# Adaptive Technologies

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**Abstract**

Adaptive learning technologies provide an environment that intelligently adjusts to a learner's needs by presenting suitable information, instructional materials, feedback and recommendations based on one's unique individual characteristics and situation. This chapter first focuses on the concept of adaptivity based on four types of learner differences that can be used by adaptive technologies: learning styles, cognitive abilities, affective states and the current learning context/situation. In order to provide adaptivity, the characteristics of learners need to be known first. Therefore, this chapter discusses methods for identifying learners' individual differences as well as how the information about these individual differences can be used to provide learners with adaptive learning experiences. Furthermore, the chapter demonstrates how adaptivity can be provided in different settings, focusing on both desktop-based learning and mobile/pervasive/ubiquitous learning. Finally, open issues in adaptive technologies are discussed and future research directions are identified.

**Keywords**

Affective states • Cognitive abilities • Context • Context modeling • Learning styles • Student modeling

## Introduction

Learning is increasingly mediated by educational technologies. The learners utilizing these technologies have different characteristics, including different prior knowledge, learning styles, cognitive abilities, motivation, and affective states. Students also learn in different situations/contexts, such as from different devices with different features and functionalities, at different locations, and so on. However, it appears that the learning systems that are most commonly used in technology-enhanced learning, namely, learning management systems (LMSs), typically present exactly the same course for every learner without consideration of the learner's individual characteristics, situation, and needs. Such a one-size-fits-all approach often leads to frustration, difficulties in learning, and a high dropout rate (Dagger, Wade, & Conlan, 2005; Karampiperis & Sampson, 2005).

Adaptive learning technologies address this issue by enabling learning systems to adapt courses, learning material and/or learning activities automatically to adjust to the learners' individual situation, characteristics and needs, and therefore provide learners with personalized learning experiences. By taking individual learning differences and contexts into account, adaptive learning systems can improve learning outcomes, require less effort, reduce time required, and result in higher learner satisfaction. A system can, for example, adapt learning material/activities to a learner's prior knowledge (Brusilovsky, Eklund, & Schwarz, 1998; Yang & Wu, 2009),

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preferred learning style (Graf, Kinshuk, & Ives, 2010; Popescu, 2010; Tseng, Chu, Hwang, & Tsai, 2008), affective states (D'Mello, Craig, Fike, & Graesser, 2009; Woolf et al., 2009), and so on. Furthermore, a system can take advantage of nearby objects or people who might be able to help in the learning process (El-Bishouty, Ogata, & Yano, 2007; Martín, Sancristobal, Gil, Castro, & Peire, 2008), consider the characteristics of the learner's environment, and take into account the features of the device a learner is using (Hwang, Yang, Tsai, & Yang, 2009).

Besides the term "adaptive technology" or "adaptive learning system," there exist other terms that are often used in similar contexts. The term "personalized learning system" emphasizes the aim of the system to consider a learner's individual differences and treat each learner as an individual person. The term "intelligent learning (or tutoring) system" refers to systems that focus on the use of techniques from the field of artificial intelligence to provide broader and better support for learners. On the other hand, the term "adaptive learning system" stresses the ability of a learning system to automatically provide different courses, learning material, or learning activities for different learners. However, many of the learning systems developed to tailor education to learners' unique characteristics and needs can be considered as adaptive, personalized, and intelligent. In order to accomplish the goal of providing adaptive learning, a system has to follow two steps: First, the respective information about a learner and/or his/her context and situation have to be identified and second, this information has to be used to provide adaptive support to learners.

The first step usually deals with student modeling and context modeling. Student modeling aims at building and updating a student model that includes information about the learners' characteristics and/or needs. On the other hand, context modeling focuses on identifying the learners' context and situation. Brusilovsky (1996) distinguished between two different methods of student modeling: collaborative and automatic. In the collaborative approach, the learners provide explicit feedback that can be used to build and update a student model, such as filling out a questionnaire or taking a test. In the automatic approach, the process of building and updating the student model is done automatically based on the behavior and actions of learners while they are using the system for learning. These two approaches also apply for context modeling, enabling a system either to identify the context information automatically or through feedback from learners. Furthermore, student modeling and context modeling can be done statically or dynamically. Static modeling refers to an approach where the student model or context model is initiated only once (mostly when the learners access the system the first time). In contrast, a dynamic modeling approach continuously monitors a learner and his/her context, and frequently updates the information in the student/context model.

