9. Six instructional approaches supported in AIED systems

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INTRODUCTION

The current chapter reviews how AIED systems support six common instructional approaches, namely:

- *Learning from problem solving* – where students develop skills and knowledge through deliberate practice in solving complex problems;
- *Learning from examples* – where students learn by studying and explaining worked-out solutions to problems;
- *Exploratory learning* – where students engage in open-ended exploration of a task, task domain or set of phenomena;
- *Collaborative learning* – where students work together on learning activities;
- *Game-based learning* – where students work in a game or gamified environment for engaged and motivated learning; and
- *Learning by teaching* – where students train or teach a computer-based agent and learn as a result.

An instructional approach is a method of instruction based on instructional theory (e.g., Reigeluth et al., 1994; Reigeluth, 1999). The theory guides the design of the instruction and lends coherence to the choice of instructional goals, the nature of the tasks that learners carry out, and the nature of the support they receive as they carry out these tasks. du Boulay (2019) uses the term "pedagogy." Any given instructional approach may be implemented in different ways, with variation in many of its instructional features, while staying true to its theoretical foundation. There are several reasons why many instructional approaches are being used in educational practice. First, it may be that different types of knowledge (e.g., facts, concepts, procedures, strategies, beliefs) might be better learned with different approaches (Koedinger et al., 2012). However, with a few exceptions (Mavrikis et al., 2022; Mullins et al., 2011), the scientific understanding of this relationship is incomplete, and more research is required. Second, in some instructional approaches (e.g., collaborative learning or exploratory learning), students engage in learning processes that in themselves are valuable to learn. Third, some instructional approaches may support greater engagement and motivation. Finally, many teachers and students may prefer variability in their learning activities.

We selected the six approaches listed above because they have been widely studied within the AIED community. For each approach, AIED implementations have proven to be effective in helping students learn. It is hard to do justice, however, in a single chapter, to the full range of instructional approaches that have been implemented and studied within the field of AIED. Our sampling of instructional approaches is not comprehensive. Other chapters in the current volume review other approaches that have been studied, including those focused on metacognition and self-regulated learning (Chapter 4 by Azevedo & Wiedbusch) and those based on natural language technologies (Chapter 11 by Rus et al.). Also, instructional approaches such as project-based learning (Blumenfeld et al., 1991; Chen & Yang, 2019; Krajcik & Blumenfeld, 2006) and productive failure (Darabi et al., 2018; Kapur & Rummel, 2012) are not strongly represented in AIED. Therefore, we do not review these approaches in the current chapter.

The instructional approaches that we review came into being outside the field of AIED. Only later they were implemented using AIED technologies. Therefore, a key question in our chapter is: What are the advantages of employing AIED technologies in the implementation of these instructional approaches? To take a systematic approach to this question, we take guidance from two established conceptual frameworks that deal with technology-enhanced learning. One framework distinguishes *levels of instructional assistance* (Soller et al., 2005; VanLehn, 2016), the second categorizes ways that assistance can be *adaptive* to students' needs (Aleven et al., 2017). Use of these two conceptual frameworks helps focus the discussion on two key dimensions of AIED support for learners. Combining these two frameworks helps us see what trends might exist across AIED implementations of these instructional approaches and helps us see commonalities and differences in how AIED supports or enhances them. Although there may not be a single right choice of the conceptual frameworks one might use in a review such as the current one, we believe our choice of frameworks is appropriate and helpful for several reasons: First, the two frameworks each focus on a (different) key dimension of technology-enhanced learning. Second, they are broad enough to accommodate our six instructional approaches, which is not the case for all instructional theories. For example, theories of deliberate practice (Ericsson et al., 1993) have little to say about game-based, collaborative, or exploratory learning. Third, compared to other broad conceptual frameworks for instruction, such as the Knowledge-Learning-Instruction (KLI) framework (Koedinger et al., 2012; Koedinger et al., 2013) and the Interactive, Constructive, Active, and Passive (ICAP) framework (Chi & Wiley, 2014; Chi et al., 2018), the ones we selected focus more strongly on technology-enhanced learning.

The chapter is structured as follows. We first briefly review the two conceptual frameworks mentioned above, to make the chapter self-contained. We then describe AIED implementations of each of the reviewed instructional approaches and relate them to the two frameworks. We also consider other key information regarding each instructional approach, such as relevant psychological or instructional theory, the kinds of learning objectives the approach seeks to support, examples and variations of the approach presented in the AIED literature, empirical results, and the kind of tools that have been developed to support *teachers*. In our discussion section, we synthesize trends across the approaches to get a sense of what AIED brings to the table.

Conceptual Background

We briefly describe the two established conceptual frameworks that we use to understand how AIED systems support different instructional approaches. The goal is to explain the conceptual lenses we use in this chapter to look at the different instructional approaches.

Levels of assistance

The first of these frameworks focuses on the level of assistance given to learners, a key concern in instructional design (cf. Koedinger & Aleven, 2007). The framework was first set forth by Soller et al. (2005) and later adapted, expanded, and generalized by VanLehn (2016). We refer to it as the "S/vL" framework and follow VanLehn's (2016) presentation of it, with slight modifications described below. Although the framework was originally conceived of as describing computer-supported collaborative learning (CSCL) only, VanLehn (2016) convincingly argues that it applies just as well to many other instructional approaches. In this framework, a computer-based learning environment is viewed as a loop in which students (working individually or collaboratively) perform a task. As they do so, a system gathers data about their performance, analyzes the data, and provides support based on that analysis. The loop is called a "collaboration management cycle" by Soller et al. (2005) and a "regulative loop" by VanLehn (2016). The support offered to students within this loop is classified into four broad categories, described by VanLehn (2016) as follows (we change some of the terms used; our new terms are shown below in square brackets):

> The regulative loop involves both a comparison of the [students' task] performance against some gold standard and an adjustment to the students' knowledge that brings their performance closer to the gold standard. Computer systems can take over varying amounts of this loop:
>
> - If the students execute the whole regulative loop themselves, the activity is called *[self/co-regulation]*.
> - If the system monitors the students' performance and presents it back to the students, then the activity is called *mirroring*.
> - If the system both monitors the students' performance, compares it to a gold standard and reports the comparison to the students, then the activity is called *[formative feedback]*.
> - If the system monitors the performance, compares it to a gold standard, and generates some advice to the students or modifies the task or context, then the activity is called *coaching*.
>
> (VanLehn, 2016, p. 108)

Although Soller et al. (2005) and VanLehn (2016) characterize these categories as phases in a regulative loop, they can usefully be viewed as increasingly greater levels of instructional assistance (cf. Koedinger & Aleven, 2007). We consider them as such in the current chapter. The first of these levels, *self/co-regulation*, refers to learner performances with no support except possibly static instructions regarding what to do (e.g., a collaboration script, in the case of collaborative learning activities; Dillenbourg, 2002). Although VanLehn (2016) uses the term "self-regulation," we prefer the term "self/co-regulation" and use it throughout this chapter, to acknowledge perspectives that focus on the joint regulation of learners working collaboratively (e.g., Hadwin et al., 2018). In this chapter, we do not say much about the category of self/co-regulation, as we focus on how AIED supports learning and not on how students learn without such support. *Mirroring* represents the lowest level of assistance found within AIED systems. In its original conception by Soller et al. (2005), mirroring appears to be concerned mainly with presenting various forms of *process* data to learners. However, AIED systems support other forms of mirroring as well. For example, as discussed below, Open Learner Models (Bull & Kay, 2008, 2016; Bull, 2020), a staple of many AIED systems, can be viewed as mirroring a student's learning state. *Formative feedback*, the next level of assistance, presents a comparison of the learner's performance against an appropriate standard. Although VanLehn (2016) uses the term "formative *assessment*," we prefer the term "formative *feedback*," because this term denotes the interactions between the system and the learner, consistent with how the other assistance levels are named. Formative feedback encompasses many different forms of feedback. The term "formative" indicates that the feedback aims to help students learn and improve, rather than providing any kind of definitive evaluation of their skill or knowledge. Fourth, *coaching* is the highest level of support in the S/vL framework. Coaching often involves giving feedback to students. In that sense, coaching envelopes the previous level, formative feedback. However, it goes beyond formative feedback in that it also encompasses advice regarding what comes next, including what the next step or goal within a given learning activity might be, or what learning activity to take on next.

VanLehn (2016) adds important extensions. First, in designing and analyzing instructional support, it is important to consider the different objectives of the instruction (VanLehn, 2016), a point supported by other conceptual frameworks for instruction as well (e.g., Rummel, 2018). In many instructional interventions, there are multiple learning objectives. For example, an AIED system that supports problem-solving practice may aim to help students acquire both domain knowledge *and* certain self-regulatory skills (e.g., help seeking; Roll et al., 2011). Similarly, an AIED system that supports collaborative learning may aim to help students acquire domain knowledge *and* strengthen collaboration skills. And so forth. In each of these instances, the different instructional objectives may require different levels of support, a key instructional design challenge. Furthermore, as VanLehn (2016) and du Boulay (2019) point out, to make sure adaptive learning technologies are effective in classrooms, it is important to consider the role of the teacher or other classroom instructor(s). Similarly, we see advantages in conceptualizing the classroom ecosystem as a synergistic student–teacher–AI partnership (e.g., Holstein et al., 2020).

Adaptivity

The ability to adapt instruction to learners' needs is often viewed as a hallmark of what AIED systems do. Following Aleven et al. (2017), we consider instruction to be adaptive to the degree that it takes into account (in its instructional choices) that learners are different in many ways and that they constantly change as they learn (e.g., by building up understanding or developing skills, interests, new ways of self-regulating their learning, and so forth). In addition, instruction is adaptive to the degree that it is designed with a deep understanding of common challenges that learners face within a given task domain. These three aspects of adaptivity have in common that, instead of asking the learners to change to match the instructional environment, we change the instructional environment to align with the needs of the learner (Plass & Pawar, 2020).

