10 Adaptivity and Personalization in Game-Based Learning

Jan L. Plass and Shashank Pawar

Introduction

Adaptive games are systems that are able to cater to the individual needs of each user (Plass, 2016). Consider, for example, the game *Mario Kart* (Nintendo EAD, 2013). The game adjusts difficulty by changing the performance of computer-controlled nonplayer characters (NPCs). In *Mario Kart*, if a player is behind in a race, the NPCs start performing worse than usual. On the other hand, if a player is leading in a race, the NPCs perform better than usual. This method makes the game challenging for players with different skill levels. Through the simple mechanism of assessing the player's performance, the game can determine what level of difficulty the player should receive.

An example related to learning is the game *Gwakkamolé* (CREATE, 2017), designed to help learners develop their inhibitory control, a subskill of executive functions (Miyake, Friedman, Emerson, Witzki, & Howerter, 2000). In *Gwakkamolé*, players smash avocados that are bold but not avocados that have spiky hats. The resulting repeated need to inhibit the initial desire to smash an avocado will, in time, train the underlying cognitive skill. Research has revealed conditions that make such practice especially effective. These include, for example, that the task should require substantial executive control and that the task's difficulty levels should progressively increase (Holmes, Gathercole, & Dunning, 2009; Klingberg et al., 2005). Since each learner has different levels of executive functions, the rate of increase will need to differ. Therefore, in this scenario, adaptivity means that the game determines the required difficulty for each user (the adapted variable) based on the accurate diagnosis of learners' current level of inhibitory control (the learner characteristics) (Shute & Zapata-Rivera, 2012). Research has shown that *Gwakkamolé* is more effective when difficulty is adjusted adaptively than when it is increased the same way for all learners (Plass, Pawar, & MacNamara, 2018).

Before we turn to a discussion of adaptivity in game-based learning, there are several terms used by scholars and practitioners that we must define. These are customization, adaptivity, adaptability, and personalization (Plass, 2016).

Customization

Customization allows a player to modify a game based on their preferences. This could include the selection of an avatar, setting specific colors or backgrounds in the system, toggling game sounds, and adjusting other game-specific properties. The goal of these changes is to optimize the acceptance of the game by the player. The results of these changes are, from a learning perspective, relatively minor surface modifications to the game.

Adaptivity

We consider games *adaptive* when they change their features or content based on the diagnosis of individual learner variables, most often the learner's current level of knowledge (Plass, 2016; Shute & Zapata-Rivera, 2012). An important distinction from customization is that changes are based on the assessment of specific learner variables rather than on learner preferences. It is also important that the system actively make these changes in a prescriptive way. The goal of adaptivity in games for learning is to optimize the learning effectiveness of the game; for instance, by maintaining an appropriate level of challenge for each learner. The results of these changes are different learning progressions, methods, or contents for different learners at different points in their learning.

Adaptability

Adaptability implies that a game provides the learner with options and choices that, similar to adaptivity, are based on the diagnoses of specific learner variables. The important distinction from an adaptive game is that an adaptable game leaves the decision of which option to select to the individual. The goal of adaptability in games for learning is twofold: to support the learners' ability to self-regulate their learning and to optimize the learning effectiveness of the game (Boekaerts, 1992).

Personalization

Personalization is a term that has been used to describe learning environments that may combine changes based on learner preferences and those on diagnosed learner variables, both prescribed by the system and chosen by the learner. In other words, personalization is often used as a broader term to describe games that could be customizable, adaptive, or adaptable.

For the remainder of this chapter, we will use the term adaptivity to describe changes in the game that are based on diagnosed learner variables, regardless of whether the game or the user initiates these changes. When this distinction becomes important, we will use the term adaptability to emphasize this fact.

What Is Adaptivity in Game-Based Learning?

The examples and definitions described earlier raise a number of questions. For example, which individual difference variables should be considered for adaptive games? How can the selected variables be measured? Finally, how should the game respond to the diagnosed level of the learner variable? (Shute & Zapata-Rivera, 2012).

What Variable Should the Game Adapt For?