In the second step, the identified information about learners' characteristics and/or their current situation/context is used to provide individualized learning experiences. Such individualized learning experiences can be provided in different ways, for example, with respect to the learning objects/activities that are presented in the course, the number of presented learning objects/activities, the sequence in which particular learning objects/activities are presented, the presentation and layout of the course itself, the amount of additional support provided to learners, the navigation within the course, and so on. Brusilovsky (2001) pointed out two distinct areas of adaptation techniques for adjusting online courses to students' characteristics and needs, namely, adaptive navigation support and adaptive presentation. Adaptive navigation support deals with providing students different ways to navigate through a course and includes features such as direct guidance, map adaptation, as well as adaptive sorting, hiding, annotating and generating of links. Adaptive presentation deals with how the content itself is presented to learners and includes, for example, adaptive multimedia presentation, adaptive text presentation, and adaptation of modality. In addition to changing the presentation and the way learners navigate through a course or course material, in a mobile and ubiquitous setting adaptive systems can also guide the learner to a particular real-life learning object, make a learner aware of other learners or experts in the vicinity, or adjust/select learning material based on the characteristics of the environment (Graf & Kinshuk, 2008).

Besides looking into *how* adaptivity can be provided, another important dimension of adaptive technologies deals with *which* information is used to provide adaptivity. The early adaptive and intelligent learning systems, such as InterBook (Brusilovsky et al., 1998), Intelligent Helpdesk (Greer et al., 1998), and AHA! (de Bra & Calvi, 1998), focused on characteristics such as learners' knowledge and learning goals. Later on, cognitive and pedagogical aspects have been considered more and more, leading to the development of systems that tailor courses and learning activities to learners' learning styles, cognitive abilities, affective states, learning interests, motivation, and the like. Furthermore, as recent technological advances make mobile, ubiquitous and pervasive learning increasingly popular, the context and situation in which learning takes place is becoming another important variable in providing adaptivity.

In this chapter, we focus on adaptive technologies that consider information about learners' learning styles, cognitive abilities, affective states, and context/situation. The first major section discusses the recent research on such technologies. In the second section, we discuss adaptive technologies in different settings, including desktop-based and mobile settings.

**Table 62.1** Accuracy of learning style identification approaches

| | Participants | Active/reflective | Sensing/intuitive | Visual/verbal | Sequential/global |
|---|---|---|---|---|---|
| García et al. (2007) | 27 | 58.00 | 77.00 | – | 63.00 |
| Graf, Kinshuk, et al. (2009) | 75 | 79.33 | 77.33 | 76.67 | 73.33 |
| Özpolat and Akar (2009) | 30 | 70.00 | 73.30 | 53.30 | 73.30 |

## Adaptivity Based on Individual Differences

### Learning Styles

There are many definitions for the term *learning style*. A general definition is provided by Honey and Mumford (1992) stating that a learning style is a description of the attitudes and behaviors that determine an individual's preferred way of learning.

The field of learning styles is complex, and although a great deal of research has been conducted, some important questions remain unanswered. Coffield, Moseley, Hall, and Ecclestone (2004) pointed out several controversial issues, including the existence of many different views, definitions, and models of learning styles, the reliability and validity of instruments for identifying learning styles, the feasibility and effectiveness of incorporating learning styles in education, and the way learning styles should be used in education. While Coffield et al. concluded that learning styles are often misused and are limited in what they can achieve, many other researchers have argued that learning styles are an important factor in education (Felder & Silverman, 1988; Graf, 2007; Lu, Jia, Gong, & Clark, 2007). Especially in the last few years, several studies have been conducted that support this argument. Examples include the development of adaptive systems that consider learning styles such as TSAL (Tseng et al., 2008), WELSA (Popescu, 2010) and an adaptive mechanism for extending LMSs (Graf & Kinshuk, 2007). Evaluations of these systems have shown that accommodating various learning styles can decrease the time required for learning and increase overall learner satisfaction (Graf & Kinshuk, 2007; Popescu, 2010; Tseng et al., 2008).

