition to fostering collaborative learning, will make it possible to study metacognitive processes in a group setting, e.g., shared goal setting, joint monitoring of learning, and co-evaluation of results.

Modular Systems

The fact that MetaTutor (Taub et al., 2019) uses various data sources, such as logs, video, and eye-tracking, allows studying dimensions of learning such as cognition, metacognition, and affect simultaneously; however, these modules can be turned on and off, allowing for different combinations of data sources. If this trend of modular systems continues, we could have more systems to address learning in a holistic manner with the ability to be disassembled and reconfigured, rather than having systems focused on a single task.

CONCLUSION

Metacognitive tutoring systems (MTSs) are computational learning support systems that use artificial intelligence to foster knowing our cognitive processes, monitoring, and regulating them.

For an intelligent tutor system to support learners' metacognitive skills, it should not have total control over decisions (adaptivity) but should give some degree of control to the learners (adaptability). Both adaptability and a mixed approach can be used for this purpose.

MTSs are less popular than Cognitive Tutors and Affective Tutoring Systems. This is reflected in the fact that ITSs' learner models are mostly based on cognitive characteristics (knowledge level, learning performance, behavior in the learning path, learning preferences, learning styles, intelligence level, and other cognitive factors), and to a lesser extent on affective characteristics (emotional factors). However, learner models based on metacognitive characteristics are expected to increase because there are already successful examples, and they could contribute to the students' autonomy, to a more active role for students in the learning process, to improve critical thinking, and to expand what has been learned to other contexts and different tasks.

Successful examples of MTSs (MetaTutor, APLUS, Amplifire, and MILA-Tutoring) gave us several lessons learned. For example, the fact that negative emotions could have a beneficial role during learning with advanced learning technologies. Another example is that learning by teaching a teachable agent with metacognitive scaffolding on how to teach is effective for students with various levels of prior competency. Also, that the use of an MTS can reduce central- line-associated bloodstream infections by 48% catheter-associated urinary-tract infections by 32%. They also let us know how to improve the performance of groups of students in inquiry-based learning tasks. It is important to study the differences between students' competence in working in teams, the effects of monitoring students by means of cameras and physiological sensors, and the opinions of decision-makers on the use of MTSs in workplaces.

Future research directions include a change in the role of ITSs as learners become instructors of the systems, what are called teachable agents, metacognitive skills support for groups of students, and modular systems that allow the enabling and disabling of different data sources during the learning processes.

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KEY TERMS AND DEFINITIONS

Adaptable Learning: Modification of educational elements in a computational environment according to learners' performance in which the learner is in control.

Adaptive Learning: Modification of educational elements in a computational environment according to learners' performance in which the machine is in control.

Cognition: The ability of living beings to process information. It is done through processes such as perception, memory, and learning.

Intelligent Computer-Aided Instruction: Use of artificial intelligence to display educational content and monitor students' learning. It was the predecessor of Intelligent Tutoring Systems.

Intelligent Tutoring Systems: Computational learning support systems based on the use of artificial intelligence and a four-module model that includes a domain module, a student module, an instructional module, and an interface.

Metacognition: The process of knowing our cognitive processes, monitoring, and regulating them.

Metacognitive Tutoring Systems: Computational learning support systems that use artificial intelligence to enhance learners' metacognition.

Scaffolding: Support offered to a learner to gain greater understanding and gradually become more independent.