The Adaptivity Grid (Aleven et al., 2017) breaks down the broad concept of adaptivity along two main dimensions: What features of the instruction are being adapted? In response to what student variables are they being adapted? Regarding the first question, the Adaptivity Grid distinguishes three broad categories of adaptation processes, which differ in the timescale at which the adaptation happens. Instruction can be adapted dynamically, at student run time, either within tasks (step-loop adaptivity; short timescale) or with respect to the choice of tasks (task-loop adaptivity; medium timescale). As a third category, instruction can be adapted at design time, that is, in-between uses of the system, based on offline analysis of data from the instructional system (design-loop adaptivity; long timescale). This third type of adaptivity focuses on updating the system so it better helps learners tackle challenges that *all* learners face (Huang et al., 2021). The distinction between a system's task loop and its step loop is based on VanLehn's (2006; 2016) notion of regulative loops. In step-loop adaptivity, the system varies elements of its support at the level of problem steps, such as prompts, hints, feedback, whether a step is given as a worked-out step for the student to explain or as an open step for the student to solve, and so forth. In task-loop adaptivity, the choice of the next task (for a given student, at a given moment in their learning process) may be based adaptively on attributes such as knowledge required, effort required, the content's topic, and so forth. As its second dimension (in response to what student variables is the instruction being adapted?), the Adaptivity Grid distinguishes five broad psychological realms. Within each, many variables can be discerned to which instruction could be (and has been) made to adapt. Four of these realms have proven to be a fruitful basis for adaptive instruction: knowledge growth, errors/strategies, motivation/affect, and self-regulation (Aleven et al., 2017). The two dimensions together make up a 3×5 matrix, the Adaptivity Grid, capturing a very large, open-ended, and constantly evolving design space for adaptivity in learning technologies. Many forms of adaptivity that have been studied within the field of AIED can readily be classified into this grid (Aleven et al., 2017).

AIED IMPLEMENTATIONS OF THE SIX INSTRUCTIONAL APPROACHES

We review AIED implementations of the six instructional approaches, listed above, through the lens of the two conceptual frameworks just introduced. Our overarching goal is to get a sense of what AIED brings to the table. What is it that AIED implementations of these approaches offer that other implementations, with or without technology, do not bring, or bring only to a lesser degree? Thus, we consider whether different instructional approaches tend to be implemented with different levels of assistance and different forms of adaptivity. In describing each instructional approach, we also address several other important themes, including a brief characterization of the approach (what are its essential properties?), relevant psychological or instructional theory, the kinds of learning objectives the approach seeks to support, examples and variations of the approach presented in the AIED literature, empirical results reported in the AIED literature regarding the effectiveness of the approach in supporting beneficial student or teacher experiences and learning, and finally, the kind of support that AIED systems give to *teachers*. This latter topic is covered in greater depth in Chapter 14 by Holstein and Olsen.

Learning from Problem Solving

A large amount of AIED research has focused on supporting learners as they engage in problem-solving practice. Systems that support problem solving, often referred to as "intelligent tutoring systems" (ITSs), provide the highest level of support in the S/vL framework (i.e., coaching), often with multiple forms of adaptivity, in terms of the Adaptivity Grid. AIED systems for tutored problem solving aim to help students acquire complex problem-solving knowledge, often a combination of skill and conceptual understanding (Crooks & Alibali, 2014). Six meta-reviews in leading educational journals summarize the strong evidence that these systems can substantially enhance the learning of students at many educational levels, compared with other forms of instruction (Kulik & Fletcher, 2015; Ma et al., 2014; Steenbergen-Hu & Cooper, 2013, 2014; VanLehn, 2011; Xu et al., 2019).

Tutored problem solving is grounded in a variety of theoretical perspectives, such as theories of scaffolding (Wood et al.,1976) and theories of deliberate practice (Koedinger & Aleven, 2022; Ericsson et al., 1993). Specific lines of work are grounded as well in cognitive science theory, including the ACT-R theory of cognitive and learning (Anderson, 1993), the KLI framework, which links knowledge, learning, and instruction (Koedinger et al., 2012) and the theory of constraint-based modeling (Ohlsson, 1992). As well, VanLehn's (2006; 2016) cataloging of the behavior of tutoring systems (extended by Aleven & Sewall, 2016) provides a useful conceptual framework, as well as a set of "Cognitive Tutor principles" formulated by Anderson et al. (1995), based on their experience building many problem-solving tutors.

The field of AIED has created many effective systems that support tutored problem solving. First, Cognitive Tutors are an approach grounded in cognitive theory and rule-based cognitive modeling (Anderson et al., 1995). Tutors of this type have been built for a variety of task domains including programming (Anderson et al.,1992), middle-school and high-school mathematics (Koedinger et al., 1997; Long & Aleven, 2017b; Ritter et al., 2007), and genetics (Corbett et al., 2010). Cognitive Tutors for mathematics were possibly the first AIED systems to be used regularly in schools (Koedinger et al., 1997; Koedinger & Aleven, 2016). In many studies, they have been shown to enhance student learning compared with other mathematics curricula without AIED components (Pane et al., 2014; Ritter et al., 2007; but also see Pane et al., 2010). They also have proven to be commercially successful.

Another widely researched and commercially successful AIED implementation of tutored problem solving is called "constraint-based tutors" (Mitrovic, 2012; Mitrovic & Ohlsson, 2016). Constraint-based tutors are grounded in cognitive science research on "constraint-based modeling" (Ohlsson, 1992), where target knowledge is captured as a set of constraints that problem solutions must satisfy. Constraint-based tutors have been developed for a wide variety of domains (Mitrovic & Ohlsson, 2016), including Structured Query Language (SQL) queries, database modeling, Unified Modeling Language (UML) class diagrams, Java programming, data normalization, and capitalization and punctuation (Mayo et al., 2000). They have been shown to be effective in enhancing student learning (Mitrovic & Holland, 2020; Mitrovic & Suraweera, 2016).

Other notable AIED systems for tutored problem solving include the Andes system for physics problem solving (VanLehn et al., 2005) and the many example-tracing tutors built with the Cognitive Tutor Authoring Tools (Aleven et al., 2016), including tutors for middle-school mathematics (Aleven et al., 2009; Aleven & Sewall, 2016), stoichiometry (McLaren, 2011) and fractions (Rau et al., 2013). Further back in time, ActiveMath (Melis et al., 2001), Sherlock (Lesgold et al., 1992) and ELM-ART (Brusilovsky et al., 1996) supported complex problem solving. Several current AIED systems support students in solving simpler problems, without much adaptivity in their step loops, including ALEKS (Fang et al., 2019; Phillips et al., 2020), ASSISTments (Heffernan & Heffernan, 2014), Duolingo (Jiang et al., 2020; Teske, 2017), Khan Academy (Kelly & Rutherford, 2017) and MathSpring (Arroyo et al., 2014), Many other systems have been built and described in the AIED literature.

AIED systems for tutored problem solving are often characterized as adaptive coaches, in terms of the S/vL framework. Typically, this type of system presents a problem-solving environment, with a user interface designed to "make thinking visible" (Anderson et al., 1995) and often with representational tools for students to use (Koedinger & Sueker, 1996). The system follows along as the student solves problems in this interface; it provides detailed guidance. Its coaching can be characterized as "directive" in nature (our term). By that term we mean that the system provides correctness feedback and insists on correct solutions. Below we contrast this form of coaching to more "suggestive" approaches that provide helpful feedback and suggestions but may not communicate fully whether a solution is correct or strongly steer students toward correct solutions. The coaching of AIED systems often exhibits several forms of step-level adaptivity, such as adaptive prompts for problem steps, correctness feedback on the student's attempts at problem steps, error-specific feedback messages (which explain why the step is wrong, sometimes with hints for how to fix it), and next-step hints (i.e., advice as to what to do next when a student is stuck). In this manner, the system adapts to the student's strategy within the given problem and the specific errors that the student makes.

Additionally, in their task loop, AIED systems for tutored problem solving often support mastery learning. In mastery learning, a student must demonstrate mastery of the learning objectives of one curricular unit before moving on to the next, as one way of personalizing instruction. Mastery learning first came into being outside of AIED. Even without technology, it has proven to be more effective than standard classroom instruction (e.g., Kulik et al., 1990). Implementations of mastery learning in AIED systems have additional benefits, compared with non-technology approaches. No separate assessment activities are needed to ascertain whether a student has mastered targeted learning objectives; the AIED system, as part of its coaching, continuously assesses students. In addition, because an AIED system often tracks students' knowledge growth with respect to very fine-grained knowledge components, it can select problems that target a student's knowledge needs with great specificity, which may help students learn efficiently. In terms of the Adaptivity Grid, mastery learning is a key way of adjusting to students' knowledge growth in the task loop. Support for mastery learning has been shown to enhance the effectiveness of AIED systems for tutored problem solving (Corbett et al., 2000; Ritter et al., 2016; but see Doroudi et al., 2019). The self-paced nature of mastery learning that is typical of AIED systems (with each student proceeding at their own pace) does, however, present challenges with respect to classroom management that the field of AIED has not yet fully solved (Phillips et al., 2020; Ritter et al., 2016; Sales & Pane, 2020).

As an additional form of support, AIED systems for tutored problem solving often feature an Open Learner Model (OLM; Bull, 2020; Bull & Kay, 2016). Typically, an OLM visualizes the system's representation of the student's learning state for the student to scrutinize (Kay, 2021; see also Chapter 6 by Kay et al.). For example, the system may show a visualization of its assessment of the student's mastery of the knowledge components targeted in the instruction. In terms of the S/vL framework, OLMs *mirror* information back to the student; this information can be viewed as *formative feedback* on the students' learning over time, based on the system's continuous assessment of student work. Evidence from a small number of studies shows that an OLM can help students learn better, compared with not having an OLM (Long & Aleven, 2017b; Mitrovic & Martin, 2007).

Design-loop adaptivity has also proven to be effective in improving systems so they yield more effective learning (Aleven et al., 2017; Huang et al., 2021). This work often focuses on the data-driven refinement of the knowledge component models underlying the instruction, followed by redesign of the tutoring system, so that it is more effective for many students.

AIED research has explored and tested many variations of the coaching behaviors to support tutored problem solving. There is a very large body of empirical research on this topic. Here we only have space to list some of the main variations that have been investigated. First, within the system's *step loop*, AIED research has tested formative feedback with elements of student control (as opposed to the more typical fully system-controlled feedback), including feedback given at the student's request (Corbett & Anderson, 2001; Schooler & Anderson, 1990) and feedback that (compared to immediate feedback) is slightly delayed so as to give students a chance to catch and fix their errors before receiving feedback (Mathan & Koedinger, 2005). As well, AIED research has studied effects of different feedback content. Several studies have found advantages of grounded feedback (also known as situational feedback), which does not directly communicate the correctness of student work, but instead, communicates consequences of student attempts (correct or incorrect) in a form or representation that is familiar or intuitive to students (Nathan, 1988; Wiese & Koedinger, 2017). It is left up to the student to infer, from the grounded feedback, whether and how the attempt needs to be improved. Other studies found positive effects of goal-directed feedback (McKendree, 1990), error-directed feedback (Gusukuma et al., 2018), positive feedback that adapts to students' uncertainty (Mitrovic et al., 2013), positive feedback that focuses on the conclusion of learning objectives (Marwan et al., 2020), and feedback focused on domain principles (Mitrovic & Martin, 2000). Similarly, some research has studied variations of the content of the next-step hints, including principle-based hints (Aleven et al., 2016) and "bottom-out hints" (i.e., hints that directly give the next step; Stamper et al., 2013). As with feedback, research has studied both hints given at the student's request and hints given proactively by the system (see Maniktala et al., 2020).