Several different techniques are used in adaptive learning systems to accommodate students' learning styles and adjust instruction accordingly. Some of the most often used techniques include changing the sequence of types of learning objects presented in each section of a course (e.g., Graf & Kinshuk, 2007; Paredes & Rodríguez, 2004; Popescu, 2010), hiding learning objects, elements of learning objects and links to learning objects that do not fit students' learning styles well (e.g., Bajraktarevic, Hall, & Fullick, 2003; Graf & Kinshuk, 2007; Tseng et al., 2008), and annotating learning objects in order to indicate how well they fit students' learning styles and therefore recommending the ones that fit best (e.g., Graf, Kinshuk, et al., 2010; Popescu, 2010).

Most adaptive systems use a static and collaborative student modeling approach, where learners are asked to fill out a questionnaire to determine their learning styles. These questionnaires are based on the assumption that learners are aware of how they learn. Jonassen and Grabowski (1993) pointed out that "because learning styles are based on self-reported measures, rather than ability tests, validity is one of their most significant problems" (p. 234). Similarly, Coffield et al. (2004) identified that many learning style questionnaires have problems with validity and reliability. In recent years, research has been performed on investigating and developing automatic approaches for identifying learning style, where information about learners' behavior in an online course is used to infer their learning styles. For example, García, Amandi, Schiaffino, and Campo (2007) studied the use of Bayesian networks to detect students' learning styles based on their behavior in the educational system SAVER. In another study, Cha et al. (2006) investigated the usage of Hidden Markov Models and Decision Trees for identifying students' learning styles based on their behavior in a course. Another example is the work of Özpolat and Akar (2009) where they used an NBTree classification algorithm in conjunction with Binary Relevance classifier in order to classify learners based on their interests and then inferred learning styles from these results. Besides using machine learning/data mining approaches to generate data-driven models that can then be used to calculate learning styles, Graf, Kinshuk, and Liu (2009) proposed a literature-based approach, where the calculation of learning styles is, similar to a learning style questionnaire, based on rules derived from literature. All abovementioned studies were applied to identify learning styles based on the Felder–Silverman learning style model (Felder & Silverman, 1988). This learning style model describes the learning style of a student in very much detail, assuming that each student has a preference on each of the four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global. The abovementioned studies were developed for different systems or for LMSs in general, and considered different behavior patterns of learners. Each of these approaches was evaluated by comparing the results of the approach with the results of the learning style questionnaire. Table 62.1 shows a comparison of the results for each of the four learning style dimensions of the Felder–Silverman learning style model. Each study used the same accuracy measure, which indicates the accuracy of the identified learning styles on a scale from 0 to 100. The study by Cha et al. (2006) has not been included in this comparison since their experiment used only data from the learning style questionnaire indicating a strong or moderate preference on a specific learning style dimension rather than including all data, as has been done by the other studies.

All of the above-mentioned studies focused on using behavior patterns such as the time a learner visited a particular type of learning object or the number of times such types of learning objects had been visited by learners. However, more complex behavioral patterns have been investigated as well. For example, Graf, Liu, and Kinshuk (2010) looked into navigational patterns, which indicate how learners navigate through the course and in which order they visit different types of learning objects and activities. Several differences in the learners' navigational patterns were identified, indicating that students with different learning styles visit learning objects in different sequences. These differences can be used to improve the identification process of learning styles. Furthermore, Spada, Sánchez-Montañés, Paredes, and Carro (2008) investigated mouse movement patterns with respect to students' sequential/global dimension of Felder–Silverman learning style model and found a strong correlation between the maximum vertical speed and learners' sequential/global learning style. Again, these findings can contribute to the improvement of the detection process of learning styles.

Since the learning style models that are commonly used in adaptive learning systems are based on the assumption that learning styles can change over time, recent research deals with considering such dynamic aspects. While the approaches described above use a certain amount of data to identify learning styles in a static manner, investigations are also being conducted on dynamic student modeling of learning styles, where the information about students' learning styles is updated frequently in the student model. Paredes and Rodríguez (2004) implemented a simple form of dynamic student modeling in their adaptive system TANGOW, which includes a mechanism that adjusts the system's record of a student's learning style whenever a behavior that is incongruent to the initially recorded learning style has been detected. Graf and Kinshuk (2013) investigated dynamic aspects of modeling learning styles in more complex settings and proposed a mathematical model to calculate how and when to revise information in the student model, assuming that new information about students' behavior is frequently added and therefore new information about students' learning styles is frequently gathered. Furthermore, they demonstrated how dynamic and automatic student modeling of learning styles can be integrated in LMSs.

