# Chapter 6
# Implementation of Adaptive Learning Systems: Current State and Potential

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## 6.1 Introduction

Countless aspects of our lives have become increasingly digitalized in the past few decades, learning being no exception. In the wake of digitalization, new forms of learning have emerged such as distance learning or technology-based learning, which are increasingly gaining importance today (Bergamin et al. 2012). Due to their flexible nature, these new forms of learning allow learners more independence and autonomy than ever before. Moreover, they overcome space-time barriers, thus granting many people the opportunity to pursue academic studies in circumstances that usually prevent or at least hinder such ambitions, e.g. full- or part-time employment or parenthood. Such flexibility allows for the inclusion of personal needs and contexts, which can differ considerably between individual learners. In higher education, such characteristics might be prior knowledge, learning skills, experience in regard to certain topics, use of strategies or affective states. Even with these differences, learners are usually expected to develop the same competences throughout their studies.

One way to achieve these comparable learning outcomes despite heterogeneous preconditions is to continuously adapt the learning process to the needs of the learners. This and related concepts can be covered under the umbrella term *adaptive learning*. In contrast to other technology-based learning approaches, adaptive learning enables the presentation of learning resources (e.g. content, support or navigation) in a dynamic form. This mostly occurs as a reaction to collected and evaluated data which can change during the learning processes, e.g. due to learning progress. In essence, adaptive learning systems continuously identify what a learner does or does not understand and provide help accordingly until a certain learning goal is

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met. This help can take different forms. One described by Oxman and Wong (2014) is the presentation of content situated just above the learner's current level in order to balance challenge and frustration. On this basis, adaptive learning has the potential to reduce dropout rates, lead to better learning outcomes and help students to achieve their learning goals faster. The notion of providing learners with assistance tailored towards their specific needs has a long history in pedagogy (e.g. in the form of one-to-one teacher support). However, technology-based adaptive learning systems provide forms of adaptivity beyond what can realistically be accomplished in traditional classroom settings in terms of resources or scale (cf. Koedinger et al. 2013).

The overall research problem addressed in this chapter is how the theoretical and conceptual foundation of an adaptive system needs to be specified in order for such a system to be implemented successfully in a university setting. This chapter aims to contribute the following to the discussion: We will first determine what it entails for a learning system to operate adaptively. In order to characterise the research in this area, we will then explore six basic questions in the design process of adaptive learning systems: why, what, what to, when, where and how a system can or should adapt (Brusilovsky 1996, 2001; Knutov 2012). We will also address the features and functions that are central to adaptive systems, followed by an overview over the current state of research in the area of adaptive learning. Practical implications and future potential of the research will also be discussed.

## 6.2 Definition of Adaptive Learning

Adaptive learning may be viewed from different theoretical and disciplinary perspectives, which is reflected in the definitions found in the literature. Depending on the perspective, the definitions may thus emphasise different elements. Jameson (2003), for example, approaches adaptivity from a computer science perspective and highlights the system's interactivity and its adaptation to different users based on user models (see below) as its core functionalities. He therefore defines a user-adaptive system as "an interactive system that adapts its behaviour to individual users on the basis of processes of user model acquisition and application that involve some form of learning, inference, or decision making" (p. 2). Interactivity and a focus on individual learners are elements also present in a more recent conceptualization by Aleven et al. (2017). In contrast to Jameson (2003), the authors argue from an educational point of view and further specify which kind of measure a system should base its adaptation upon. The authors identify three conditions a learning environment must meet in order to be considered adaptive. First off, its design needs to reflect topic-related challenges that learners often encounter. Secondly, the environment's pedagogical decision-making has to be based on psychological measures of individual learners (such as current knowledge, skills or affective states). Lastly, it is required to respond interactively to learner actions. All three of these aspects require data about learners, which are either pre-existing (condition 1) or collected and processed by the system (conditions 2 and 3).

In our view, these two definitions, although emphasising important learning-related components of adaptivity, do not explicitly address instructional aspects of adaptive learning. One element we deem crucial in this context is the monitoring of changes regarding the learners' progress. In our understanding, adaptive learning thus refers to technologies that monitor learning progress and repeatedly or continuously adapt the teaching process to the behaviours and needs of individual learners (see Adams Becker et al. 2018).

## 6.3 Core Components of Adaptive Learning Systems and Their Implementation

As indicated by the definitions of adaptive learning systems, there are certain elements that need to be accounted for when implementing such systems. Three core elements commonly found in adaptive learning systems, regardless of their degree of sophistication, are the domain model, the learner model and the adaptive model (cf. Vagale and Niedrite 2012). The *domain model* (also known as *content model* or *expert model*) refers to the content and structure of the topic to be taught, i.e. the relationships between the domain elements, and can address the intended learning outcomes as well as their sequence. The *learner model* (also known as *user model* or *student model*) is – as the name implies – a representation of the learner. The model consists of sensors and the learner modeller. The sensors capture and measure specific learner characteristics and pass the information to the learner modeller which then either uses the information as is (e.g. age, gender, prior knowledge) or further processes it (e.g. current knowledge, abilities, learning styles, motivational or emotional state). Depending on what characteristics the sensors measure, learner models can be either static or dynamic. While static models assess learner characteristics once, dynamic variants repeatedly measure and update them. In order for the learner model to be sound, the assessment of the learner characteristics (and the ensuing inferences) needs to be reliable and valid (see Shute and Towle 2003). The information from the sensors is in turn processed by the learner model and then further relayed to the *adaptive model* (also known as *adaptation model*, *instructional model*, *pedagogical model* or *tutoring model*). This model combines the processed information from the learner model with information from the domain model. The adaptive model can proceed to adapt content, instruction, or recommendations accordingly to support the learner in their progress. The model encompasses an instructional strategy that determines not only what can be adapted but also the context in which the adaptive process will occur.