One of the most important questions related to adaptivity is what specific learner attribute to adapt for. Given our definition of an adaptive system, to provide learners with information they need, the first step is to determine what kinds of needs a learning environment should address. Usually the focus of adaptive systems is on cognitive variables—the learner's current knowledge. In fact, the 2012–2013 report *Adaptive Educational Technologies* by the National Academy of Education suggests that adaptive learning technologies "take account of current learner performance and adapt accordingly to support and maximize learning" (Natriello, 2013, p. 7). However, in addition to learner performance, there are many other variables that could be used for adaptive responses; for example, a learner's emotional state, their cultural background, or social variables. Examples are shown in table 10.1.

Even though this table is by no means a complete account of all possible variables to consider as a basis for an adaptive system, it shows that the focus of most current adaptive systems on current levels of knowledge means they only address a very limited number of potential variables to adapt for.

Of course, a particular game can only adapt for a very limited number of variables, possibly only one of them. How should this variable be determined? There are several considerations to take into account that can guide such a decision. The first is whether the variable has been shown to predict the type of learning outcome the game aims to help learners achieve. One of the reasons why a learner's current knowledge is used so frequently as the variable to which the system responds adaptively is the substantial body of research showing that prior knowledge predicts learning outcomes (Bransford & Johnson, 1972; Dochy, Segers, & Buehl, 1999; Shapiro, 2004). However, research has shown similar relations for the other variables listed in the table (Craig, Graesser, Sullins, & Gholson, 2004; Fan & Chen, 2001; Picard, 1997).

A second issue to consider is therefore whether this variable can be assessed within the context of the learning game. Two corresponding questions are whether the variable can be assessed at all and whether such an assessment can be embedded into the game. We discuss these questions in the next subsection. The third question is whether there is enough variability on the variable expected among the learners in the target audience to justify the need for individualized approaches. In other words, would the expected effect size of the gains resulting from adaptivity be sufficient to

Table 10.1
Examples of cognitive, motivational, affective, and sociocultural variables for which games can adapt

Cognitive variables	Current knowledge
	Current skills
	Developmental level
	Language proficiency
	Learning strategies
	Cognitive abilities/skills
	Self-regulation
	Cognitive load
Motivational variables	Individual interest
	Situational interest
	Goal orientation
	Theory of intelligence
	Self-efficacy
	Persistence
Affective variables	Emotional state
	Appraisals
	Emotion regulation
	Attitudes
Sociocultural variables	Social context
	Cultural context
	Identity/self-perception
	Relatedness
	Social agency

warrant such an approach? The fourth and final consideration is whether there is a sufficient theoretical or empirical basis to inform how the system should adapt to the learner differences along the identified variable (Plass, 2016). We discuss this question further.

How Do We Measure the Variable the System Will Adapt For?

There have been many recent advances in measurement of cognitive and noncognitive skills that can provide a foundation for adaptive games (Natriello, 2013; Williamson, Behar, & Mislevy, 2006). In order for a variable to be measured reliably in a game, a number of conditions have to be met. First, a behavior-based measure of this variable needs to exist or needs to be designed and validated. For example, a game that adapts based on the learner's ability to self-regulate their learning would need to be able to measure self-regulation based on the learner's behavior while playing the game (Zap & Code, 2009). Such assessments can be compatible with game design, but they need to be considered in the early stages of the conceptualization of a game (Mislevy, Behrens, Dicerbo, Frezzo, & West, 2012).