## Cognitive Abilities

Cognition can be defined as the mental process of knowing, including aspects such as awareness, perception, reasoning, and judgment. Cognitive abilities are abilities to perform any of the functions involved in cognition. Humans have a number of cognitive abilities. Several of these abilities are crucial for learning. These include abilities such as working memory capacity, inductive reasoning ability, information processing speed, associative learning skills, meta-cognitive skills, observation ability, analysis ability, abstraction ability, and so on.

Research on adaptivity based on cognitive abilities deals with identifying cognitive abilities of learners and then using this information to provide different support for learners with different cognitive abilities. Little research has been done in this area and what does exist is still in its early stages. Kinshuk and Lin (2003) provided suggestions for considering working memory capacity, inductive reasoning ability, information processing speed, and associative learning skills in online courses. These suggestions are based on the Exploration Space Control project (Kashihara, Kinshuk, Oppermann, Rashev, & Simm, 2000), which included elements that can be changed to create different versions of courses to suit different cognitive needs such as the number and relevance of paths/links, the amount, the concreteness and the structure of content, as well as the number of information resources. For example, for learners with low working memory capacity the authors suggested that an adaptive system might automatically decrease the number of paths and increase the relevance of paths in a course. Furthermore, less but more concrete content should be presented and the number of available media resources should increase. In contrast, for learners with high working memory capacity, fewer relevant paths can be presented while the amount of content as well as its level of abstractness can also be increased.

Jia, Zhong, Zheng, and Liu (2010) proposed the design of an adaptive learning system that is based on fuzzy set theory and can consider cognitive abilities such as induction, memory, observation, analysis, abstraction, deduction, mathematic, association, imagination, and logic reasoning. These cognitive abilities, together with the students' knowledge level, goals and preferences, are taken into consideration when learning resources are suggested to the learners. Furthermore, Jia et al. (2010) proposed a student model that detects students' cognitive abilities based on test questions about the learned topics.

Another way of identifying students' cognitive abilities is to infer them from students' behavior in a course. Kinshuk and Lin (2004) introduced the Cognitive Trait Model (CTM), which is a student model that profiles learners according to their cognitive abilities. Four cognitive abilities, namely, working memory capacity, inductive reasoning ability, processing speed, and associative learning skills are included in CTM. The CTM offers the role of a "learning companion," which can be consulted by different learning systems to provide information about a particular learner. The CTM can still be valid after a long period of time due to the more or less persistent nature of cognitive abilities of human beings

(Deary, Whiteman, Starr, Whalley, & Fox, 2004). When a student uses a new learning system, this system can directly access the CTM of the particular student, and does not need to "re-learn the student." The identification of the cognitive abilities is based on the behavior of learners in the system. Various patterns, called Manifests of Traits (MOT), are defined for each cognitive ability. Each MOT is a piece of an interaction pattern that manifests a learner's cognitive characteristic. A neural network was used to calculate the cognitive traits of the learners based on the information of the MOTs (Lin & Kinshuk, 2004).

A challenge of using learners' behavior and performance to infer their cognitive abilities is to get enough reliable information to build a robust student model. As a solution, the use of additional sources can help to get more information about the learners (Brusilovsky, 1996). In this context, investigations have explored the relationship between cognitive abilities and learning styles (Graf, Liu, Kinshuk, Chen, & Yang, 2009). In adaptive systems that consider either only learning styles or only cognitive abilities, this relationship can lead to more information. For example, a system that only considers learning styles can use this relationship to also have some information about the learners' cognitive abilities. In systems that incorporate learning styles as well as cognitive abilities, the relationship can be used to improve the detection process of the respective counterpart (e.g., improving the detection process of cognitive abilities by additionally considering data about learning styles and vice versa). This leads to a more reliable student model.

Graf, Liu, et al. (2009) investigated the relationship between the Felder–Silverman learning style model and working memory capacity. First, a comprehensive literature review was conducted. Second, a pilot study was performed where the learning styles and working memory capacities of 39 students were identified through questionnaires/tasks and then analyzed to explore any relationships between learning styles and working memory capacity. Since the results from the literature review and the pilot study were promising, a main study with 297 students was conducted (Graf, 2007; Graf, Liu, et al., 2009), using a similar research design as for the pilot study. The results of these experiments and detailed analysis showed that relationships exist between working memory capacity and three of the four dimensions of the learning style model. The identified relationships have high potential to improve the student modeling process of cognitive abilities and learning styles and encourage further research on relationships between learning styles and other cognitive abilities.