Another way to look at adaptive learning systems is to focus on the design process. One way to characterise this process and its facets is by considering the six dimensions of the classic adaptive hypermedia approach (cf. Brusilovsky 1996): the

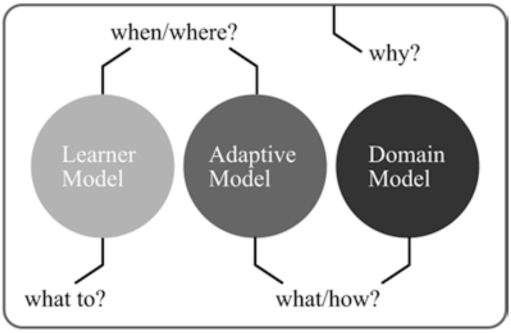


**Fig. 6.1** Core components of adaptive learning systems and facets of the design process

goals, targets, sources, temporal contexts, situational contexts and methods/techniques of adaptation. These dimensions can be rephrased as the following six questions: *Why* is adaptation wanted? *What* can or should a system adapt? *What* can or should it adapt *to*? *Where* and *when* can it be applied? And *how* does the system adapt? These questions will be elaborated on in the following sections, starting with the *why* question. Due to similarities between them, some of the subsequent questions will be bundled, specifically the *when* and *where* questions that both concern the context of adaptation and the *what* and *how* questions which both address the adaptive model. The relation between the three core components and the six questions is illustrated in Fig. 6.1.

### 6.3.1 Why *Is Adaptation Wanted? The Reasons for and Goals of Adaptation*

The first didactic question for the development of adaptive learning objects or entire systems is why adaptation of learning to particular needs is even desired (Knutov 2012). On the one hand, it relates to the identification and fulfilment of user-related needs that require such methods and techniques in the first place (i.e. the goals of adaptation). Through adaptive learning, personal learning paths, assistance and advice, a variety of learning requirements can be met, which is difficult to achieve in traditional learning settings. For instance, uneven levels of prior knowledge between learners, which could lead to adverse effects (e.g. overwhelming inexperienced learners while simultaneously boring advanced learners), can be mitigated through adaptive instructional design. Another example is adaptive learning systems can support novices that require navigational help, e.g. by limiting the amount of alternatives or recommending relevant links (Brusilovsky 1996). On the other hand, this question concerns the course designers' motivation behind applying different adaptive methods and techniques (i.e. the reasons for adaptation). In principle, the *why* question thus concerns the pedagogical rationale underlying the implementation of adaptive systems (cf. Mavroudi et al. 2018). The pedagogical rationale itself can be derived from a variety of different basic theories, such as aptitude-treatment interactions, the zone of proximal development, fading scaffolds, the expertise reversal paradigm and self-regulated learning.

The concept of *aptitude-treatment interactions* (see Cronbach and Snow 1977) refers to the circumstance that instructional strategies (Cronbach and Snow refer to these as "treatments") are not equally successful for each individual learner and may instead depend on specific abilities of the learners that forecast their potential success – in other words, their *aptitude*. From this point of view, adaptive learning provides options to find optimal treatments to match individual learners' aptitudes. Another concept which adaptive learning can build on is the *zone of proximal development* (see Vygotsky 1978). The core idea of this concept is to give the learners tasks they are able to complete with guidance, as opposed to tasks they are able to do unaided or task they cannot complete even with guidance. As the learner progresses, this guidance can gradually be reduced (cf. the concept of *fading scaffolds*; Collins et al. 1988; van Merriënboer and Sluijsmans 2009). The importance of adapting the learning process to characteristics of the learner is further supported by the finding that instructional techniques (e.g. guidance by a tutor or detailed instructions) that benefit novices can lose their effectiveness or even be counterproductive to experts, a phenomenon known as the *expertise reversal effect* (Kalyuga et al. 2003).

In this context, "reversal" refers to the idea that the effectiveness of instructional techniques may be reversed for different levels of expertise, e.g. that instructions may help novices yet hinder experts (Lee and Kalyuga 2014). The expertise reversal effect is usually explained by the *Cognitive Load Theory* (Sweller 1988). The basis of the theory is the notion that the cognitive load, i.e. information that is currently stored and processed in the working memory, cannot exceed its limitations. While the long-term memory holds cognitive schemata with varying degrees of complexity within an unlimited storing capacity, the working memory is thought to be quite limited in its capacity to store information, both in terms of amount and duration (van Merriënboer and Sweller 2005). Classic accounts of the Cognitive Load Theory differentiate between two kinds of cognitive load, the intrinsic load and the extraneous load. *Intrinsic load* refers to cognitive processes involved in processing novel learning materials, which may be affected by the (perceived) complexity of the material. *Extraneous load* concerns factors that affect cognitive processes despite not being directly related to the task at hand, such as convoluted instructional design or unfavourable presentation of the learning material (Kalyuga 2009).