The second condition is that the game design must allow for such a measure to be embedded. This involves the design of assessment mechanics (Plass et al., 2013, mechanics that elicit user behaviors that allow the observation of the target variable (Leutner & Plass, 1998). In a game where learners do not have to make choices that require regulation of their learning, such an observation of related behavior would not be possible. In cases where such assessment mechanics can be embedded, the third condition is that it must be possible for measures to be updated in real time. In other words, new user behavior needs to be taken into account to update the learner model. Examples of such real-time measures are Bayes nets that are updated after each learner action (Shute & Zapata-Rivera, 2012). These models of variables should be designed by experts and mapped onto mechanics using a method such as evidence-centered design (ECD) (Mislevy, Steinberg, & Almond, 2003). When using a learner's knowledge as the basis for adaptivity, for example, knowledge space theory has been developed as a basis on which knowledge can be modeled (Doignon & Falmagne, 1985). In addition to using in-game behavior, the measurement of some variables can also involve the use of biometrics, such as facial behaviors to measure emotions (Ekman, Friesen, & Hager, 2002) and affect (D'Mello, Picard, & Graesser, 2007), electroencephalograms (EEGs) to measure engagement (Berka et al., 2007), or electrodermal response (EDR) to measure engagement and emotions (Kapoor, Burleson, & Picard, 2007).

How Should the Game Adapt Based on the Variable?

Once an appropriate variable for adaptivity has been selected, and that variable's assessment in a game has been implemented, the final step in the design of adaptive games for learning is to determine how the game should be adapted based on the determined state of the variable. Figure 10.1 shows the adaptivity loop that involves the observation of learner performance, the diagnostic of the variable of interest, and then the adaptive response of the game. Here, we are concerned with the "Adaptivity" box on the right. How should the game change when, for example, low levels of motivation or high levels of self-regulation skills are detected?

The process of determining how the game should adapt should be based on theoretical insights or empirical evidence that could inform how the system should respond to learner differences along the identified variable (Plass, 2016). Research that investigates how learner variables moderate the effectiveness of an educational intervention is referred to as attribute by treatment interaction (ATI) research (Corno & Snow, 1986; Cronbach & Snow, 1977; Leutner, 1995; Leutner & Rammsayer, 1995; Plass, Chun, Mayer, & Leutner, 1998). However, there have been few contributions to this line of research in recent decades, as it suffered from methodological shortcomings. As a result, many of the variables on learning shown in table 10.1 have been investigated

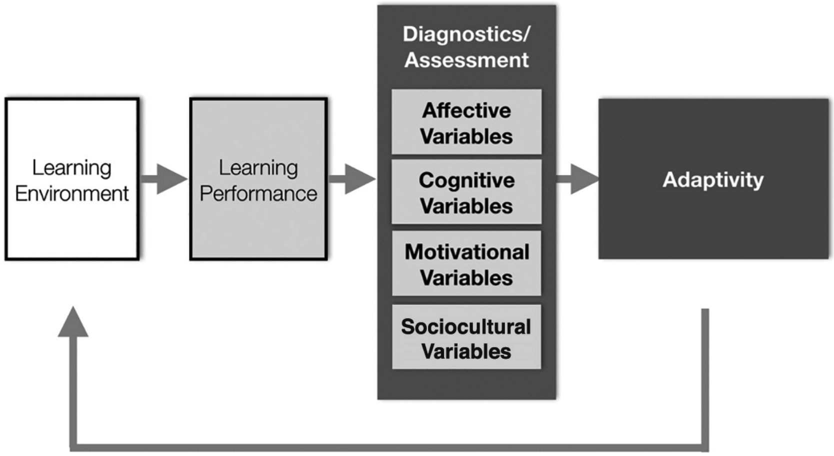

Figure 10.1
Learning environment adaptivity loop.

as general effects, but their interaction with different designs of learning environments has not. This leaves the designers of adaptive systems with the need to first conduct research to determine how the system should respond to specific states or levels of the learner variable of interest. One such example for the design of scaffolding based on a learner's level of self-regulation is described by Azevedo and Hadwin (2005).

The final consideration is which game feature can be used to implement the adaptive response based on the variable of interest. Examples of these features, based on the playful learning design framework by Plass, Homer, and Kinzer (2015) and in chapter 1 of this volume are described in the following subsection.

What Game Features Can Be Used for Adaptivity?

Adaptivity can be implemented in learning games in various ways. Virtually all game components can be designed to adapt based on a player model. In this section, we provide examples of adaptive designs for various game components. This is a nonexhaustive list of examples based on the expanded adaptivity model presented in figure 10.2. This figure shows that these components include scaffolding and cues, feedback and guidance, interaction type, mode of representation,the rehearsal schedule, difficulty progression, and conceptual progression. We discuss examples for how each of these elements has been used for adaptive games for learning.