Other features that have been found effective in AIED implementations of tutored problem solving are support for self-explanation (Aleven & Koedinger, 2002; Conati & VanLehn, 2000) and the use of multiple representations (Azevedo & Taub, 2020; Rau et al., 2013; Rau et al., 2015; Nagashima et al., 2021). Some systems adaptively break down problems into steps, in response to student difficulty (Heffernan et al., 2008), rather than (as is typical in AIED systems for tutored problem solving) right from the start. This way, the student has a chance to decompose problems themselves, without the system always taking over that important aspect of problem solving. Other work explored advantages of after-action review, also known as post-problem reflection, or reflective follow-up, where students are supported in reflecting on their problem solution (Katz et al., 2003; Katz et al., 1997). Some AIED systems "fade" their support as the learner gains proficiency (Collins et al., 1989; Jordan et al., 2018; Salden et al., 2010). Although it is often assumed that the fading of scaffolding is important in tutored problem solving (Collins et al., 1989; VanLehn et al., 2000; Wood et al., 1976), it is fair to say that this topic is underexplored in the field of AIED; there is limited scientific knowledge on which to base the design of fading mechanisms. As a final variation of tutoring behavior within an AIED system's step loop, some work focused on supporting aspects of self-regulated learning or metacognition in the context of problem solving (Koedinger et al., 2009; Long & Aleven, 2016, 2017; Roll et al., 2011; see also Chapter 4 by Azevedo & Wiedbusch).

Additionally, many variations of the systems' *task loop* have been developed and tested. For example, a large amount of work has focused on refining the methods for personalized mastery learning used in AIED systems, such as Cognitive Mastery based on Bayesian Knowledge Tracing (Corbett & Anderson, 1995), often by creating more accurate methods for estimating a student's knowledge state or predicting performance (Pelánek, 2017). As a second variation in the task loop of systems for tutored problem solving, a significant amount of work has focused on studying combinations of problem solving and worked example studying, including adaptive combinations. This work is described below in the next section, "Learning from Examples."

Recent AIED research has focused on designing tools to help teachers better guide students in their (the students') work with problem-solving tutors. Different projects explored tools associated with different use scenarios, including real-time support for teachers (i.e., support for teachers as they help students *during* their work with tutoring software) (Holstein et al., 2018), support for in-class discussion of homework carried out with AIED tutoring systems (Kelly et al., 2013), and support for tailoring lesson plans based on analytics from a tutoring system (Xhakaj et al., 2017). One study (Holstein et al., 2018) demonstrated that a teacher awareness tool, working in conjunction with an AI system for tutored problem solving, can help students learn better, especially those students who have most to learn; see also Chapter 15 by Pozdniakov et al.

Learning from Examples

A substantial amount of work in the field of AIED has focused on providing adaptive support for learning from (interactive) examples. In this instructional approach, students are given a problem with a step-by-step solution and asked to study the solution. Typically, these examples are of the same type as the problems that students eventually will learn to solve themselves. Oftentimes, learning from examples is combined with learning from problem solving. Typically, students are prompted to explain the solution steps in terms of underlying domain concepts, problem-solving principles, or problem-solving goals. Most of the time, students are given examples that show correct problem solutions but some interesting work (both within and outside of AIED) has shown that having students explain example solutions with errors (often referred to as "erroneous examples") can be effective as well (Adams et al., 2014; Booth et al., 2013; McLaren et al., 2016). Example studying tends to be particularly effective in helping students acquire conceptual understanding and promoting conceptual transfer (Renkl, 2014).

AIED work on learning from examples builds upon the extensive literature in cognitive and educational psychology on learning from examples (Renkl, 2014), self-explanation (Wylie & Chi, 2014), and "expertise reversal" (Kalyuga, 2007). Much past work on worked examples is grounded in cognitive load theory (Mayer & Moreno, 2003; Sweller, 2020). A key finding in this literature is that studying many worked examples early on during skill acquisition, followed by problem-solving exercises, is a highly effective combination of instructional approaches (expertise reversal; Kalyuga, 2007). Therefore, AIED implementations of example studying often combine support for studying examples with tutored problem solving (as described in the previous section). Some gradually fade out examples as the student gains competence in explaining the examples (Salden et al., 2010) or interleave examples and problems (McLaren et al., 2008). Another key finding in literature on example studying is that students learn the most when they self-explain the steps of example solutions (Renkl, 2014; Wylie & Chi, 2014). Therefore, AIED systems that support example studying often prompt students to provide explanations; they also provide formative feedback on these explanations. AIED systems use a variety of input formats for explanations: some systems offer menus from which explanations can be selected or structured interfaces for piecing together explanations (e.g., Aleven & Koedinger, 2002; Conati & VanLehn, 2000), whereas others let students type explanations in their own words and provide feedback on the typed explanations (Aleven et al., 2004).

In line with past work on expertise reversal (Kalyuga, 2007), work within AIED has found advantages of combining worked examples with tutored problem solving (Hosseini et al., 2020; Liu et al., 2016; McLaren et al., 2016; McLaren et al., 2008; Olsen et al., 2019; Salden et al., 2010; Salden et al., 2010; Zhi et al., 2019). One study found, by contrast, that an all-examples condition (without any problem solving) was most beneficial (McLaren & Isotani, 2011). This work goes beyond mere replication of earlier results in the cognitive and educational psychology literature in that it finds that worked examples tend to be effective even when added to problem-solving activities in learning environments that (in contrast with those studied earlier) have high levels of assistance (Salden et al., 2010). In addition, some AIED work has confirmed the importance of supporting self-explanation in this context (Conati & VanLehn, 2000; McLaren et al., 2012; Richey et al., 2019), in line with earlier work on cognitive and educational psychology (e.g., Renki, 2014).

In terms of the S/vL framework, AIED systems for studying examples offer assistance in the form of formative feedback and other forms of coaching. Their feedback typically focuses on the correctness of students' explanations; they typically insist on correct explanations from students, before allowing the student to move on to the next example or problem. They often provide hints regarding how to explain example steps (e.g., what the underlying problem-solving principle might be and how it might apply to the step at hand). Another aspect of their coaching is the selection of examples, sometimes in a manner that adapts to students' knowledge growth, as discussed in the next paragraph.

AIED systems that support example studying have implemented different forms of adaptivity. In their step loop, some systems give adaptive feedback on students' explanations of example steps (Salden et al., 2010). One system adaptively selects example steps to explain based on an individual student's knowledge state, so students are only asked to explain steps for which they have limited knowledge – from which they have most to gain (Conati & VanLehn, 2000). In their task loop, one system adaptively fades worked examples, gradually transitioning from presenting worked examples to presenting open problems for students to solve in a personalized way (Salden et al., 2010). The example-fading procedure takes into account a student's state of explanatory knowledge, evidenced by their performance on example explanation steps. Another system adaptively selects erroneous examples based on students' errors (Goguadze et al., 2011). Finally, one project focused on a form of design-loop adaptivity, in that they created a pool of erroneous examples based on analysis of student errors in log data from an ITS (Adams et al., 2013).

A practical takeaway from this work is that AIED systems for tutored problem solving should support studying examples. Interesting open questions are what the ideal mix of examples and problems might be and how the ideal mix might vary by, for example, student and situation (Salden et al., 2010).

Exploratory Learning

Under the broad category of exploratory learning, we include a variety of approaches and systems that encourage students to explore a knowledge domain or engage in inquiry and experimentation as part of the learning process. We group together several related approaches such as discovery, exploratory, or inquiry learning (see Alfieri et al., 2011; Rieber et al., 2004; Quintana et al., 2004; van Joolingen, 1999). Digital tools associated with these approaches range from simulators to virtual labs, and from microworlds to task-specific virtual manipulatives or other open-ended environments. We refer to them collectively as exploratory learning environments (ELEs). Several provide coaching for learners as they carry out their explorations.

AIED support in this context is aimed at helping students acquire domain-specific conceptual knowledge or other high-level skills such as inquiry, problem solving in general or self-regulated learning. For STEM in particular, ELEs provide learners with opportunities to engage with a domain and explore a range of possibilities that would otherwise be difficult to experience directly. The main theoretical basis for this work is constructionism (or "framework of action" as described in DiSessa & Cobb, 2004), which puts exploratory learning at its core but also emphasizes that students learn most effectively by not only exploring but also by making and sharing artifacts (Harel & Papert, 1991). For example, mathematical microworlds and interactive science simulations allow students to explore key concepts through the structure of objects within the environment. Especially in mathematics, students are encouraged to explore external representations that make such concepts concrete and accessible (Hoyles, 1993; Thompson, 1987). For example, dynamic geometry environments such as the widely used Geogebra (http://geogebra.org/) make external representations available for exploration (Healy & Kynigos, 2010). Other topic-specific microworlds have been researched as well in the field of mathematics education (Noss et al., 2009), including microworlds for algebra (Mavrikis et al., 2013) and fractions (FractionsLab; Hansen et al., 2016; Mavrikis et al., 2022). Similarly, in ELEs for science learning, learners can manipulate variables or observe outcomes in order to answer "what if" questions, or understand the model underlying the simulation (McLaren et al., 2012; Roll et al., 2018). Characteristic examples are the PhET simulations (Wieman, Adams, & Perkins, 2008), which are designed specifically to provide opportunities for experimentation. In some ELEs, students learn by building executable models of scientific phenomena, running the models, observing the consequences (e.g., by analyzing data generated by running the model), and revising their models as needed (Biswas et al., 2016; Bredeweg et al., 2016; Joyner & Goel, 2015).

Research in AIED has been trying to address the lack of instructional support for which constructionist-oriented approaches have often been criticized (Kirschner et al., 2006; Mayer, 2004). The lack of support is particularly detrimental in classrooms where one-to-one support from a teacher is not practical (Mavrikis et al., 2019). The goal in AIED systems that support exploratory learning, therefore, is to guide students toward effective explorations and inquiry without compromising the exploratory nature of the learning processes.