The two forms of cognitive load interact with one another so that an abundance of extraneous load (e.g. by giving learners too much unnecessary information or by having a cluttered visual design) reduces the capacity left for proper processing of the learning material due to the working memory's limitations. Importantly, the current cognitive load of a learner also depends on learner characteristics such as expertise. In parts, expertise is represented by cognitive schemata with varying degrees of complexity and automation housed by the long-term memory (van Merriënboer and Sweller 2005). When schemata become automated through training, space in the working memory is freed, which then reduces the intrinsic load, leaving more cognitive capacity for the processing of new content (Kalyuga 2009). This implies that instructional interventions should be adjusted (adapted) to the learners' cognitive load when teaching complex content (Rey and Buchwald 2011; Somyürek 2015). This may be achieved through instructional guidance: low levels of guidance or instructional scarcity can affect novices negatively as they might lack the expertise to compensate for the missing or incomplete information, which can lead to poor problem-solving strategies or mere guess work. Experts on the other hand are not affected as much since they can rely on their prior knowledge. When the amount of guidance is overabundant, the inverse effect may occur: novices benefit from the detailed instructions while experts' cognitive load is increased since they need to compare and contrast the flux of incoming information with their prior knowledge, inflating their intrinsic load (cf. Kalyuga 2007). Consequently, at the start of the learning process, novices should be provided with instructional guidance (e.g. step-by-step instruction) in order to guide them through their tasks and reach an optimal level of cognitive load. The concept of fading scaffolds applies here again (Collins et al. 1988; van Merriënboer and Sluijsmans 2009).

The educational implications of the Cognitive Load Theory and its role in explaining the expertise reversal effect have been explored and confirmed in numerous studies (e.g. Rey and Buchwald 2011). However, the cognitive load approach is limited to a specific learning goal in its application, namely, the acquisition of subject-specific knowledge (Kalyuga and Singh 2016). Other learning goals such as enhancing self-regulated learning are beyond the scope of the approach and may best be addressed by other theoretical perspectives within adaptive learning. *Self-regulated learning* refers to self-directive processes and motivational self-beliefs that learners use to proactively acquire academic skills (Zimmerman 2008). These skills include the setting of challenging goals, the employment of appropriate strategies to achieve these goals and the self-monitoring of one's activities and effectiveness until said goals are met. Adaptive learning environments can support self-regulated learning, e.g. by facilitating monitoring via continuous self-assessments and improving regulation of learning processes via instructional guidance (Scheiter et al. 2017).

These theories all provide guidelines for pedagogical decision-making. Despite representing vastly different perspectives, they are not mutually exclusive. The pedagogical strategies of adaptive learning systems can draw from multiple theoretical sources at once, e.g. by combining self-regulated learning with fading scaffolds.

### *6.3.2 What Can or Should Be Adapted and How? The Objects, Methods and Techniques of Adaptation*

The next questions concern what can be adapted within a system to meet the guidelines illustrated above and how this may be accomplished. On one hand, the *what* question depends on the domain model since that model provides a structure of the topic also entailing which aspects can be adapted (see Knutov 2012). Brusilovsky (2001) suggests two aspects that can be adapted, namely, presentation and navigation support. *Adaptive presentation* focusses – as the name implies – on the presentation of the content in accordance with various learner characteristics (which will be discussed later). For example, a more experienced learner may be provided with less detailed instructions for a task, while novices may receive additional explanations to support their understanding of the topic. *Adaptive navigation support* is based on personalised learning paths that are supposed to guide the learner to appropriate learning content. Knutov (2012) adds a third approach in the form of *content adaptation support*, which addresses the presence or absence of specific bits of information, thus regulating their accessibility. This kind of support may also vary the emphasis that is put on the information. Other parts of the instructional design that can be adapted include hints, prompts and recommendations.

On the other hand, the *what* question also revolves around the adaptive model, as does the *how* question. How the adaptive process works can be described on two levels, either on a conceptual/design level or on an implementation level. The adaptive process involves *techniques*, which are usually applied at the implementation level of a system and adhere to specific approaches or algorithms, as well as *methods*, which are generalisations of techniques (Knutov 2012). Examples for techniques in content adaptation support include inserting, removing or modifying information, which change the accessibility of information, thus altering the content itself. Other techniques, which are also shared by adaptive presentation support, do not change the content but rather lead the learner to focus only on parts of the content. These include dimming, sorting, zooming or stretchtext (Knutov 2012). The latter two are also useful techniques when presenting information that only needs to be seen by a subset of learners. Techniques applied in the context of adaptive navigation support can either be enforced or recommended. These techniques include guidance (e.g. by recommending links, which can also be classified as an adaptive presentation support technique), link generation or link hiding (Knutov 2012).

The decision between enforced or recommended paths taps into the self-regulation dilemma, which concerns the amount of control that is given to the system versus the control given to its user (see Bergamin and Hirt 2018; Kobsa et al. 2001). On one end of the spectrum, learners are given complete control over their learning process (i.e. choice of topics, resources and support). Such systems are also called *adaptable* systems. The learner-control approach might entail positive consequences since freedom can be a motivating factor and learners may enjoy being in control. However, this level of freedom may also overwhelm and thus demotivate learners, especially at the beginning of the learning process, when learners lack self-regulation skills, or when a complex topic is concerned. On the other end of the spectrum, *adaptive* systems choose and present learning content, which may lead to decisions that are more sound than decisions that novices would make, but the lack of control on the learner's part may frustrate them, especially when the decisions by the system are faulty or not what the learner anticipates. This may be the case when the learner model is not accurate enough or when the learner's view is skewed. One way to bypass the dilemma is by allowing the control to be shared between the system and the learner, which is often achieved by implementing *recommender systems*. These systems offer learners recommendations or advice on how to adapt their learning process (e.g. by recommending tasks, supplementary material and so on) instead of forcing a system-made decision upon them. The learner is thus free to follow the recommendation or ignore it.