Scaffolds and cues Scaffolds help players become independently competent with gameplay. They are temporary elements that fade away when players demonstrate a certain level of competence (Reiser & Tabak, 2014). Video games commonly use scaffolds

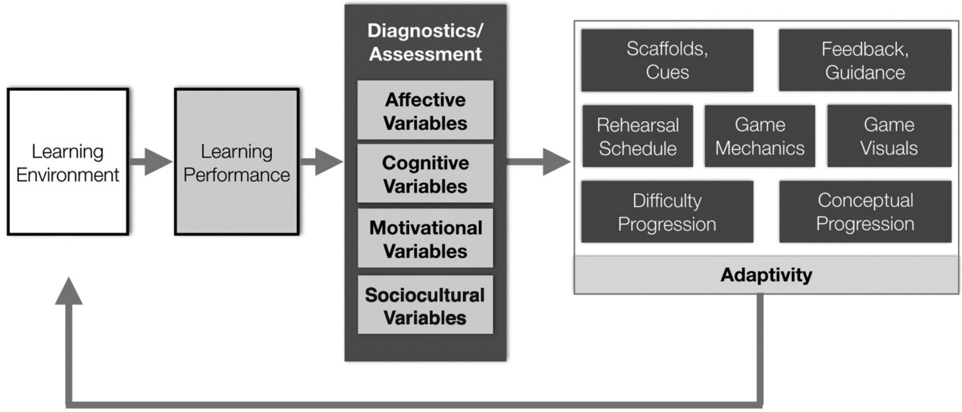

Figure 10.2
Learning game features supporting adaptivity.

to help players learn the game. Nonplayer characters (NPCs), agents that introduce players to game environments and mechanics in the tutorial phase of games, are a common example of game scaffolds. Cues serve a function similar to scaffolds and guide player attention toward important game elements. They can be audio, visual, or haptic in modality and provide subtle guidance to players. Some common applications of cues include distinct visual marking of interactable game elements, such as ladders or ledges to help player navigation, audio clips to signal correct or incorrect actions when interacting with game objects, or controller vibrations on impact with objects in racing games.

Scaffolds and cues can be adapted in games to enhance players' learning outcomes. In *Prime Climb* (Conati, Jaques, & Muir, 2013), a game that teaches number factorization, a pedagogical agent provides scaffolding through gameplay hints. The agent makes inferences based on a student model and displays personalized hints when students are predicted to be missing key domain knowledge. A similar approach has also been implemented in interactive narrative learning games such as *Crystal Island* (Lee, Rowe, Mott, & Lester, 2014) and *Tactical Combat Casualty Care* (Magerko, Stensrud, & Holt, 2006). In these games, an NPC guides players through game scenarios and adaptively provides hints when players are struggling. Adaptive cues are also an effective way to support players during gameplay. With the help of adaptive cues, players' attention can be directed to crucial information at an appropriate time. The language-learning game *We Make Words* implements adaptive visual cues to help players learn new Mandarin words (Demmel, Köhler, Krusche, & Schubert, 2011). It does so by dynamically adjusting the opacity of a silhouette of a word according to players' experience with that word.

Feedback Feedback also helps players with gameplay, but unlike scaffolds and cues, feedback is generated in response to player actions. There is a large body of literature exploring the effects of different types of feedback on learning (Hattie & Timperley, 2007; Shute, 2008). The findings from these studies have inspired many learning games to implement adaptive designs for game feedback. Serge, Priest, Durlach, and Johnson (2013) employed an adaptive design that manipulated the abstraction level of feedback (detailed to general or general to detailed) in a game for learning search procedures. Another way of providing feedback is through NPCs. In *ELEKTRA* (Peirce, Conlan, & Wade, 2008), a game that facilitates learning of optics, a character representing the famous astronomer Galileo provides feedback to players through dialogue. The game *Tactical Combat Casualty Care* (Magerko et al., 2006) implements this by using a military training officer, who talks with cadets to provide feedback. In the game *Graphical Arithmetic Model* (Pareto, Schwartz & Svensson, 2009), players learn by teaching an adaptive agent. The teachable agent develops knowledge based on its interactions with the player. During gameplay, the agent asks questions based on its current knowledge, which in turn is a representation of the player's knowledge level at the time. The questions asked by the agent act as feedback in an indirect way and help players reflect on their learning.