At a high level, the support offered to students within ELEs has many similarities with that in the tutored problem-solving approaches presented earlier, in that the system acts as a coach and provides feedback. However, the support in ELEs operates at a different level of granularity and is suggestive rather than directive, compared with ITSs. It is closer to what Elsom-Cook (1988) described as "guided discovery." Compared with tutored problem solving, the interfaces of ELEs tend to be more open-ended and are not typically designed to prompt and make visible a learner's step-level thinking in answering a structured problem. The problems that learners tackle are more open ended and in most cases ill defined (see Lynch et al., 2009). Due to the open-ended nature of the interaction, it is more difficult to model the learner and to model effective inquiry or exploration processes, particularly because the knowledge that the learner is expected to develop is an outcome of the process of exploration. The fact that in exploratory learning there are often no right or wrong answers makes it much harder to apply commonly used techniques in AIED for tracking student knowledge growth, such as Bayesian Knowledge Tracing (BKT) (Corbett & Anderson, 1995; Käser & Schwartz, 2020). Consequently, very few ELEs employ a learner model that captures students' knowledge state. Rather, ELEs tend to focus on analyzing students' interactions with the environment (e.g., aspects of their inquiry process) and the outcomes without making inferences about a student's knowledge state. For example, Cocea et al. (2009) present a case-based knowledge representation to model learner behavior as simple cases and collection of cases (i.e., strategies). Mavrikis et al. (2010) advocate modeling "ways of thinking" or other complex cognitive skills as manifested in the ELE (e.g., through a series of actions similar to the cases above) and provide a layered conceptual model for ELEs. Other notable learner models in ELEs include Bunt and Conati (2003) and Cocea and Magoulas (2017).

The results of the modeling process are used to recognize learners' interactions within a range of possibilities or feed into other reasoning and analysis techniques, in an attempt to guide or coach the student toward effective inquiry or exploration of the environment and/or completing the task at hand (Gutierrez-Santos et al., 2012). As such, in contrast with feedback in tutored problem solving, there is less emphasis on the correctness of answers. Mavrikis et al. (2012) provide a framework of pedagogical strategies for supporting students' exploration in ELEs based on both empirical evidence and theoretical perspectives. These strategies vary from supporting interaction with the digital environment (e.g., by drawing attention to its affordances) to encouraging goal-orientation (e.g., by supporting students to set and work towards explicit goals) to domain-specific strategies (e.g., inducing cognitive conflict or showing counterexamples).

Commercial successes in this area include Inq-ITS, an ITS for scientific inquiry for late primary or early secondary students (Gobert et al., 2013). Using Inq-ITS, students manipulate simulations, formulate hypotheses, conduct experiments, and collect data, for example, by changing the values of parameters in a simulation. In order to assess student work and coach students, the environment makes inferences about students' inquiry skills using models that can detect if students are carefully testing hypotheses and conducting controlled experiments (Gobert et al., 2013). (How these models were created using machine learning is described in Chapter 7 by Aleven et al.). An earlier ELE is Smithtown (Shute & Glaser, 1990), a simulation where students change parameters in a hypothetical town to experiment with changes in market supply and demand. Smithtown models students' microeconomic knowledge and their scientific inquiry skills. In mathematics, FractionsLab (Hansen et al., 2016; Mavrikis et al., 2022) and eXpresser (Mavrikis et al., 2013) are intelligent ELEs. These systems typically provide feedback (using rule-based engines) that does not interrupt the learner as long as they are not manifesting some problematic interaction toward their goal that might be defined based on a given task. The goal is often to encourage effective exploration. Some systems employ a strong model of inquiry to evaluate student inquiry and give correctness feedback, including TED, a tutor for experimental design (Siler et al., 2010), and EarthShake, a mixed-reality environment for young children that supports a predict–explain–observe–explain cycle of exploration, with strong benefits for student learning (Yannier et al., 2020).

In some systems, students can ask for support (e.g., by means of a help button). These systems may still intervene proactively (at the system's initiative) when the system detects that a user has deviated a lot from the expected interaction. For example, the most common type of feedback in simulation environments, such as Smithtown, targets a behavior such as repeatedly changing several variables at once (thus violating a key maxim of scientific inquiry, that experimental conditions should differ only by the independent factors whose effect one is testing). It responds by suggesting alternative strategies (e.g., controlling a single variable at a time; see Shute & Glaser, 1990). Similarly, in mathematical constructions (such as in eXpresser or GeoGebra), a common strategy is to draw attention to the lack of generality of a construction by "messing it up" and helping students distinguish variants and invariants that emerge directly from their own actions (Mavrikis et al., 2013). Some systems provide feedback that targets students' motivation and effort that is separate or additional to domain- or task-specific feedback. Examples include the affective support provided in FractionsLab (Grawemeyer et al., 2017) or the motivation and problematizing support in the Invention Coach (Chase et al., 2019).

Lastly, like tutored problem solving, an emerging area is teacher dashboards and other Teacher Assistance tools (Mavrikis et al., 2019). The combination of intelligent analysis of interaction data from ELEs and the targeted design of tools for teachers has been shown to support classroom orchestration through, for example, increased awareness (Amir & Gal, 2013; Dickler et al., 2021) or support for grouping students according to their ELE constructions (Gutierrez-Santos et al., 2017). This is important because even effective AIED implementations of these systems will not be able to fully automate the desired support for students; it is therefore important to support teachers to use ELEs in the classroom and to take decisions based on students' interactions (Mavrikis et al., 2019).

Collaborative Learning

Collaborative learning can be defined as "a situation in which two or more people learn or attempt to learn something together" (Dillenbourg, 1999, p. 1). In this section, we provide an overview; for a more detailed review of collaborative learning in AIED, see Chapter 19 by Martinez-Maldonado et al. In collaborative learning settings, learning results from interaction between the learners (for an overview, see Chi & Wylie, 2014). Although different theoretical perspectives posit different interaction processes as being central to learning (Slavin, 1996), all collaborative learning settings encourage learners to engage in interaction that leads to constructing new knowledge together, with both the construction and the togetherness being key (Stahl et al., 2006). King (2007) provides a list of activities during collaborative learning that can promote learning when they occur, such as verbalizing and clarifying thoughts, making connections between concepts explicit, and reconciling cognitive discrepancies that arise from opposing perspectives. These activities can, for example, take place in pairs (dyads) of students (e.g., in reciprocal teaching; Rosenshine & Meister, 1994), in small groups of learners (e.g., in a jigsaw script; Aronson, 2002) or with the whole class (e.g., using a wiki-writing approach; Larusson & Alterman, 2009). Several meta-analyses have shown that collaborative learning yields better learning outcomes than when students learn individually (Hattie, 2009; Pai et al., 2015) and that dedicated computer support can additionally enhance student learning (Chen et al., 2018). The field of computer-supported collaborative learning (CSCL) is based on the idea of facilitating or supporting collaborative learning by means of digital tools (Stahl et al., 2006). Often these tools provide targeted support in the form of a "script" that guides the collaboration by providing a set of roles, activities, or interactions for the students to follow. However, even with computer support that can help to guide and scaffold students' collaborative processes, a one-size-fits-all approach to support can lead to over- or under-scripting, which in turn can inhibit learning (Dillenbourg, 2002). *Adaptive* scripting can address these concerns by personalizing the collaboration support based on the characteristics of the individual learners (Fischer et al., 2013; Vogel et al., 2021; Wang et al., 2017). More generally, adaptive needs-tailored support is a strength that AIED brings to collaborative learning approaches.

To account for the breadth of support for collaborative learning, previous research has reviewed adaptive, collaborative systems to identify several dimensions along which the adaptivity can vary (Magnisalis et al., 2011; Walker et al., 2009). These dimensions are summarized in a framework for CSCL developed by Rummel (2018). As captured in this framework, adaptation can occur before, during, or after a collaborative learning activity; an example of the former is adaptive group formation (Amarasinghe et al., 2017). In the current section, we focus on the support that is given *during* the collaborative activity. For the adaptation that occurs during collaborative learning, we focus on the target of the support (i.e., cognitive, metacognitive, social, affective, and motivational processes) as a key influence on the modeling needed to support the adaptivity. A system can provide adaptive support for one or more of these targets while providing either no support or fixed support for the other aspects.

The combination of AIED and collaborative learning began with the promise of extending traditional ITSs, designed for individual learning, to adaptively support collaboration (see Diziol et al., 2010; Lesgold et al., 1992). This goal made cognitive support (i.e., support focused on learning domain knowledge) a key aspect of the system and provided some of the same support and modeling as described in the section on problem solving. It appears, however, that models for tracking knowledge growth need to distinguish between individual and collaborative opportunities (Olsen et al., 2015). As early as 1992, Lesgold and colleagues (1992) investigated how to support collaborative learning within ITSs. In the intervening years, researchers have extended several ITSs to include collaboration support within such domains as algebra (Walker et al., 2014), fractions (Olsen et al., 2019), chemistry (Rau & Wu, 2017), and computer science (Harsley et al., 2017). For example, the Fractions Tutor (Rau et al., 2013) was extended to provide fixed (i.e., non-adaptive) collaboration support directly to the students through distributed roles (i.e., different students had different responsibilities and/or access to different information, so as to encourage collaboration), in addition to the adaptive cognitive support typical of an ITS through on-demand hints and feedback (Olsen et al., 2019). The collaboration support in this tutor version was fixed in that it supported different roles with different affordances in the interface (information, available actions) but did not respond to how students were actually collaborating.

On the other hand, systems can also provide adaptive support targeting the collaboration process. The data that are used in these systems vary greatly. For example, systems that use screen-based or robotic conversational agents may focus on the dialog occurring between the students by modeling students' conversational patterns (Adamson et al., 2014; Rosenberg-Kima et al., 2020). Researchers have also used log data from the system to provide adaptive support around collaborative actions. For instance, in a tabletop interface, the touch interaction patterns of the group can be used to facilitate the collaboration by having students vote on actions that will impact the global state of the project or lock out actions for a user to encourage a group focus (Evans et al., 2019). As another example, the COLLER system provided support to students around the collaborative process through a pedagogical agent by tracking problem solutions and participation (Constantino-Gonzalez et al., 2003).

At this point in time, only a small number of studies have tested the value of adaptive collaboration support by comparing adaptive and non-adaptive versions of collaboration support within the same system. For example, a study by Walker et al. (2011) found that an adaptive script supported higher levels of collaboration – but not individual learning gains – than a fixed script. Another example of a comparison that was successful was in LAMS where students who received adaptive rather than fixed prompts for discussion around missing keywords had higher knowledge acquisition (Karakostas & Demetriadis, 2014). This type of study is rare, however. Most researchers focused their evaluation studies on comparing students working individually to collaboratively.

In the tradition of ITSs, most AI support for collaborative learning has been directed at supporting students directly. However, recently the focus has turned to teachers. In the context of collaborative learning and CSCL, the teacher plays a large role in making sure the types of interactions that occur between students are effective for learning (Kaendler et al., 2015; Van Leeuwen & Janssen, 2019). It is, however, a demanding task for the teacher to monitor multiple groups at the same time and provide adequate support at any given moment without disrupting the collaborative process. A possible way to aid teachers in this task is by providing them with information about their collaborating students, collected automatically (i.e., analytics) (Van Leeuwen & Rummel, 2019). The assumption is that by enhancing teachers' understanding or diagnosis of the collaborating activities of their students, teachers can provide more adequate support, and in turn enhance the effectiveness of the collaboration. It is thus assumed that such tools aid the teacher to *orchestrate* student collaboration, in the sense of coordinating the learning situation by managing and guiding the activities within the collaborating groups (Prieto et al., 2011).