Since instructional interventions in this type of system are dependent on the learner's initiative, they are referred to as *non-embedded* (Clarebout and Elen 2006). A more *embedded* alternative exists in the form of the *two-step approach* (cf. Bergamin and Hirt 2018). In the first step, the system selects a set of appropriate learning objects (e.g. tasks), which the learner is then able to choose from. The main advantage of this approach is that learners can be prevented from being overwhelmed by countless options or from selecting counterproductive tasks while still being allowed to be in control, at least to a degree. Chou et al. (2015) present another option that allows simultaneous shared control between the system and the learner, the *negotiation-based adaptation mechanism*. This mechanism compares the system's learner model with the student's self-assessment, and if they do not match, modifications to the learner model will be "negotiated" between the learner and the system. It supports learners with low meta-cognitive skills while allowing learners to correct inaccurate learner models.

Moreover, methods and techniques applied in adaptive learning systems can vary substantially in terms of complexity and level of detail. A common distinction is made between *rule-based* and *algorithm-based systems* (Murray and Pérez 2015; cf. Oxman and Wong 2014). The former usually relies on a series of if-then functions with varying degrees of complexity (e.g. through different branching paths). If learners get answers right, the system directs them to the next task, and if they do not, it provides assistance in the form of a hint, repeated content or different explanations of the same content. Rule-based adaptive systems are transparent in their functionalities, which makes them easier to use; however, they do not tap into the computational potential that more sophisticated systems do. Algorithm-based approaches are far more complex and often involve methods related to machine learning, such as item-response theory (e.g. Wauters et al. 2010; Pliakos et al. 2019), Bayesian Knowledge Tracing (Corbett and Anderson 1995), fuzzy-logic (Ennouamani and Mahani 2019) or deep learning (Goodfellow et al. 2016). Additionally, they may involve elaborated techniques such as (big) data mining (e.g. Yuan 2019) or learning analytics in order to continuously predict the success of an individual learner based on specific bits of information. As Ge et al. (2019) note in their literature review, there is a tendency for adaptive systems to rely on established algorithms, rather than implementing game engines or developing their own algorithms.

A noteworthy example for algorithm-based approaches are *micro-adaptive systems* (Vandewaetere et al. 2011). Micro-adaptive systems are learning systems that employ micro-adaptive instructions that dynamically decide which instructional treatments are the most appropriate at any given time (e.g. intelligent tutoring systems). They accordingly provide tailored on-time instructions based on within-task measures. The fine-grained and precise measures this approach requires are thought to warrant the implementation of artificial intelligence techniques. However, this alleged necessity has attracted controversy since some authors, e.g. Essa (2016), argue that domain-specific micro-adaptivity should be regarded as "the primary realm of the instructor" (p. 11). The authors speculate that for the foreseeable future, machine learning will not surpass the instructor's knowledge and experience, at least as far as providing feedback and correcting errors is concerned. We would like to emphasise that machine learning and the instructor's experience are not mutually exclusive and may complement one another. Examples for this are supervised machine learning and co-creation strategies (see Dollinger and Lodge 2018).

### 6.3.3 *What Can or Should Be Adapted to? The Basis of Adaptation*

The fourth question concerns which characteristics of the learner should be captured by the sensor part of the learner model. As these characteristics form the basis for adaptive processes, they need to be selected carefully. What characteristics are most valuable in the context of a learning task, a course or even degree programmes to be adapted in regard to a particular goal is not a trivial question and has led to some disagreement in the literature (see Granić and Nakić 2010). In order to provide a potential answer, Nakić et al. (2015) conducted one of the most encompassing literature reviews regarding adaptation to learner characteristics. The authors explored 22 different learner characteristics over 98 studies released between 2001 and 2013, which include age, gender, working memory capacity, (meta-)cognitive abilities, anxiety and so on.

Given how wide the variety of characteristics to choose from is, several attempts have been made to categorise them. Vandewaetere et al. (2011) differentiate between three categories, which they derive from the combination of empirical research with theoretical propositions. These three categories are (1) cognition (working memory capacity, intelligence, prior knowledge, cognitive and learning styles), (2) affect (frustration, confusion, delight, mood and self-efficacy) and (3) behaviour (need for learner control, help and/or feedback, self-regulated learning, number of tries per task and grades). Although these categories seem to differ clearly, the boundaries between them are often blurred. The category *affect* includes states that are blends between affect and cognition (e.g. confusion and self-efficacy), while the characteristics in the *behaviour* category can be viewed as consequences of cognitive and affective states. Another classification stems from Aleven et al. (2017) who identify five groups of learner characteristics: prior knowledge and knowledge growth; strategies and errors; affect and motivation; self-regulated learning strategies, metacognition and effort; and learning styles. As they note, determining which characteristics are worth adapting to the most is ultimately an empirical question. Based on the results of the studies that Nakić et al. (2015) examined, the authors conclude that adapting to one or more of the following characteristics proves to be the most successful: learning styles, prior knowledge, cognitive styles, preferences for particular types of learning materials and motivation. The latter is noted to have been subject to increasing attention in research, along with characteristics such as emotions and metacognitive abilities (Nakić et al. 2015). Adapting to cognitive abilities and personality is also deemed promising, although those characteristics have been explored to a lesser degree (see, e.g. Afini Normadhi et al. 2019). Further details will be provided in the section discussing the current state of the research.