Rehearsal schedule Each player progresses through the game at a different pace. To address differential learning rates, adaptive engines can adjust gameplay time for each player. In addition, games can add, remove, or rearrange game scenarios to cater to individual needs of players. With such an approach, games can provide appropriate practice to each player and ensure mastery of concepts. Rehearsal schedule adaptations are usually implemented through manipulations to game levels or learning modules. In the game *Code Red Triage* (van Oostendorp, van der Spek, & Linssen, 2013), learning modules are structured into tiers. During gameplay, if a player demonstrates competence on tasks of a given tier, the game deletes the remaining learning modules in that tier and introduces modules from the next tier. This allows quick progression to higher tiers and decreases time to completion. A military medic simulation developed by Niehaus and Riedl (2009) builds on this design. It not only removes modules once competence is demonstrated but also adds or replaces modules when more or a different type of practice is required to ensure skills proficiency. A slightly different approach to promote efficient practice is to generate levels in real time. When a player fails at a level in the game *Fuzzy Chronicles* (Clark, Virk, Barnes, & Adams, 2016), instead of repeating the same level, the player is presented with a new level addressing the same learning concept and with the same level of difficulty.

Game mechanics Game mechanics are the building blocks of games (Salen & Zimmerman, 2004). They are independent components that function in an interactive system to generate the gameplay experience. A combination of different mechanics drive the game experience, and adding, removing, or modifying mechanics of a game can lead to big changes in gameplay. Manipulating mechanics therefore changes gameplay in a holistic fashion and allows designers to have more control over adaptivity. For example, the game *Tactical Combat Casualty Care* (Magerko et al., 2006) has an adaptive director that can introduce and move game characters to generate custom scenarios for players. The adaptive director tracks players' demonstration of skills and customizes scenarios accordingly.

A game can also adapt mechanics by introducing new game components. Magerko, Heeter, Fitzgerald, and Medler (2008) used this technique in a game for learning microbiology. They adapted game components based on playing styles. The adaptations were as follows: explorers, who are more intrinsically motivated, received bonus trivia; achievers, who are more performance driven, played with a game timer and a leaderboard; and winners, who are more extrinsically motivated, were provided with a tutorial. These components changed the gameplay substantially, allowing players to play according to their prior inclinations.

Game visuals Visual design of game components influences gameplay. Studies have shown that game visuals independently affect a learner's emotional state (Plass, Heidig, Hayward, Homer, & Um, 2014) and learning outcomes (Ober et al., 2017; Plass et al., 2014). These findings suggest that game visuals play a role in games' learning outcomes and must be considered an important component of the design of learning games. Some learning games have built on this idea and implemented adaptive game visuals. For example, Soflano, Connolly, and Hainey (2015) adapted game visuals in a game for learning Structured Query Language (SQL). In this game, learning content was presented through text or pictures according to the player's preferred presentation format. The game adapted by changing content in the conversational (chat) system of the game. With the help of the adaptive system, players received learning content from the conversational system according to their preference for text or pictures.

Difficulty progression It is crucial to manage task difficulty in learning games. If the game is too difficult, players get frustrated, and if it is too easy, players get bored. To avoid this situation, many games increase difficulty incrementally. Each player, however, learns at a different rate. This poses a major challenge for learning game designers because the preset increase in difficulty can be suboptimal for many players, and unlike in commercial games, in learning games it is important to cater to the needs of each player. To address this challenge, many games adapt task difficulty according to player performance. In the game *All You Can E.T.* (CREATE, 2016), the falling speed of aliens is adjusted to provide players with appropriate time to react before the aliens disappear below the horizon. Similarly, *Cognate Bubbles* (Sampayo-Vargas, Cope, He, & Byrne, 2013), a language acquisition game, adjusts difficulty by manipulating the number of word choices offered to the players. For example, when a player is struggling with a task, the game reduces the number of options, making it easier for the player to make the correct choice.