## Affective States

Another aspect that can influence the learning process is one's affective state. The term *affective state* is typically used as a collective term for emotions, feelings, moods and attitudinal states. Affective states that are considered to be especially relevant in the learning process include, for example, boredom, confusion, frustration, confidence, satisfaction, and independence. Providing adaptivity with respect to affective states is a new area of research and only few adaptive learning systems have been designed and implemented addressing this issue. An example of such a system is AutoTutor (D'Mello et al., 2009), which detects learners' boredom, confusion and frustration and uses this information to select pedagogical and motivational dialogue strategies. Furthermore, an embodied pedagogical agent is implemented in the system, which considers learners' affective states and expresses emotions through verbal content, facial expressions and affective speech. Two versions of AutoTutor were implemented to provide empathy and encouraging responses if negative states had been detected. The first version provided more formal and supportive comments while the other provided more informal comments, attributing the source of the emotion to the learners themselves. Another example of an adaptive system that considers affective states is Wayang Outpost (Woolf et al., 2009), which is an intelligent tutor that lets students interact with a learning companion who reacts after a student has answered a question/problem by communicating with the student through text messages and/or mirroring his/her emotions. Affective states such as learners being confident/anxious, frustrated, excited, and interested/bored are considered within these communications. Furthermore, Khan, Graf, Weippl, and Tjoa (2010) proposed a framework consisting of several modules that attempt to incorporate learning styles and affective states including confidence, effort, independence, and confusion into LMSs. Once negative affective states are determined, the system provides additional guiding elements based on the learner's learning styles.

In order to identify affective states, either a collaborative or automatic student modeling approach can be used. In a collaborative student modeling approach, learners are asked to self-reporting their affective states from time to time. This approach runs the risk that learners are not honest about their affective states or get annoyed by reporting about them frequently. An automatic approach can use data from hardware sensors or behavior patterns. Woolf et al. (2009) summarized investigations of several hardware sensors, including facial expression cameras, pressure mouse sensors, skin conductance sensors, and posture analysis seat sensors to recognize different affective states. They concluded that sensors can help in predicting affective states relevant for learning and provide useful information about when students are in non-productive states and whether interventions worked or not. Khan et al. (2010) proposed an approach to identify affective states including confidence, effort, independence, and confusion by observing how students behave in an online course. These behavior patterns mainly dealt with the types of learning objects visited and the time students spent there.

## Context and Environment

Instead of providing a definition, the term "context" is often described in the literature by giving examples or replacing the term with other terms. A general definition is provided by Dey (2001), describing context as "any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves" (p. 5).

Due to the recent advances in mobile technologies, learning can take place anytime and anywhere, using not only desktop-computers but also mobile devices such as smart phones and tablets for learning. The learner's current context/situation as well as the characteristics of the surrounding environment in which one learns, therefore, become part of another important aspect to be considered by adaptive technologies. By incorporating information about the learner's context and environment into the adaptation process, new possibilities for providing adaptivity open up.

For example, an adaptive system can interact with learners and involve them in learning activities, considering their current context and surrounding environment. An example for such adaptive support is shown in the language learning system JAPELAS (Yin, Ogata, & Yano, 2004). JAPELAS teaches foreign students Japanese polite expressions. When a learner starts talking to another person, the system provides suggestions about the level of polite expression based on hyponymy, social distance and situation, by receiving information about the other person from his/her device and about the current context from sensors of the learner's device. For example, a different politeness level would be suggested if a learner meets a friend in a lecture hall or a professor in a park. Another example is the language learning system TANGO (Ogata et al., 2004), which detects objects around the learner, using RFID tags, and involves these objects in learning activities, for example, asking the learner to close a window or move a can from one place to another.