When we consider how this support fits into our frameworks, we can see a range of support provided. As the S/vL framework began in a collaborative setting, it may come as no surprise that the support provided spans the categories captured in this framework. Mirrored information can include both the social level (such as who is contributing and how much; Bachour et al., 2008; Strauß & Rummel, 2021) and cognitive level (such as who knows what information; Janssen & Bodemer, 2013). For formative feedback, some collaborative learning systems have given formative feedback on domain-level work. Finally, coaching systems are common in more adaptive systems that provide advice (as an example, Karakostas & Demetriadis, 2014). In terms of the Adaptivity Grid, much of the adaptivity occurs at the step and task levels, which may roughly correspond to the idea of micro and macro scripting, where micro scripts influence the interaction processes and macro scripts guide the learning activities and conditions (Häkkinen & Mäkitalo-Siegl, 2007).

Despite the examples in this section, much of the work that focuses on social support (i.e., collaboration support) as the target is still developing methods that can be used to track the state of students' interaction and provide adaptive recommendations. For example, in the field of multi-modal learning analytics, much of the focus has been on developing new models of the learning process (Chng et al., 2020; Olsen et al., 2020). As one explanation, in the context of collaboration, it is difficult to provide automated, adaptive support as discussed by Walker et al. (2009). Although promising steps have been made concerning adaptive collaboration support, it remains challenging to automatically determine the appropriate support at any single time point because there are several levels on which assistance needs to be delivered during student collaboration. Furthermore, depending on the data used to assess the collaboration, it can be difficult to collect and analyze those data in real time, such as for speech data. This is not to say that AIED cannot make progress in providing social support. One solution is to consider how to combine adaptive support provided directly to the student and that provided to the teacher where the teacher may be able to facilitate the last 10% of support.

Game-Based Learning

Learning games were originally conceived as a novel and motivational learning platform (Castell & Jenson, 2003; Gros, 2007) with their effectiveness eventually supported by various studies and meta-analyses (e.g., Clark et al., 2016; Ke, 2016; Mayer, 2019; Hussein et al., 2022). In many cases, students' interactions with a learning game environment are fundamentally different from those of other platforms, such as intelligent tutors. For example, in the game *Crystal Island* (Lester et al., 2013; Sawyer et al., 2017), students learn about microbiology by solving a realistic problem involving disease diagnoses, interacting with non-player characters (also called "pedagogical agents" or "learning companions") as they proceed. In *AutoThinking* (Hooshyar et al., 2021), students learn programming not by writing code but by controlling a mouse to evade two cats in a maze. Thus, game-based learning qualifies as its own instructional approach, with an emphasis on immersing students in fantasy (or virtual) environments that are game-like. More formally, we define a digital learning game as an interactive, computer-based system in which users (i.e., players) engage in activities involving fun, challenge, and/or fantasy, in which instructional and entertainment goals are part of the system, and in which predefined rules guide game play. An expanded definition and description of game-based learning can be found in Chapter 20 by McLaren and Nguyen.

In recent years, game-based learning has increased in general interest and prominence due to at least two key developments. First, more and more children are playing digital games (Lobel et al., 2017). For example, some reports have stated that as many as three-quarters of American children play digital games (NPD Group, 2019). Second, a variety of researchers (Chi & Wylie, 2014; Gee, 2003; Mayer, 2014; Plass et al., 2015; Prensky, 2006; Shute et al., 2015) have focused on the relationship between engagement and learning, and digital games have clearly been shown to prompt engagement in young learners. Much of this work is grounded in Czikszentmihalyi's theory of *flow* (1990), which proposes that people learn best when they are so engaged in an activity that they lose their sense of time and place and engage in activities for the simple joy of it, not for external rewards. There are other theories that are often cited in connection with game-based learning, as well, such as intrinsic motivation (Malone, 1981; Malone & Lepper, 1987) and self-determination theory (Deci & Ryan, 1985; Ryan et al., 2006).

The AIED community in particular has ramped up research on digital learning games over the past 15 years (see Arroyo et al., 2013, Arroyo et al., 2014; Benton et al., 2021; Conati et al., 2013; Easterday et al., 2017; Hooshyar et al., 2021; Jacovina et al., 2016; Johnson, 2010; Lester et al., 2013; Lomas et al., 2013; Long & Aleven, 2017a; McLaren et al., 2017; Shute et al., 2019; Wang et al., 2022). We have found it useful to divide the existing AIED digital learning games into four general categories. These categories have elements of the S/vL framework previously discussed.

1. *AI-based Adaptation games*. These are games that use AI to adapt in real time during gameplay. These games provide personalized support to students in the form of adapted problems, hints, and error messages. Thus, this category of games is aligned with the "coaching" level of the S/vL framework.
2. *AI-based Decision Support games*. These are digital learning games that instead of (or in addition to) automatically adapting to students, as in *AI-based Adaptation*, provide a dashboard with information on students' growth and progress, or make recommendations based on this information (e.g., Hou et al., 2020). This category of games is aligned with the "mirroring" and "coaching" levels of the S/vL framework.
3. *AI Character Interaction games*. Other AIED digital learning games use an AI-driven non-player character (NPC) to support student learning. These NPCs are often called pedagogical agents or learning companions.

4. *Games that use Learning Analytics (LA) and/or Educational Data Mining (EDM) for player analysis and/or improvement.* Perhaps the most prominent use of AI in digital learning game research has not been the actual integration of AI into real-time gameplay but rather the use of machine-learning techniques to do *post-hoc* analyses. This kind of analysis has been done either to better understand how students interact with games or to iteratively improve the games (i.e., a form of design-loop adaptivity in terms of the Adaptivity Grid).

In what follows, we provide examples of games and research that has been done in each of the above categories, as well as some thoughts on the future of AIED digital learning games. This review is necessarily brief; for a more elaborate discussion, see Chapter 20 by McLaren and Nguyen.

In the category of *AI-based Adaptation games*, there have primarily been games that have focused on adapting to support student mastery and/or to stay within a student's zone of proximal development (Vygotsky, 1978). For example, *MathSpring* (Arroyo et al., 2013, 2014) is a math learning game for fourth to seventh graders that adapts problem selection based on three dimensions of student behavior: attempts to solve a problem, help requested and time to answer (task-loop adaptivity). *MathSpring* also adapts based on student affect. *MathSpring* has led to improved performance in mathematics and improved engagement and affective outcomes for students overall but more specifically for females and low-achieving students. Another game that adapts to support mastery is *Prime Climb* (Conati et al., 2013), in which pairs of fifth- and sixth-grade students work together in solving number factorization problems by climbing a series of "number mountains," composed of numbered hexagons. The student model of *Prime Climb* uses a probabilistic algorithm to assess each student's factorization skills and then, in turn, uses this assessment to present adaptive hints at incrementally increasing levels of detail to support learning (step-loop adaptivity). Another example, one that is focused on adapting for a combination of fun and learning (rather than just learning) is *AutoThinking* (Hooshyar et al., 2021), a single-player game designed to promote elementary students' skills and conceptual knowledge in computational thinking (CT). The player takes the role of a mouse that is trying to collect cheese pieces in a maze to score as many points as possible, while at the same time avoiding two cats. To this end, the player writes "programs" using icons representing programming steps to create solutions to evade two (non-player) cats. Using a Bayesian Network algorithm, one of the two cats adapts to try to promote game fun and learning. The smart cat adaptively chooses between different algorithms that vary in how close the cat tends to get to the mouse. In a classroom study, *AutoThinking* improved students' CT skills and conceptual knowledge more than a more conventional, computer-based approach. Other key AI-based adaptive games that have been developed and experimented with include *Navigo* (Benton et al., 2021), *iStart-2* (Jacovina et al., 2016), and *Policy World* (Easterday et al., 2017).

AI-based Decision Support games also use adaptation algorithms but, as mentioned, typically for the purpose of collecting recommendations to present to students to make their own decisions rather than making automated decisions for them. In terms of the S/vL framework, we view recommending as a form of coaching, where the learner is in control of whether to follow the recommendation or not. These games are designed to support self-regulated learning, the notion that students, perhaps with some guidance and scaffolding, can make effective instructional decisions for themselves. A good example of this category of games is *Decimal Point* (McLaren et al., 2017; Hou et al., 2020; 2022), a single-player game that helps fifth- and sixth-grade kids learn decimals and decimal operations. *Decimal Point* is based on an amusement park metaphor, with a series of mini-games within it, each mini-game focused on a common decimal misconception. The original game was found to lead to better learning than a comparable computer-based tutoring system (McLaren et al., 2017). A variant of the game provided an adaptive recommender system that used Bayesian Knowledge Tracing (BKT; Corbett & Anderson, 1995) to make game suggestions (Hou et al., 2020; 2022). In a study comparing the Bayesian-supported dashboard, focused on skills, versus an enjoyment-focused dashboard, Hou et al. found that the enjoyment-focused group learned more efficiently, and that females had higher learning gains than males across all conditions.

Another game that provides a recommender is *Physics Playground* (Shute et al., 2019), a single-player, physics learning game designed to enhance physics understanding. The goal of *Physics Playground* is to solve problems related to hitting a balloon with a ball using as support a variety of tools provided in the game environment. To encourage student performance and use of learning supports, the authors added an incentive and recommendation system called *My Backpack* based on a "stealth assessment" of students' physics concepts and skills, as well as a space to customize game play. Students can use the My Backpack feedback to help them choose their next activity, that is, students can get task-loop adaptive recommendations from the game. Studies with the *Physics Playground* have indicated that students both learn the target skills and enjoy the game. There have been other *AI-based Decision Support* games – or gamified instructional tools – such as *Lynnette*, a mathematics intelligent tutor that Long and Aleven (2016) extended with game mechanics (i.e., badges, achievements) to "share" control of problem selection between student and system. A classroom experiment found that gamified shared control over problem selection led to better learning outcomes than full system control.