Conceptual progression Some games implement adaptivity to modify the sequence of learning content. In games with multiple interrelated learning goals, it is possible to rearrange content according to player needs. We use the term conceptual progression for this type of adaptivity because it adapts content based on the conceptual understanding of players. Conceptual progression is exclusive to learning games, as the adaptations are based not on in-game content but on conceptual knowledge of players. *Adaptive Educational Interactive Narrative System* (AEINS) is a learning environment for ethics and citizenship education that provides customized story paths for players (Hodhod, Kudenko, & Cairns, 2009). In this game, stories are customized by arranging teaching moments according to the player model. Teaching moments are domain-level concepts that are part of the whole story, and player interactions with them are utilized for adaptations. By doing so, the game creates a smooth narrative closely coupled with the learning goals.

A macroadaptive approach to conceptual progression is implemented in the math reasoning game *Ecotoons 2* (Carro, Breda, Castillo, & Bajuelos, 2002). The game selects and sequences minigames according to the conceptual knowledge of players. The adaptivity is implemented in two stages: structure generation, and story adaptation through selection of available activities and games. In the first stage, the engine uses player features such as age, primary language, and media preferences to generate a unique game structure for each player. The game structure includes multiple activities themed around an encompassing story. In the second stage, a subset of the chosen activities is made available to the player through an in-game menu. The player can then select one of the available activities. When a player selects an activity, the most appropriate minigame is chosen according to the player's conceptual knowledge at the time. If possible, the minigame is constructed in real time according to the player model; otherwise, a pregenerated version is presented. With this type of adaptivity, the game creates a custom path for the conceptual growth of each player. Having reviewed how adaptivity can be implemented in games, we next discuss research on the effect of adaptivity on desired outcomes.

Research on Adaptivity in Games

Many scientists have studied adaptivity using the value-added research paradigm (Conati & Zhao, 2004; Soflano et al., 2015; van Oostendorp et al., 2013). This allows studying players' learning outcomes with and without an added feature, and making inferences about the feature's effect on learning outcomes (Mayer, 2014). For adaptive learning games, value-added research is conducted by studying adaptivity as a feature.

Most experiments have compared an adaptive version (treatment group) with a nonadaptive version (control group) (Hwang, Sung, Hung, Huang, & Tsai, 2012; Lee et al., 2014). A few studies, however, have used more treatment conditions to investigate multiple adaptive designs (Clark et al., 2016; Serge et al., 2013). For example, Serge et al. (2013) used four treatment groups and a control group to study the effects of adaptive feedback. The detailed feedback group always received direct game-specific feedback; the general feedback group received abstract guidance in the form of general principles; the direct-general adaptive feedback group received feedback that was direct at first but gradually became general; and the general-direct adaptive feedback group received general feedback first, gradually turning into detailed information. This study did not find any significant differences among treatment groups. Clark et al. (2016) conducted a similar study by comparing a nonadaptive control group with two treatment groups. The first treatment group was provided self-explanatory feedback, and the second treatment group received adaptive self-explanatory feedback that changed from detailed to general in the level of abstraction. In this case, researchers found differences in posttest scores between control and treatment conditions, with adaptive treatment getting the highest mean scores.

Along with different research designs, studies have also explored adaptivity for different player traits, including presentation preference, modes of thinking, domain knowledge, and game performance. Soflano, Connolly, and Hainey (2015) conducted a study with an adaptive design based on players' preferences for content presentation. They compared two nonadaptive control groups with an adaptive treatment group. The treatment group received adaptive visuals that changed between text and pictures according to real-time presentation preference predictions of the player. Results showed that the adaptive treatment group outperformed all other groups in postgameplay SQL understanding. Hwang et al. (2012) studied a different type of adaptivity by categorizing players according to their mode of thinking (sequential thinkers and holistic thinkers). They compared a treatment group that played an adaptive version supporting their thinking approach with a control group that received a version opposite to their thinking approach, and found that learning outcomes as well as motivation were higher in the adaptive group.