Furthermore, based on the location of the learners, adaptive systems can guide them to suitable places containing certain real-life learning objects where the system can present learning activities that are relevant and appropriate in the current environment. In order to help learners navigate to locations where learning can take place more realistically, adaptivity deals mostly with location-awareness and planning suitable learning activities. For example, a system can generate a personalized learning path based on learners' prior knowledge and guide them to places where they can learn concepts that are new or difficult to understand for them (Chang & Chang, 2006). Hwang, Tsai, and Yang (2008) described a similar scenario where the system asks a student to go to specific places to observe and identify particular plants.

In addition, information about the context and surrounding of a learner can enable adaptive systems to help learners in communicating synchronously with peers and experts in their vicinity, assisting them in forming learning groups or showing them who might be able to answer their questions. For example, Martín et al. (2008) presented a location-based application that gives information about people who are close to the learner. Furthermore, a system can provide suggestions for building learning groups based on the students' location as well as other characteristics of students, as proposed, for example, by Graf, Yang, Liu, and Kinshuk (2009).

Most systems that consider contextual information, focus on information such as learners' current location, surrounding objects, and peers/experts who are in the vicinity. A few other systems (El-Bishouty, Ogata, Ayala, & Yano, 2010; Hwang et al., 2009) have recently started to provide personalized recommendations for learning tasks and/or peer assistance not only from the information about the learners' environments but also from basic information contained in learners' profiles, namely, learners' knowledge and/or performance. Furthermore, Graf, Yang, et al. (2009) proposed a learning system that considers a learner's current location as well as different learner characteristics such as their progress, learning styles, interests and knowledge level, problem solving abilities, preferences for using the system, and social connectivity.

As for other learner characteristics, the identification of learners' current context/situation and the characteristics of their environment is a crucial part for an adaptive system that aims at using this information to provide adaptivity. While such context modeling can be achieved through a collaborative modeling approach (e.g., by asking the student about his/her location), in most cases context modeling is done automatically. A very common approach to identify context information is through the use of sensors, such as microphones, Web cameras, GPS, accelerators, and more. Hwang et al. (2008) provide a detailed explanation of different kinds of information that can be gathered to make a system context-aware and how it can be gathered, including not only sensors but also other sources of information. Five types of situation parameters have been identified: personal context, environmental context, feedback from the learner interactions with the mobile device, personal data and environmental data. The first situation parameter includes information concerning the students' personal context, which is sensed by the system, such as students' current location, the time of their arrival, and issues such as heartbeat and blood pressure. Another kind of information that can be sensed by the system is the environmental context, which includes information about the environment around a sensor, such as the sensor's location, the temperature around the sensor, and information about approaching objects/people. Furthermore, information can be gathered from the students' interaction with the system, including for example, stored documents, given answers to questions, and certain settings the learner made in his/her user interface. Moreover, the system can access a database, where students' personal data and environmental data are stored. Personal data can include the students' learning styles, course schedule, prior knowledge, progress in the course and so on. Environmental data provide more detailed information about the environment, such as a schedule of arranged learning activities or notes for using the site.

## Adaptive Technologies in Different Settings

While the previous section discussed the current state of research about adaptivity based on learners' individual differences, this section looks into the use of adaptive technologies in different settings and modes of learning, including for example desktop-based and mobile/ubiquitous/pervasive learning; formal, nonformal, and informal learning; individual and collaborative learning; and instruction-based, assessment-based and game-based learning. In this section, we focus on desktop-based settings, where students learn via a desktop computer, and mobile/pervasive/ubiquitous settings, where students learn via a mobile device, and discusses how adaptive technologies can be used in these two settings is provided.

Many educational institutions, including universities, use LMSs for offering desktop-based learning in either blended or fully online courses. LMSs, such as Moodle (2011), Blackboard (2011) and Sakai (2011) aim at supporting teachers in creating, administering, and holding online courses by providing them with a variety of features. Such features assist them in administrative issues (such as enrollment), allow them to create courses with many different activities and resources, support communication between teachers and students as well as among students, and much more. However, LMSs typically do not consider individual differences of learners and treat all learners in the same way regardless of their needs and characteristics. In contrast, adaptive learning systems provide desktop-based learning that focuses particularly on supporting learners, tailoring courses to learners' characteristics and needs. However, such adaptive systems typically provide only basic functions for supporting teachers and administrators, which might be one of the reasons why they are only rarely used by educational institutions.