In the category of *AI Character Interaction*, learning game research has taken advantage of modern game frameworks (e.g., Unity) and advances in natural language processing to build realistic in-game characters (Non-Player Characters or NPCs) that can interact and learn with the student. Games in this category can foster an immersive learning experience while reducing the social anxiety associated with typical classroom activities (Bernadini et al., 2014). Perhaps the two most prominent AIED games in this category are *the Tactical Language and Cultural Training System* (*TLCTS*; Johnson, 2010; Johnson & Lester, 2018) and *Crystal Island* (Johnson, 2010; Lester et al., 2013; Sawyer et al., 2017). *TLCTS* is a game and virtual learning environment for helping learners master a foreign language and unfamiliar cultural traditions (Johnson, 2010). *TLCTS* has been used to help learners, predominantly military personnel, with Arabic, Chinese, and French, as well as other languages and cultures. Learners control a game character that interacts with NPCs. They do this by giving voice commands in the target language. The NPCs intelligently interact with learners in genuine cultural situations, so the learners can learn and understand both language and culture. Three studies with *TLCTS*, in which knowledge of Arabic and the Iraqi culture were the focus, showed that learners significantly increased their understanding of Arabic. Participants in two of the studies also reported significant increases in speaking and listening self-efficacy. A second prominent line of research in this category is *Crystal Island* (Lester et al. 2013), a narrative-based game for learning microbiology. In the game, the student plays the role of a medical agent who investigates an infectious disease plaguing the island's inhabitants. They can interact with a wide range of environmental objects and NPCs to collect data and form hypotheses. Results from several studies of the game identified a consistent learning benefit, while also shedding light on central learning game topics such as agency, affect, and engagement (Sawyer et al., 2017; Sabourin et al., 2013). Other games that have deployed NPCs to support learning include the computer science learning game *TurtleTalk* (Jung et al., 2019) and the conceptual math game *Squares Family* (Pareto, 2009; 2014), which also uses a teachable agent to support learning (see the next section).

The final category of AI applied to digital learning games is *Games that use Learning Analytics (LA) and/or Educational Data Mining (EDM) for player analysis and/or improvement.* Here, data mining, often using machine learning, and learning analytics, commonly with techniques used to analyze log data from ITSs, are used to assess student behavior post-play and/or to iteratively revise and improve games (a form of design-loop adaptivity, in terms of the Adaptivity Grid). For example, Baker et al. (2007) used learning curve techniques to model the acquisition of skills in the game *Zombie Division* (Habgood & Ainsworth, 2011) to help with game (re)design. Likewise, Harpstead and Aleven (2015) employed learning curve analysis to help in identifying student strategies and, consequently, redesigning the game *Beanstalk.* An important vein of research in this category has been using data mining to identify student affect. This is important given the key hypothesis behind digital learning games, that engagement is a mediator that leads to student learning. For instance, *Physics Playground* (Shute et al., 2015) was analyzed using structural equation modeling; it was discovered that in-game performance can be predicted by pretest data, frustration, and engaged concentration. Several of the games previously mentioned have also been the subject of EDM and LA analyses, both of student behavior and student affect, including *Decimal Point* (Nguyen et al., 2020), *Prime Climb* (Conati & Zhou, 2002), and *Crystal Island* (Sabourin et al., 2013; Sawyer et al., 2017).

As mentioned, there are several parallels between the above game categories and the S/vL framework. For example, to maintain engagement, games commonly provide feedback on players' actions, in the form of in-game credits or interface changes, a form of *mirroring.* Game-based adaptivity, where the game dynamically adjusts its difficulty to match the student's performance, is likewise analogous to *coaching* in tutoring systems. Finally, games with AI-based decision support both provide *formative feedback* and foster *self/co-regulation* in students. All in all, these similarities indicate that, despite their game-based nature, digital learning games can provide a rich, learning experience, structured sometimes like a formal tutoring system (see Easterday et al., 2017). At the same time, learning games also enable a much wider range of student–system interactions (e.g., through AI-powered game characters or immersive environments), whose potential learning benefits open up a promising area of future research. Furthermore, while learning games typically allow students to progress at their own pace, there is potential in developing teacher-focused tools to leverage the teacher's expertise in helping students self-regulate while playing.

Learning-by-Teaching

In *learning-by-teaching*, one student provides guidance to another as they both learn a topic (Lachner et al., 2021). It is thus a form of collaborative learning. There is no assumption (as one might perhaps expect) that the student in the role of teacher has fully mastered the material. Rather, both students are often peers within the same social group, working on the same learning objectives (Duran, 2017). Learning-by-teaching shares much of its theoretical grounding with collaborative learning, in that students benefit from building and articulating knowledge (Roscoe & Chi, 2007). When students prepare for teaching, they often gain a deeper understanding of the materials (Biswas et al., 2004). During the teaching, they engage in further learning through structuring, taking responsibility, and reflecting.

In AIED systems that support learning-by-teaching, the role of the "tutored student" is taken on either by another human (e.g., in peer tutoring; Walker et al., 2011) or by the system (e.g., with simulated students such as teachable agents; Blair et al., 2007). The system supports the learning process by scaffolding the teaching process, by building intelligence into the simulated student, or by doing both. In this section, we discuss both types of support. We also look at the factors that influence their impact.

AIED systems that support peer tutoring (among human peers) closely resemble those discussed in the section on collaborative learning in that they provide support for the communication within the group. They also typically provide help-giving assistance, that is, assistance regarding how one student might effectively help another student learn. For example, the *Adaptive Peer Tutoring Assistant (APTA)* provided the student instructor with adaptive resources including help-giving hints tailored to the problem and feedback tailored to the help that the student instructor had provided (Walker et al., 2011). An empirical study found that, compared with fixed support, this adaptive support improved the conceptual help provided by the student instructor. Recently, researchers have begun to expand this adaptive support to rapport. Students in high-rapport dyads (i.e., students who get along well) tend to provide more help and prompt for more explanations than those in low-rapport dyads (Madaio et al., 2018). The level of rapport can be detected automatically, which may allow for adaptive support within peer-tutoring systems that varies based on the students' current level of rapport (Madaio et al., 2017). AIED systems with simulated students may provide adaptive coaching to support the human student (in the teacher role) in becoming better tutors, as is the case in Betty's Brain (Kinnebrew et al., 2014). As these examples illustrate, the support provided in these systems to help students become better tutors is similar to the type of support that is provided in other AIED systems that support collaborative learning, discussed above in the section on collaborative learning.

A significant amount of AIED research has focused on the creation and study of learning-by-teaching systems in which the human student teaches simulated students. Although the student in the teaching role is aware that the simulated student is not a human, there are still motivational advantages for the student in the teaching role. Being responsible for someone else's learning, as students are in learning-by-teaching scenarios, can lead to greater motivation compared to being responsible for one's own learning (Chase et al., 2009). This phenomenon has been dubbed the "protégé effect" (Chase et al., 2009). A central capability of AIED systems is that the simulated student often can actually learn (using machine learning) or can reason with the information given by the human student (using AI inferencing methods), a unique advantage of AIED implementations. Feedback to the student instructor is often provided through the behavior of the simulated student such as how it performs in solving problems or on a quiz. The system learns and models productive learner behaviors allowing for adaptivity to the student instructor's behaviors (Blair et al., 2007). In other words, the simulated student will show learning that is dependent on what the student instructor teaches them.

The AIED field has produced several systems that support learning-by-teaching with simulated students, often called "teachable agents." For example, *Betty's Brain* (Biswas et al., 2005, 2016) has the student instructor "teach" Betty, an AI-driven teachable agent, about scientific phenomena. Betty uses a causal map of a task domain constructed by the student to reason about a given problem and answer quiz questions. The questions Betty can answer and how she reasons about the problem depends on how the (human) student has taught her (i.e., the causal map they constructed) and thus provides situational feedback. This feedback provides an incentive for the student to update the map in light of Betty's incorrect answers to quiz questions, so Betty can do better on the next quiz. Studies with Betty's Brain have found strong learning gains in multiple-choice and short-answer item questions but not in causal reasoning and other conceptual casual information (Segedy et al., 2015). Similarly, in *SimStudent* (Matsuda et al., 2011), the student instructor teaches by choosing a math problem for the simulated student to work through. As the simulated student attempts to solve the problem, the human student provides correctness feedback and correct answers when the simulated student is stuck. The simulated student learns a rule-based model based on this information and gradually becomes better at the task. Studies with SimStudent have shown limited benefits when students have low prior knowledge compared to tutored problem solving. In another system that supports learning by teaching with a simulated student, *Bella* (Lenat & Durlach, 2014), the main goal of the interactions between the human students and the teachable agent is for the system to learn about the knowledge of the human student. Although Elle (the teachable agent) appears to the human students to be learning, in reality, Elle learns from the system, which is different from the simulated students that we have previously discussed. Learning by teaching can also take place in digital learning games in which the human student tutors the simulated student on how to play the game (Pareto, 2014) and within classification tasks, such as in *Curiosity Notebook* (Law et al., 2020).

In the above examples, the simulated students take the form of virtual agents. However, researchers have also expanded to physical forms with the use of robots. Using robots, as opposed to virtual agents, allows the simulated student to interact with the physical space and to use gestures. For example, the *Co-writer* project (Hood et al., 2015) incorporates feedback from user demonstrations of how to write letters to learn the appropriate shapes, allowing the system to adapt to the writing input from the student instructor. As writing is a very physical activity, this interaction allows the robot to simulate realistic writing skills. In the *Co-reader* project (Yadollahi et al., 2018), human students taught the robot to read using a physical book that the robot could gesture toward. The pointing gestures of the robot were beneficial for student learning. Robots can also support language learning by having students use gestures and physical items to teach the robot by making associations with different words (Tanaka et al., 2015).

AIED research has also investigated how different features of the simulated students impact learning of the human student that teaches them. When agents engage in reciprocal feedback, there is a positive impact on learning (Okita & Schwartz, 2013). Furthermore, students learn more when there is greater rapport with the agent (Ogan et al., 2012) and the rapport and learning increase when agents speak socially and adapt to match the learner's pitch and loudness than when they just adapt (Lubold et al., 2019). Also, when the simulated student asks deep follow-up questions, students with low prior knowledge gain greater conceptual knowledge (Shahriar & Matsuda, 2021). Although many types of support and interactions have been assessed in teachable agents, adaptive agents have rarely been compared with fixed agents or human peers.

When we consider learning by teaching within our two conceptual frameworks, the support given to the students tends to focus on domain support, unlike with collaborative learning where students may also be provided with social support. In addition, students may be given coaching support on how to tutor, as in *Betty's Brain* (Kinnebrew et al., 2014) and *APTA* (Walker et al., 2011). This type of support is often at the step level. Due to the set-up of learning-by-teaching, students also get formative feedback based on the tutee's performance. As this feedback often occurs at the end of a problem or on a test/quiz, it is more often within the task loop. It can be viewed as situational feedback – the human tutor needs to figure out how to help the tutee do better based on the quiz results. Some systems (e.g., *Betty's Brain*) provide coaching in this regard.