### *6.3.4 When and Where Can Adaptation Be Applied? The Context of Adaptation*

Knowing on which pedagogical basis we want to adapt what aspects to which characteristics with which techniques, the final questions are when and where adaptation takes place. One way to answer both of these questions at once is by addressing loop levels, which determine when and where instructions can be varied within the adaptive model. According to Bergamin and Hirt (2018), there are three levels on which adaptation can occur: the curriculum loop, the task loop and the step loop. In the *curriculum loop*, the adaptive system recommends (or enforces) learning domains (curricula) based on the learners' needs and preconditions. This can be illustrated with an example: A learner succeeds in a particular course and may thus be recommended an advanced course on the same topic. Since it concerns in-between-course adaptation, the curriculum loop only occasionally adapts to the learner model.

In the *task loop* (also known as *outer loop*), the system makes decision regarding the instructional support, complexity of the content or sequencing (i.e. task selection) depending on the individual learner's current conditions. An adaptive system may thus recommend (or enforce) more challenging tasks to successful learners while presenting tasks that involve more assistance to less proficient learners. Since it concerns tasks, the task loop adapts to the learner model more frequently than the curriculum, but less frequently than the step loop. In the *step loop* (also known as *inner loop*), the system provides hints, feedback and prompts regarding the current learning activity within a learning object (e.g. a task). This adaptation depends on the individual learner's most recent learning behaviour. Aleven et al. (2017) also differentiate between three loop levels; but instead of the curriculum loop, they include a *design loop* in their conceptualisation. Design-loop adaptivity refers to data-driven changes between different iterations of the same course on the basis of similarities between learners. For example, a course designer may receive the feedback that a high percentage of students displayed the same misconception in a physics task, which leads to them accounting for that misconception in the next version of the course. In contrast to the other loops, this loop does not concern the individual learner and takes on a different perspective (namely, that of a course designer charged with redesigning an existing course).

The *when* and *where* questions can further be addressed by considering another aspect of adaptive systems, namely, their application area. While e-learning remains the main application area of adaptive learning, its range has expanded significantly over the years. Adaptive learning systems are applied in various educational institutions (primary school, secondary school, senior school, university, etc.) as well as organisations, e.g. for training purposes. Moreover, there has been an increase in context-aware adaptive systems that try to incorporate context characteristics in addition to learner characteristics, e.g. the time and place of a learning activity or the device used by the learner. This can be achieved by either expanding the learner model or adding a fourth model to the three core components (for instance, a *context model*; see Knutov 2012).

## 6.4 Current State of the Research

In this next part, we will concentrate on three aspects of current application-oriented research: the evaluation of the effectiveness and efficiency of adaptive learning systems, the satisfaction of learners with such systems and their actual implementation. We highlight application-oriented research over theoretical literature to emphasise the practical implementation of adaptive learning systems.

### *6.4.1 Learner Performance: Effectiveness and Efficiency of Adaptive Learning Systems*

Instructional effectiveness and efficiency are key aspects of adaptive learning since optimising learning is one of the central objectives of this approach (Sottilare and Goodwin 2017). *Instructional effectiveness* refers to enhancing learning capacity to acquire knowledge or skill. Importantly, the time in which this learning gain is supposed to transpire is fixed and the learning content is varied, so that at the end of the course, learners may be below, at or above their expected level (Sottilare and Goodwin 2017). In contrast, *instructional efficiency* refers to the acceleration of learning, which means a reduction of the time learners need to reach a desired level of knowledge or skill. By providing learners with instruction tailored to their needs (e.g. based on their current level of knowledge), the amount of information they are presented with can be reduced. However, allowing learners to skip information is not always recommended since learning materials may need to be revisited from time to time to retain proficiency (Sottilare and Goodwin 2017). Adaptive learning reveals its potential addressing both of these points, as it permits a large variety of learning materials and instructional strategies to be tailored to the needs of individual learners. Effectiveness and efficiency depend, among other things, on the context of the deployment of adaptive learning, higher education being by far the most common context (see Xie et al. 2019, for an overview).

One part of the literature concerns the effectiveness and efficiency of adaptive learning systems. This line of research is concerned with the research question how effective and efficient adaptive learning systems are, usually in comparison to either non-adaptive alternatives or other adaptive systems with diverging features. Accordingly, most researchers hypothesise that adaptive learning systems are more effective and efficient than their non-adaptive counterparts. While some studies have assessed both effectiveness and efficiency of adaptive learning systems, others have focussed on one of these two performance measures. Verdú et al. (2008), for example, examined the evidence for the effectiveness of adaptive learning by comparing studies that analysed adaptive systems in various institutional contexts. They found that with varying levels of statistical significance and effect sizes, all 18 of the studies in their pool reported positive results, i.e. students improved in their academic achievement when using adaptive systems in comparison to control groups. The variation between effect sizes indicates a vast range of effects. One study yielded an effect size of 0.1, which indicates a small, statistically not significant learning gain. Large effects (i.e. effect sizes of at least 0.66) were found in ten of the studies, with the remainder yielding medium to small effects. Further studies show that the results concerning the effectiveness and efficiency of adaptive learning are rather mixed: while there is evidence to suggest that the implementation of adaptive learning can lead to improved achievements, higher self-perceived learning gains and reduced cognitive load (e.g. Yang et al. 2013), other studies were only able to detect positive effects on learning outcomes under specific conditions. In their evaluation of an adaptive online learning system, Griff and Matter (2013) only found positive effects in two out of the six participating institutions. Similarly, Murray and Pérez (2015), who implemented a micro-level adaptive approach, only found a negligible impact of adaptive learning on learning outcomes when compared to a traditional non-adaptive approach. In a recent experimental classroom study, Eau et al. (2019) did not find any significant impact of adaptive learning on exam scores, course grades or progress. In contrast, Ghergulescu et al. (2016), who conducted a field study with a total sample size of 10,000 students across 1700 mathematics sessions, report significant improvements across ability levels (i.e. ranging from low to high achievers). Low achievers improved more than high achievers, thus reducing the achievement gap.