Many studies have also investigated adaptivity based on domain knowledge (Conati & Zhao, 2004; Lee et al., 2014; van Oostendorp et al., 2013). These studies test the effectiveness of an adaptive engine at changing gameplay by predicting players' domain knowledge. Studies by van Oostendorp, van der Spek, and Linssen (2013) and Lee, Rowe, Mott, and Lester (2014) found that adaptive versions were significantly better than nonadaptive versions when considering learning outcomes. Conati and Zhao (2004) found marginally significant results for the adaptive version of *Prime Climb*, but observed a large effect size ($d = 0.7$). Similar as for domain knowledge, research on adaptivity based on game performance has also yielded promising results (Sampayo-Vargas et al., 2013). Game performance is closely linked to learning outcomes in many learning games and thus can be used as a proxy for the learning progress of players. In a study by Sampayo-Vargas et al. (2013), a treatment group received a version of the game that changed task difficulty based on player performance. This group had higher learning outcomes than the control group.

In addition to studies focusing on adaptivity to enhance learning outcomes in specific subject areas, some investigations sought to determine whether adaptivity could enhance the effectiveness of games that train cognitive skills such as executive functions (Blair & Razza, 2007; Müller & Kerns, 2015). Reviews of such research have shown that adaptivity can indeed enhance executive function training under specific conditions. Two studies by Plass, Pawar, and McNamara (2018) found that adaptive difficulty adjustments in a game to train the *shifting* subskill of EF improved scores for high school students and adults but not for middle school students.

The model for adaptivity shown in figure 10.1 includes four categories to adapt for: cognitive, motivational, affective, and sociocultural. Previous studies, however, have only explored the cognitive and motivational categories (Clark et al., 2016; Lee et al., 2014; Peirceet al., 2008; Serge et al., 2013). Of the two, adaptive interventions have found more success with cognitive factors compared to motivational factors. Adaptivity studies of adaptivity with games such as *Prime Climb* (Conati & Zhao, 2004), *Crystal Island* (Lee et al., 2014), *Fuzzy Chronicles* (Clark et al., 2016), and *Code Red Triage* (van Oostendorp et al., 2013) have succeeded in the cognitive domain, while most studies observing the motivational impacts of adaptive interventions have not found significant results (Peirce et al., 2008; Sampayo-Vargas et al., 2013; van Oostendorp et al., 2013). Some researchers have studied the impact of adaptivity on both cognitive and motivational outcomes (Hwang et al., 2012; Sampayo-Vargas et al., 2013; van Oostendorp et al., 2013). Sampayo-Vargas et al. (2013) observed the effect of an adaptive engine on learning outcomes and player motivation and found significant effects for learning outcomes but not for motivation. Van Oostendorpet al. (2013) looked at engagement as a dependent variable in addition to learning outcomes. The adaptive version of their game helped improve learning outcomes but did not improve player engagement. The lack of motivational effects may result from an inability to increase motivation, which is already high in nonadaptive versions of games. When comparing motivations within the same game, it can be challenging to find significant effects compared to finding effects when comparing a control group and a game group.

Implications

In this section, we discuss the theoretical and practical implications for adaptivity in game-based learning.

Theoretical Implications

Even though no robust meta-analyses of adaptive game-based learning could be found, the studies we reviewed in this chapter provide empirical support for the effectiveness of adaptive games compared to nonadaptive games. This supports the notion that game-based experiences that are able to accommodate the learners' needs can foster learning more effectively than games that use the same approach for all learners. However, the number of variables currently considered for adaptivity is small, resulting in a narrow approach to adaptivity. Most of these variables are cognitive variables; in some cases, motivational variables were considered also. Additional variables should be considered, especially from affective and sociocultural domains. Additional research is needed to investigate the effectiveness of these variables, and we presented a model that may be able to provide useful theoretical and practical guidance for the selection of these variables.