DISCUSSION

In this chapter, we review AIED implementations of six instructional approaches that have been well studied within the field of AIED, using two conceptual frameworks to guide our comparison, Soller et al.'s (2006) assistance levels, as modified by VanLehn (2016), and the Adaptivity Grid (Aleven et al., 2017). Our review finds a rich variety in how these instructional approaches are conceptualized and implemented as AIED systems.

Let us now turn to our question: what does AIED bring to the table and how does AIED enable and enrich implementations of these six instructional approaches? To address this question, we synthesize the findings from our discussion so far, by looking for trends across the different instructional approaches. In doing so, we continue to take guidance from the two conceptual frameworks we have used throughout this chapter. Specifically, we ask: within and across instructional approaches, what assistance levels, as defined in the S/vL framework, are common in the AIED state-of-the-art, and (how) does AIED help in implementing them? Within and across instructional approaches, what range of adaptivity, as defined in the Adaptivity Grid, do we see within the AIED state-of-the-art? How does AIED help?

Levels of Assistance in the Instructional Approaches

We look at how the levels of assistance found in AIED systems vary depending on the instructional approach. We are not aware of any prior work that has addressed this question. Our review finds that, for each of the six reviewed instructional approaches, AIED systems provide adaptive coaching as their main form of assistance. They often provide formative feedback as an integral part of coaching, with mirroring being prevalent as well.

Across instructional approaches and AIED systems, we find many variations of *coaching*. As we were doing our review, we found it useful to distinguish between *more directive* and *more suggestive forms of coaching*. We see these notions as endpoints of a continuum. We do not provide necessary and sufficient conditions for these notions, but rather provide archetypal examples, sketched with a broad brush. We see this distinction as preliminary, albeit informed by a substantial amount of AIED literature. More precise definition is left for future work.

In *more directive coaching*, the AIED system tends to provide a high degree of structure within the learner's task. It is capable of fully evaluating the correctness or quality of student work, and the system's coaching focuses squarely on guiding students efficiently toward correct or high-quality work. The system may insist that students generate correct work (e.g., that they solve each problem correctly before moving to the next problem), while providing ample (step-level) guidance to the student such as hints and correctness feedback. To help students efficiently master the targeted skills or knowledge (i.e., individualized mastery learning), the system may require that students demonstrate mastery of one topic before moving on to the next. It may select problems for students to help them with these goals. This type of tutoring is typically made possible by a strong domain model (see Chapter 7 by Aleven et al.).

In *more suggestive coaching*, by contrast, the system's coaching is milder and not as demanding. The system can recognize a certain limited set of desirable or undesirable qualities in the student's work (i.e., in the process or product of the work), and can generate advice and feedback accordingly. However, systems that operate suggestive coaching often do not have a strong model of the targeted skills or knowledge. Their coaching does not focus strongly on (full, overall) solution correctness or quality, either because the system (lacking a strong domain model) is not capable of assessing it, or because, within the given instructional approach, evaluating and assessing is viewed as part of the student's task. As examples of more suggestive coaching, in collaborative learning, the system might look at whether the contributions to an on-going dialog are evenly divided among the participating students, on the assumption that an even distribution might result in the most learning for these students. The system might provide formative feedback or mirroring based on that information, without being capable of fully understanding the dialog and without assessing who is saying insightful things in the dialog. Similarly, a system for exploratory or inquiry learning, after the student has induced a general rule or conclusion from their explorations or inquiry, might show a counterexample that contradicts the student's rule, but it may leave it up to the student to recognize it as a counterexample and to figure out whether to repair their general rule, as doing so is viewed as an essential part of inquiry. As a final example, in an argumentation game, when a student's argument was not successful in convincing a judge or jury (within the game), that might be so because the argument position that the student was given the task of defending was inherently weak, or because the student failed to make the best possible argument. It may be up to the student to figure that out, as part of the instructional goals.

Before diving in, let us make two final comments regarding these two coaching styles. First, as mentioned, our distinction is just a first cut at trying to characterize differences in coaching, albeit one that is in tune with a wide range of AIED literature. We see a need for a nuanced, multi-faceted taxonomy of coaching, possibly with many more categories than our two, although we do not attempt to provide one in the current chapter. Second, we are not the first to try to characterize coaching styles. Our notions bear some semblance to the contrasting notions of tutoring (e.g., Anderson et al., 1995) versus issue-based coaching (e.g., Burton & Brown, 1979), respectively, that have a long history in AIED. As well, they connect to notions in other frameworks such as "directivity" and "coercion" (Rummel, 2018), or guidance versus information (Porayska-Pomsta, Mavrikis, & Pain, 2008), or learner control (Kay, 2001). We leave exploring connections with other frameworks as an interesting area for future work.

Our review finds that the directiveness of an AIED system's coaching tends to vary both with the system's main instructional approach and with the type of learning goals that the system aims to support. More directive coaching is found, first and foremost, in AIED systems *for tutored problem solving*. Many AIED systems for *example-based learning* also exhibit forms of directive coaching, for example, by providing feedback on students' explanations of example steps and by insisting on correct explanations (Conati & VanLehn, 2000; Salden et al., 2010; McLaren et al., 2008). Some AIED systems that support *game-based learning*, in particular those that guide students during problem-solving activities (see Conati et al., 2013; McLaren et al., 2017; Shute et al., 2015, 2019) have elements of directive coaching similar to those used in problem-solving tutors. Some of the directive coaching in game-based learning comes in the form of context-specific hints (Arroyo et al., 2014; Conati et al., 2013; Easterday et al., 2017; McLaren et al., 2022) or feedback (Easterday et al., 2017; Habgood & Ainsworth, 2011). Even systems for game-based learning that do not directly derive from tutoring systems (see Lester et al., 2013; Johnson, 2010) apply principles from tutoring, supporting more directive coaching. On the other hand, making recommendations (e.g., for the next task the student could take on), as many games do, should be viewed as a more suggestive (less directive) form of coaching.

Suggestive coaching approaches are found in AIED systems for *exploratory learning*, *collaborative learning*, and *learning-by-teaching*. The main goal behind coaching approaches in systems that support *exploratory learning* tends to be to support students in exploring effectively, while honoring the exploratory nature of the activity. In contrast to more directive coaching, feedback in these systems may not tell the student whether their exploration processes are "correct." Instead, these systems may prompt students to demonstrate strategies that are more likely to lead to conceptual understanding or provide opportunities for developing higher cognitive skills such as inquiry. Often, these systems coach without a strong model of inquiry or exploration. There are exceptions, however. Some AIED systems do more directive coaching (e.g., provide correctness feedback) during exploratory tasks (Gobert et al., 2013; Grawemeyer, 2017; McLaren et al., 2012; Siler et al., 2010). Similarly, AIED systems for *collaborative learning* tend to implement suggestive coaching aimed at helping students learn productive collaborative behaviors (which in the section above is referred to as "social support"), for example, with prompts or alerts that adapt to aspects of social interaction such as who is talking too much or too little (Dillenbourg & Fischer, 2007). AIED systems that support collaborative learning often do not have strong models of collaboration; some (e.g., APTA; Walker et al., 2011) conduct coaching based on a minimal model or an issue-based approach. These systems tend to combine suggestive coaching of collaborative behaviors with more directive coaching at the domain level (which in the section above is referred to as "cognitive support"), especially in projects that worked on individual learning first and then segued to support of collaborative learning (Baghaei et al., 2007; Olsen et al., 2019; Walker et al., 2011). Finally, systems that support *learning-by-teaching* have yielded some interesting forms of suggestive coaching. Some systems have tutor agents that coach the student in the role of tutor with the aim of helping them improve their tutoring strategies (Biswas et al., 2016; Leelawong & Biswas, 2008; Matsuda et al., 2011). Note that while most AIED learning games are firmly in the directive coaching category, as previously discussed, some do have more open-ended game structures for which more suggestive coaching is more appropriate (see Lester et al., 2013).

Moving to the next assistance level within the S/vL framework, *formative feedback* is plentiful in AIED systems, most often as an integral and central element of coaching. Strong correctness feedback is often a key element of *directive coaching*, for example in AIED systems that support *tutored problem solving*, *example-based learning* and *game-based learning*. These systems sometimes also provide elaborated error-specific feedback, as part of a directive coaching strategy. Some systems that support collaborative learning give correctness feedback on the domain-level aspects of students' work. On the other hand, formative feedback in AIED systems for exploratory learning and collaborative learning tends to focus on a limited set of desirable or undesirable aspects of student work (rather than providing a complete valuation of correctness), as part of a suggestive coaching strategy. Systems for *exploratory learning* sometimes give formative feedback when there are specific tasks/goals (sometimes, what to explore is left up to the student and the system does not know), or in response to a student's request for additional support. Sometimes, an inherent part of the coaching strategy is to *withhold* formative feedback, so as not to spoil the exploratory nature of the learning process. Similarly, when systems that support collaborative learning give formative feedback on collaboration, it is not strongly directive. Interestingly, "situational feedback" (Nathan, 1998) in both *games* and in systems for *learning-by-teaching* could be viewed as more suggestive coaching. Rather than providing correctness information, the system shows the student the consequences of their actions in the simulated world that the student is working in. It is up to the student to make sense of these consequences and infer how to improve their knowledge and work.

Regarding the third level of the S/vL framework, *mirroring* is a common form of assistance in AIED systems, across instructional approaches. We see two forms of mirroring in AIED systems. First, OLMs (a staple of *problem-solving tutors*, but present in other types of AIED systems as well, such as learning games) mirror the student *state*, as estimated by the system and captured in the system's student model, such as, for example, their (ever-changing) state of knowledge. In other words, the OLM may visualize how well a student, at any given point in time, masters targeted knowledge components. As discussed, a few empirical studies have tested whether OLMs of this type can support effective reflection and greater learning and have confirmed that they can (Long & Aleven, 2017b; Mitrovic & Martin, 2007). Second, many AIED systems support mirroring of *process* data, displaying, for example, how many problems a student has completed or how much time the student has spent. Systems that support *problem solving* often provide a variety of reports to students (e.g., Arroyo et al., 2014). Also, some studies focused on visualizations within the tutor interface itself, including visualizations of learning behaviors such as "gaming the system" (Baker et al., 2006; Walonoski & Heffernan, 2006). Furthermore, AIED systems that support *collaborative learning* may display or visualize the distribution of talk among the collaborating partners or the distribution of actions within the learning software among the team members. Often, the mirrored information is presented on a student dashboard or awareness tool (e.g., De Groot et al., 2007; McLaren et al., 2010). Mirroring of multimodal analytics is increasingly common, especially in collaborative learning (see Echeverria et al., 2019; Schneider & Pea, 2013). Some systems that support *exploratory learning* also mirror process data. As well, *games for learning* have long had dashboards (showing a student's advancement through the game's levels, for example), sometimes combined with suggestions or nudges for moving to the next level (see Hou et al., 2020; 2022; Long & Aleven, 2014).