Although many adaptive learning systems have been developed to support desktop-based learning and evaluations of such systems have demonstrated positive effects and benefits for learners, very little research has been done on combining the advantages of today's LMSs to support teachers and administrators with the advantages of adaptive technologies to support learners. Examples of such attempts include work on incorporating adaptivity based on learning styles in LMSs. Graf and Kinshuk (2007) developed an adaptive mechanism that extends LMSs by enabling those systems to automatically compose courses that fit students' learning styles. An evaluation of this adaptive mechanism with 473 students showed that learners who learned from a course that matched their learning styles spent significantly less time in the course and achieved on average the same grades as learners who got a course that either did not match their learning styles or included all available learning objects (Graf & Kinshuk, 2007). Subsequently, the adaptive mechanism has been extended by making it more generic and applicable for different types of courses, such as courses with practical versus theoretical foci (Graf, Kinshuk et al., 2010). Another example for incorporating adaptive technologies into LMSs is the EU-funded project GRAPPLE (de Bra, Smits, van der Sluijs, Cristea, & Hendrix, 2010) that attempts to incorporate an adaptive learning environment into popular LMSs.

Desktop-based adaptivity mostly focuses on considering learners' characteristics such as prior knowledge, interests, learning styles, cognitive abilities, and affective states, and aims at fitting courses to those learner characteristics. In most cases, when using a desktop computer, the context and environment in which one learns is assumed to be constant and therefore, not much research has been done on adapting to different contexts and environments for desktop-based learning. However, in a mobile/pervasive/ubiquitous setting, the context and environment change frequently and become an important aspect to consider for providing learners with content and activities that are tailored to their current situation.

Mobile, pervasive and ubiquitous learning environments overcome the restrictions of classroom or workplace-restricted learning and extend e-learning by bringing the concepts of anytime and anywhere to reality, aiming at providing people with better educational experience in their daily living environments. The use of devices such as mobile phones and tablets allows new opportunities for learners by being intensely connected. Therefore, educational content can be accessed and interaction can take place whenever learners need it, in different areas of life, regardless of space and time.

Adaptivity based on the learners' context and environment can play a major role in such mobile, pervasive and ubiquitous settings since learning can take place differently in different situations and different support is required from the learning system depending on the respective situation and context. In contrast to desktop-based learning, many mobile devices have a variety of sensors embedded that can be used for rich context modeling, providing an adaptive system with accurate information about a learners' current situation. Furthermore, such sensors can contribute to the identification of learners' characteristics such as their affective states. Such rich information supports the adaptation process and can enable a system to provide learners with the right support at the right time.

## Conclusions

Adaptive technologies have high potential in drastically improving instruction (Woolf et al., 2010) and much research has focused on designing adaptive learning systems, including the development of mechanisms for providing adaptive courses, learning materials and activities as well as approaches for identifying learners' characteristics, situations and needs. However, at present, adaptive learning systems are mainly used as research prototypes rather than in large-scale educational environments.

Therefore, one of the main open issues with respect to adaptive technologies is to bring these technologies into the classroom and to the learners. There are different ways of achieving this goal, including the development of add-ons and services that can be integrated into existing and commonly used learning systems such as LMSs. However, the focus here should be to combine the advantages of both adaptive technologies and LMSs and to create systems that have rich support for teachers and at the same time are able to tailor education to learners' characteristics and needs. This will require adaptive technology researchers and developers to focus not only on learners but also on making these systems easy to use by teachers and administrators. Furthermore, very little research has been done on using adaptive technologies for supporting teachers in their daily tasks of helping learners. This can include providing teachers with useful information about the learning processes of their students, alerting teachers if and when the system identifies that a student seems to have problems in learning, and so on. Furthermore, a system can make teachers more aware of how students use an adaptive system and what benefits it brings to their students.

Another open issue in the area of adaptive technologies deals with enriching adaptivity by combining different information about students' characteristics and context, and considering these different types of information when providing adaptivity. Open questions related to the combination of characteristics and context information include whether and how characteristics and context influence/compensate each other and how such effects influence the provision of adaptivity in the system. Another open question in this context deals with the selection of characteristics/contexts that should be considered when providing personalized courses and whether these characteristics/contexts should be the same for all learners or might vary for each learner or in different situations. Furthermore, another open question deals with the interdependencies between different characteristics and contexts for student modeling and context modeling, whether relationships exist between different characteristics/contexts, and whether they can help in improving the student modeling and/or context modeling process.

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