Another part of the literature addresses effectiveness and efficiency in relation to the temporal context the systems operate in as well as the learner characteristics their learner model is based on. Here we will illustrate this based on the findings by Aleven et al. (2017), who evaluated the effectiveness of adapting to various learner characteristics by systematically reviewing studies that either addressed design-loop, task-loop or step-loop adaptations to learner characteristics stemming from their previously presented five categories (prior knowledge, strategies and errors, affect and motivation, self-regulation of learning and learning styles). Since we do not consider design-loop adaptivity to be on the same dimension as the task and step loops as explained above, we will only include the latter two in our overview.

First off, Aleven et al. (2017) present evidence to support the effectiveness of adapting to prior knowledge. Evidence on the task-loop adaptivity suggests that adapting the task selection to the learners' prior knowledge improves both effectiveness and efficiency of learning. Corbett et al. (2000), for instance, observed that students scored twice as high in the assessment of an algebra problem and 10% higher in a standard test when using the Cognitive Tutor Algebra I in comparison to traditional courses. Cognitive Tutors are intelligent tutoring systems that present tasks which train aspects students are unlikely to have mastered yet. Comparable results have been achieved by promoting learning by analogue problem-solving, where students solve problems by transferring knowledge from an analogue, adaptively selected example (cf. Muldner and Conati 2007). Increased learning gains were also observed when examining step-loop adaptivity, even though the evidence is not quite as abundant in this context. Conati (2013), for example, reported larger learning gains after implementing a self-explanation coach for physics problem-solving (i.e. a system that adaptively selected steps of worked examples and provided a structure template as well as feedback). This effect was larger for students with low levels of prior knowledge, which is also what Albacete and VanLehn (2000) observed. The opposite was found by Own (2006): in his study, the difference in learning progress was only significant for students that had more prior knowledge. E. Verdú et al. (2008) identified differences in contexts, systems and analyses between the studies as the most likely cause for this discrepancy.

Overall, Aleven et al. (2017) note that the evidence supporting the value of adapting to prior knowledge is consistent with the widespread notion that learners' prior knowledge is a key factor in learning. In fact, the authors assert that adapting to prior knowledge within the task-loop yielded the largest effects out of all the possible combinations between the learner characteristics and loops they examined.

Adapting to learners' affect was also found to improve effectiveness and efficiency. An example concerning task-loop adaptivity is a study by Walkington (2013), who implemented interest in her tutoring system by adapting the cover stories of algebra problems to students' interests. This resulted in higher accuracy and increased learning efficiency in the course and led to accelerated learning later on. Regarding the step loop, affect-aware tutoring systems were found to enhance learning. Examples include studies by D'Mello et al. (2010), who used *AutoTutor*, a system capable of detecting boredom, confusion, frustration and neutral affective states, or D'Mello et al. (2012), who implemented eye-trackers in their tutoring system in order to detect and adaptively counteract disengagement. Some systems even feature hybrid adaptivity, i.e. algorithms that combine affective with cognitive factors (e.g. Mazziotti et al. 2015). In contrast, Aleven et al. (2017) note that research focussed on adapting to learners' motivation has been comparatively scarce with only the groundwork being laid, e.g. in the form of self-efficacy-detecting algorithms using machine-learning models (McQuiggan et al. 2008).

Task-loop adaptivity to self-regulation can be effective as well, even though the evidence seems to be mixed. The most promising approach appears to be a combination between open learner models (i.e. a representation of the learner characteristics used by the system, often presented to the learner in a visual form) and self-assessment support (cf. Arroyo et al. 2014; Long and Aleven 2013). There is also evidence to suggest that adapting to self-regulated learning yields positive results in the step loop by improving learners' self-regulated learning processes (e.g. help-seeking, Tai et al. 2013).

In contrast, the evidence for the effectiveness and efficiency of adapting to learners' learning strategies and error patterns is mixed (Aleven et al. 2017). While step-loop adaptivity to strategies and errors is also deemed effective, particularly when applied in the form of step-level feedback (see Koedinger and Aleven 2007), the evidence presented by Aleven et al. (2017) does not support any clear advantage of task-loop adaptivity over non-adaptive tutoring. Adapting to learning styles also yielded little conclusive evidence, despite the popularity of the concept in past and present research (e.g. Kolekar et al. 2019). Many researchers argue that learning styles lack a firm theoretical basis (e.g. Aleven et al. 2017; Kirschner and van Merriënboer 2013; Lu et al. 2003), an issue that is further compounded by other controversies surrounding the topic, with some researchers even dismissing them as a "myth" (see Kirschner 2017).