Regarding teacher tools – as mentioned, a strong focus in current AIED research – we summarize for which instructional approaches such tools have been explored. A more in-depth treatment of teacher support tools can be found in Chapter 14 by Holstein and Olsen and Chapter 15 by Pozdniakov et al. Teacher awareness tools are starting to become available in AIED systems for *problem solving* and *collaborative learning*. In the former, the tool can inform the teacher of students' progress and struggle as they (the students) are working through the tutoring system's problem sets. In the latter, the focus tends to be on collaboration analytics. Having a teacher in the loop may compensate for not having strong models of collaboration (see De Groot et al., 2007). Teacher tools are also emerging in systems for *exploratory learning*. Teacher tools in such systems may mirror aspects of students' exploratory processes to teachers and (analogous to teacher tools for collaborative learning) may compensate for not having strong models of inquiry or exploration. Although, with a few exceptions (Gauthier et al., 2022), there are not many dedicated teacher tools integrated into AIED systems for *game-based learning* and *learning-by-teaching*, such tools have the potential to be highly useful.

Adaptivity in the Instructional Approaches

Looking at the six instructional approaches through the lens of the Adaptivity Grid (Aleven et al., 2017), our review finds many interesting examples of adaptivity in AIED systems, confirming the notion that adapting to students' needs is a central property of AIED systems and confirming earlier findings that adaptivity is a multifaceted concept. The current discussion highlights some forms of adaptivity not discussed in earlier reviews (e.g., Aleven et al., 2017) and contributes some new insights into how AIED systems' adaptivity tends to vary with their instructional approach. We also note that, interestingly, quite a few AIED systems combine multiple forms of adaptivity (e.g., adaptivity in the task loop and in the step loop, or different forms of adaptivity applied to different instructional goals). It has been shown empirically that, in some cases, combining several forms of adaptivity within a single system can be synergistic (see Corbett, 2001), although there is limited scientific knowledge regarding what forms of adaptivity work well together.

We first consider forms of *step-loop adaptivity* in the different instructional approaches that we studied, typically as part of their coaching strategy. As mentioned, step-loop adaptivity comprises adaptations at a small grain size and timescale, namely, within a given problem, at the level of problem steps. In systems that support *problem solving*, we often find forms of step-loop adaptivity as part of a directive coaching strategy, including step-level correctness feedback and hints that adapt to students' errors and strategies. We also came across some forms of step-loop adaptivity that are less typical, such as adapting feedback to student uncertainty (Mitrovic et al., 2013) and adaptive scaffolding in response to students' errors, for example by breaking down a problem into steps when a student makes an error (see Heffernan & Heffernan, 2014).

Similarly, in the support given by AIED systems for *example studying*, also characterized by directive coaching, we find interesting forms of step-loop adaptivity, including formative feedback that adapts to students' errors (typically, feedback on explanations) and the selection of example steps within a given worked-out example that a student is prompted to explain, based on their (estimated) state of knowledge (Conati & VanLehn, 2000). This way, the student's efforts can focus on explaining steps that involve knowledge that the student is yet to master.

We also find forms of step-loop adaptivity in systems for *exploratory learning*, whose coaching tends to be suggestive in nature. Systems for exploratory learning often provide a simulated world that adaptively responds to student interactions (e.g., manipulating variables, querying a model or simulation of the phenomena being explored, posing what if questions, or creating and running executable models). This form of adaptivity is not captured in the Adaptivity Grid but is a key part of the functionality of these systems and the way learners interact with them. Additionally, systems for *exploratory learning* often provide adaptive feedback aimed at the *process* of exploration or inquiry. The feedback may point out certain desirable or undesirable properties of student work, to encourage effective exploration or inquiry. By contrast, a few systems in this category employ a strong model of inquiry to provide directive (and adaptive) coaching in the step loop (Gobert et al., 2013; Grawemeyer, 2016; Siler et al., 2010).

Systems for *collaborative learning* may provide adaptive support during a task targeting different processes (cognitive, metacognitive, social, affective, and motivational) with different forms of adaptive support. Conversational agents may provide collaboration support in a manner that adapts to ongoing conversations between collaborating students, as a form of step-loop adaptivity. This form of coaching is sometimes combined with more directive coaching at the domain level, for example in systems that support collaborative problem solving. These systems may have some of the forms of step-level adaptivity described above.

Several *digital learning games* also implement forms of step-loop adaptivity, sometimes as part of directive coaching, including hints whose level of detail adapts to students' knowledge (e.g., Conati et al., 2013; Lesgold et al., 1992). Furthermore, some games, in their step loop, adapt to student affect (Conati et al., 2013; Arroyo et al., 2013, 2014) or adapt to a combination of fun and learning (Hooshyar et al., 2021). A key form of adaptive step-level support is situational feedback: the consequences of student actions are shown in the game world. The consequences are contingent on – or adapt to – the actions. As mentioned under exploratory learning above, this form of adaptivity is not captured well in the Adaptivity Grid.

In systems for *learning-by-teaching*, we see several interesting and unusual forms of step-loop adaptivity. First, a simulated student's answers to questions and its performance on quizzes is a form of (adaptive) situational feedback. Even the gestures of teachable robots may function as situational feedback. In addition, AIED systems for learning-by-teaching provide adaptive feedback on the teaching or tutoring by the (human) student, tailored to the problem and with feedback tailored to the help that the student instructor had provided. An interesting novel idea (though one that appears not to have been implemented yet at the time of this writing) is to create adaptive support for peer tutoring that varies based on the students' current level of rapport (Madaio et al., 2017).

Let us now turn to *task-loop adaptivity*, that is, adaptations in the choice and sequencing of learning activities or problems. Task-loop adaptivity tends to be more typical of directive coaching, perhaps because typical forms of it (e.g., individualized mastery learning) depend on being able to assess the correctness of students' solutions (e.g., in Bayesian Knowledge Tracing; Corbett & Anderson, 1995). Indeed, individualized mastery learning remains a key form of task-loop adaptivity of AIED systems that support *problem solving*. We also find task-loop adaptivity in systems that support *example studying*, such as adaptive selecting of erroneous examples so they match specific student errors (Goguadze et al., 2011) and the adaptive fading from examples to open problems based on growth in a student's explanation knowledge (Salden et al., 2010). Adaptive task selection is also found in several *digital learning games*, often presented to the student in the form of recommendations, a suggestive form of coaching (Hou et al., 2022), compared to the directive approaches found in typical implementations of individualized mastery learning. We also see forms of "hybrid task-loop adaptivity" in which the system adapts its task-level decisions based on a combination of student variables, such as measures of recent performance, effort, and affect; these approaches have been explored both in *games* (Arroyo et al., 2013, 2014; Conati et al., 2013; Hooshyar et al., 2021) and in systems that support *exploratory learning* (Mavrikis et al., 2022).

Finally, we turn to *design-loop adaptivity*. In design-loop adaptivity, as mentioned, a system is updated (by its designers) based on analysis of data collected during previous use of the system. Where past reviews (Aleven et al., 2017; Aleven & Koedinger, 2013) have highlighted instances of *design-loop adaptivity* in AIED systems for *problem solving* and *example studying*, the current review finds additional interesting instances of design-loop adaptivity in *digital learning games* and in systems that support *exploratory learning*. As discussed, it is becoming increasingly common that digital learning games are updated based on analysis of log data or game analytics. Our review in fact defines an entire category of games for which design-loop adaptivity is a distinguishing characteristic. Interestingly, some work on design-loop adaptivity in games has focused on exploring and adapting to student affect. As an example of design-loop adaptivity applied to *exploratory learning*, the model of scientific inquiry used in the Inq-ITS system to provide feedback was created by applying machine learning to log data from the inquiry environment (Gobert et al., 2013). The development of Inq-ITS coaching model is described in Chapter 7 by Aleven et al.

CONCLUSION

Our review applies two established, complementary conceptual frameworks, Soller et al.'s (2006) assistance levels, as modified by VanLehn (2016), and the Adaptivity Grid (Aleven et al., 2017), to compare AIED implementations of six instructional approaches. For each, we find a rich variety in the ways AIED systems assist learners and adapt their instruction to learners' needs. Increasingly, AIED systems are also designed to support teachers' needs, an important addition to past research.

Across instructional approaches, adaptive coaching is the most frequent form of assistance. Formative feedback is highly frequent as well, typically as part of adaptive coaching, and a great many AIED systems support mirroring. Adaptive coaching is what sets AIED apart from many other forms of instructional technology. AIED implementations of the different instructional approaches vary in their assistance levels and adaptivity. To the best of our knowledge, the relation between instructional approach and the forms of assistance and adaptation has not been explored in prior reviews. Given the great variety in how adaptive coaching is implemented in today's AIED systems, we find it useful to distinguish between two "flavors," which we call more directive and more suggestive coaching. Directive coaches focus strongly on – and may even insist on – correctness and mastery of knowledge. Suggestive coaches provide helpful feedback but without a full evaluation of correctness, either because the system does not have strong enough knowledge to do so, or because a suggestive coaching strategy is viewed as more compatible with the given instructional approach. We note that our distinction is only preliminary. More conceptual work is needed to describe the richness of coaching. The field of AIED may benefit from a more fine-grained taxonomy of coaching, a very interesting challenge for future work.

Our review highlights many forms of adaptivity, including forms of adapting to student affect, collaboration, and rapport, often in combination with other student variables (i.e., hybrid adaptivity in the terminology of Aleven et al., 2017). The design space for adaptivity in learning technologies is open-ended and constantly evolving. The scientific understanding of what forms of adaptivity are most helpful to learners may be a unique contribution of AIED to the field of technology-enhanced learning. Our review also finds that supporting multiple instructional goals within a single AIED is more common in AIED systems than we expected. Doing so poses a challenging design problem. We expect the field will produce new forms of adaptivity, for example, to help (dynamically) balance support for different instructional goals.

As our review indicates, a great amount of empirical research has documented the effectiveness of AIED implementations of all six instructional approaches, often by means of studies conducted in real educational settings (schools, university courses, academic online learning environments, etc.). Although the amount of empirical evidence that has been produced varies substantially across instructional approaches, all instructional approaches have proven to be effective in empirical studies.

By providing effective adaptive assistance, AIED has the potential to render feasible, at scale, the use of instructional approaches that (without AIED support) might require too much instructor involvement to be fit for use in classrooms or use by larger numbers of students. We are already seeing that kind of scaling in educational practice for AIED implementations of tutored problem solving. However, we see a great opportunity and great promise in bringing AIED implementations of the other instructional approaches reviewed to scale.

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