Practical Implications

Our review may also provide guidance for game designers implementing adaptivity in their own learning games. Most importantly, designers should consider all possible types of variables—affective, cognitive, motivational, and sociocultural—for the design of adaptive systems. The selection should include variables that are most likely to vary among learners, while also having an effect on the desired outcomes that have been empirically validated. We described different game features that can be used to implement the different types of adaptivity, focusing, for example, on adaptive scaffolds and cues, feedback, rehearsal schedules, game visuals, game mechanics, the difficulty progression, and the conceptual progression in games. We illustrated considerations required when designing adaptive games for learning and showed that practice needs to be informed by research and theory in order to be effective.

Limitations and Future Research

In this final section, we discuss limitations of current research and provide suggestions for future research.

Limitations

Current research on adaptivity in games for learning has conceptual, empirical, and methodological limitations. On a conceptual level, the way in which adaptivity is defined is very narrow, mostly focusing on a small number of cognitive variables, such as learners' current state of knowledge, and affective variables, such as frustration and boredom. Moreover, many commercial systems that implemented adaptivity do not reveal the way in which the adaptive engine works. This lack of transparency makes it difficult to evaluate the efficacy of these systems. Also hampering adaptive systems is a general lack of research that can guide the design of any adaptive solution. Since attribute-by-treatment research was largely abandoned in the 1990s because of methodological problems, few investigations studied the moderating effect of specific learner variables on learning outcomes. Without this knowledge, the design of theory-based adaptive systems is difficult. Finally, the definition of adaptivity implies that decisions are made for the learner, not by the learner. Conceptually, this is a problem when the ability of learners to self-direct their learning is considered a learning outcome.

Limitations on the methodological and empirical side include the use of variables such as learning styles as the basis of adaptivity. As Pashler, McDaniel, Rohrer, and Bjork (2008) showed, there is no empirical evidence that learning styles have an effect on learning outcomes. As a result, their use as a variable for adaptive systems is not supported by research. Another methodological limitation has been the lack of focus on learner experience. Previous studies have focused on examining various learning outcomes associated with different adaptive designs. However, few studies have discussed the processes through which adaptive systems influence learners' gameplay. For example, studies implementing adaptive difficulty adjustments have not included event-based analysis of adjustments made by the adaptive system and the effect of such adjustments on the learner. Analyzing adaptive systems from a learner's viewpoint can guide future designs and enhance their utility and acceptance.

Future Research

For future research on adaptive games for learning, we propose the following points for consideration, following the questions that guided the first part of this chapter.

What variable should the game adapt for? As our review has shown, the number and breadth of variables that are being used for the design of adaptive games are very limited. Additional research should investigate which other variables should be considered for adaptive games. The list of variables provided in table 10.1 may be useful for selecting learner variables for this research.

How do we measure the variable the system should adapt for? Games collect extensive logs of user behavior that allow predictions of a range of variables. In addition, biometrics allows the collection of physiological data that can be synchronized with the user logs. Finally, contextual data can come from the game and other observations. Together, these data can be triangulated and used to construct new measures for learner variables. Assessment mechanics can be designed to make sure the game produces the kinds of data that will create the kinds of situations that allow observation of the target variable (Plass et al., 2013). These new measures need to be designed and validated.

How should the game adapt based on the variable? A systematic research agenda on how games can be adapted for different learner characteristics should be developed. This includes investigating the moderating or mediating effect of learner variables on the effectiveness of specific interventions, and studying which specific game features should be used for adaptivity. The game features we discussed may provide examples of how adaptivity may be implemented in games for this research.

In this context, it is worth considering whether a new generation of the ATI research paradigm could be developed. An improved approach to these kinds of studies could address the methodological shortcomings that were identified for this research three decades ago based on the new learner variables that were identified since that time and the new measures that were developed to diagnose them.

Finally, future research should expand the overall approach to how the game responds to the learner's needs. Critics already suggest that adaptivity is a new form of behaviorism (Rouvroy, 2015) that prescribes instruction rather than affords learners choices. Researchers should design and study adaptable games; that is, systems that use the diagnosed learner variable to provide the learner with smarter choices and therefore with agency.

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