A learner characteristic not present in the overview presented by Aleven et al. (2017) that was recently investigated was aptitude (Eldenfria and Al-Samarraie 2019). In their study, Eldenfria and Al-Samarraie (2019) found their aptitude-based adaptive mechanism to be effective, which was supported by EEG data.

Current research thus shows that adaptive learning can be both effective and efficient, be it in general or addressing specific temporal contexts (i.e. loops) or learner characteristics. The effects found in the literature may vary in their size from no effect to large effects, but all reported effects are positive, supporting the potential for future research.

### *6.4.2 Satisfaction Among Learners*

Effectiveness and efficiency are not the only measures to indicate the success of a learning system. No matter how effective a system is, the prospects of success are jeopardised if students and/or teachers reject it. Assessing student satisfaction is therefore key when judging the quality of a system. Moreover, studies have shown positive links between student satisfaction and motivation, student retention and recruitment (see Schertzer and Schertzer 2004). Levy (2007) additionally shows that dropouts occur at substantially higher rates in e-learning as compared to offline courses, stressing the importance of student satisfaction for student retention. The research question that guides this strand of research is thus how satisfied students are with adaptive learning systems. Usually, students are hypothesised to feel satisfied with adaptive learning systems. Verdú et al. (2008) compared the results of 11 studies that assessed the level of students' satisfaction with adaptive learning systems via questionnaires. Since the results were based on questionnaires with different scales, the values were normalised before the comparison. One study reported medium (0.5) and the others high learner satisfaction (0.66–0.81) with adaptive learning systems. They conclude that most learners thought that the adaptive systems supported their learning progress and met their requirements.

In a more recent study, Dziuban et al. (2017) investigated how students from two contextually different universities reflected on the adaptive learning platform *Realizeit*. Despite differing in demographic and educational backgrounds, most students reacted positively to the adaptive system by giving it high marks regarding its perceived educational effectiveness and were able to make a near-seamless transition from non-adaptive systems. However, there are certain conditions that have to be met in order for learners not to reject adaptive systems. If systems are unstable, unreliable, too cumbersome in their use or plagued by usability problems, the risk of students (and teachers) abandoning it rises. Lack of transparency is an additional risk factor that can lead to trust issues (e.g. when the system is perceived as a "black box" without any comprehensible rationale behind its decisions; see Khosravi et al. 2020).

Assessing the usability of adaptive systems is therefore worthwhile (cf. Khosravi et al. 2020). Alshammari et al. (2015), for example, compared an adaptive learning system with a non-adaptive version in an experimental setting and found that the adaptive learning system yielded higher ratings regarding its perceived usability than its non-adaptive counterpart. Similarly, Vesin et al. (2018) examined the usability of the adaptive learning system *ProTuS* using the *System Usability Scale* (*SUS*). The resulting score was 67.2 out of 100, indicating a marginally acceptable usability, i.e. on the verge of being acceptable (with a score of 70 being the threshold). More recently, a German translation of the SUS was used to assess the usability of adaptive courses in the learning management system *Moodle* (Pancar et al. 2019). In contrast to previous results, the adaptive courses yielded lower usability scores (55.08 and 57.8) than their non-adaptive counterparts (62.87 and 67.51), meaning their usability was "ok".

As the research above illustrates, adaptive learning systems tend to be satisfying to learners, which is an important condition for the success of such systems. However, research on their usability opened up a clear gap which needs to be further addressed. Given how crucial usability is to the acceptance of adaptive learning systems, improving it is a key challenge.

### *6.4.3 Implementation of Adaptive Learning Systems*

Another avenue of research within adaptive learning concerns the actual implementation of adaptive systems in practice, providing potential answers to the *how* and *when*/*where* dimensions. The research questions in this area are thus if adaptive learning systems can be successfully implemented in educational practice and under what conditions. Despite the wealth of studies on adaptive learning systems, there has been a notable lack of successfully implemented adaptive technology-based learning systems in practice (Cavanagh et al. 2020; Somyürek 2015), with a few exceptions, e.g. the previously mentioned study by Ghergulescu et al. (2016). Scanlon et al. (2013) found what they called a "surprising failure" (p. 4) to translate research results in the field of technology-enhanced learning, including prototypes, into commercial products. This gap between research and successful application is the so-called valley of death, which can be caused by a lack of funding, weaknesses in the didactic concept, scalability-related issues, inaccuracies in the core components or lack of sustainability.

Moreover, as Lerís et al. (2017) point out, technological issues are a contributing factor as well since one of the main reasons why some adaptive systems have failed is a lack of easy-to-use technology for the teachers meant to design adaptive tasks and instructions. Instructors that produce and follow sound instructional designs are essential to adaptive learning, which is why it is key to involve them from the very beginning (cf. Shelle et al. 2018). One potential solution is to implement adaptive learning within environments that teachers are already familiar with, such as learning management systems (e.g. *Moodle*). In one of our own studies, we demonstrate how a simple rule-based adaptive design based on a recommender system can be implemented in a physics course on Moodle (see Imhof et al. 2018). Our system recommended tasks with either detailed or non-detailed instructions to our students, depending on their current level of knowledge (i.e. a prior knowledge test score for the first task and task performance for the remainder of the task set). We deemed the implementation successful enough to serve as a good basis for future, more complex adaptive instructional designs in the same or similar contexts.

## 6.5 Practical Implications and Future Potential of Adaptive Learning Systems

The results presented above have practical implications for designing and implementing adaptive learning systems. In this discussion, we will refer to the six questions introduced in the beginning of this chapter again. *Why* is adaptation wanted? Research reveals arguments for the implementation of adaptive learning systems by demonstrating effectiveness and efficiency. *Where* and *when* can adaptation be applied? Adaptive learning systems have yielded positive effects in a variety of different contexts, be it in terms of institutions, the topics to be learned (despite the noticeable focus on STEM topics, especially in the realm of micro-adaptivity; cf. Essa 2016), the target audience or the loop levels within the adaptive model. *What* can or should it adapt *to*? Not all options are equally recommendable in regard to learner characteristics. For instance, the evidence for adapting to learning styles is mixed at best (cf. Aleven et al. 2017), despite their popularity. Importantly, no matter which learner characteristics are chosen, they need to be assessed reliably and validly in order for the system to adapt to the learners' needs accurately. *What* can or should it adapt and *how*? In contrast to the other questions, these two are difficult to answer on the basis of the literature we considered. To our knowledge, systems usually follow one specific approach in terms of methods and techniques and stick to them. This renders direct, unbiased comparisons with other approaches nigh impossible, since the list of potential confounding variables is vast (e.g. learning support, learning topics, educational contexts, outcome variables, learning devices, differences between learners and so on; cf. Xie et al. 2019).

Moreover, adaptivity on its own is no guarantee for success. In our view, the success of an adaptive system is instead linked to three crucial elements of its adaptive design, each addressing multiple of the six basic questions:

1. The concept behind an adaptive learning system needs to be specific and sound. Adaptive learning has unique requirements and is, as Freda (2016) states, not a "magic bullet". The quality of the adaptive design (and thus the recommendations a system makes) depends on the monitoring and diagnosis of changing learning requirements, which could result in insufficient adaptation rules if neglected (cf. Dounas et al. 2019).
2. The loop level the system operates on has to be specified. As Essa (2016) notes, a considerable amount of research has been dedicated to the inner loop (i.e. step loop or micro-adaptivity), whereas research on the outer loop (i.e. task loop or macro-adaptivity) has been described as "modest" (Rus et al. 2013).
3. Special care ought to be given to the algorithms behind the adaptive learning system. Most systems rely on existing algorithms (cf. Ge et al. 2019) which are not necessarily the ideal solution in every individual case.

In summary, adaptive systems need a concise concept behind them as well as a suitable adaptive mechanism supported by the proper algorithms. Differences in these three design elements could explain why some studies found adaptive learning systems to be effective (Eldenfria and Al-Samarraie 2019; Ghergulescu et al. 2016) while others did not (Eau et al. 2019) or had mixed results (Griff and Matter 2013). This is especially important when estimating the effectiveness of adaptive learning systems in practice.

Furthermore, the results illustrated above highlight that usability should be a major focal point when designing and implementing such systems (Khosravi et al. 2020). Systems burdened with usability problems satisfy neither learners nor teachers, increasing the risk of systems being swiftly abandoned.

As our overview depicts, the processes of designing and implementing adaptive learning systems are very complex since there are countless options one could choose when designing adaptive systems. Not only are these processes non-linear since the questions inform and influence each other; there is also a notable lack of guidance for them, at least currently (Hou and Fidopiastis 2017).

All in all, the practical implications of adaptive learning are somewhat limited at the moment since there are still various challenges that adaptive learning systems have to overcome in order to truly bridge the gap between research prototypes and application tools. In their Delphi study, Mirata and Bergamin (2019) identified three dimensions of the challenges for adaptive learning: technology; teaching and learning; and organisation. In the dimension *technology*, the challenges are *infrastructure and hard- and software*, which include the usability of adaptive learning systems, and *perceptions and beliefs about adaptive technology*, e.g. acceptance and attitude towards technology, both from the lecturers' and students' points of view. In the context of the dimension *teaching and learning*, the identified challenges are *instructional and curriculum elements* (e.g. the need to redesign courses) as well as *lecturer and learner characteristics* (e.g. their motivation and commitment). The final dimension, *organisation*, contains *institutional strategies* (including commitment on the part of the management), *management* (e.g. support for lecturers and learners) and *resources* (e.g. the hiring of instructional designers). Further challenges are identified by Zliobaite et al. (2012), who present additional technological challenges, and Freda (2016), who highlights the organisational challenges. Zliobaite et al. (2012) add scalability and having to deal with "realistic data" as additional challenges for technology. In order to improve usability, trust and acceptance, they state that the practical application of adaptive learning systems might have to be broken down into adaptive tools that non-experts are also able to use. This latter point is also stressed by Cavanagh et al. (2020), who include understanding of the mechanism behind adaptive learning systems as one of the items on their list of pedagogical best practices.

Similar to Mirata and Bergamin (2019), Freda (2016) stresses securing monetary resources and convincing parties other than students and teachers of the value of adaptive learning (e.g. project managers and instructional technologists) as two important obstacles when transitioning from traditional to adaptive learning systems.

Future research has the potential to address most if not all of these issues, thereby getting closer to bridging the gap between research and application, potentially leading to widespread successful implementations of adaptive learning systems. As the research presented in this chapter shows, adaptive learning systems hold considerable potential to improve scalability (i.e. reaching more learners with less effort) and learners' performance. This complex development is still ongoing, but the current state of the research indicates great promise for the future.

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