Educationally Adaptive: Balancing Serious Games

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Abstract
A key factor for the success and efficacy of an educational medium is the extent to which it is capable of addressing the preferences, abilities, strengths, weaknesses, and goals of individual learners. Research in the field of learning and instruction has demonstrated in the past that one on one tutoring is the most effective and powerful way of teaching. Ever since, the research community attempted to equip artificial systems with the strength and abilities of human tutors. Specifically in a medium such as educational computer games an appropriate personalization is a key factor for fun, immersion, and ultimately learning. The same holds true for serious, in particular educational, games. Because the key strength of serious games is seen in their intrinsic motivational potential, it’s all about focusing on the learners. More importantly, in contrast to conventional educational systems, in games this means accounting for both, a game related and a learning related hemisphere. This report attempts to emphasize the importance of advancing a construct such “educational game AI” and it illustrates recent technologies and approaches.

KEYWORDS: EDUCATIONAL GAMES, ADAPTATION, GAME BALANCING, PERSONALIZATION

Introduction
Over the last decade, serious games have become accepted educational tools and the idea of using the great strength of modern computer games for educational purposes experienced a significant boost.

From an educational perspective, computer games offer a promising approach to make learning more engaging, satisfying, and probably more effective. Current approaches to learning/teaching with computer games are ranging from utilizing commercial entertainment games (the so-called ‘commercial off the shelf games’, COTS) to games designed and developed for primarily educational purposes. The major strength of digital games in education is a high level of intrinsic motivation to play and to proceed in the game and, thus, to learn within the context of a meaningful and continuous storyline and within the related para-social dimension provided by game characters. These strengths are acknowledged as supportive in the context of education for a long time. According to Malone (1981) the factors forming that strength and making games fun are challenge, fantasy, and curiosity. Educational games provide clear goals and rules, a relevant learning context, an engaging storyline, immediate feedback, a high level of interactivity, challenge and competition, random elements of surprise, and rich and appealing learning environments (cf. Prensky, 2001). These factors determine
motivation to play but are also considered being important for successful and effective learning (for reviews see Merrill, 2002 or Schulmeister, 2004). On the other hand, educational games have also major disadvantages such as difficulties in (i) providing appropriate balance between gaming and learning activities, (ii) providing a continuous balance between challenge and ability, (iii) aligning the game with national curricula, or (iv) the extensive costs of developing high quality games (for a review see van Eck, 2006). Due to these problems, most of today’s educational games cannot compete with their commercial counterparts in terms of gaming experience, immersive and interactive environments and storytelling, or intrinsic motivation to play. Moreover, most educational games do not rely on sound instructional models thus leading to a separation of learning from gaming and often they provide gaming actions only as reward for learning. Therefore, such games do not differ significantly from other traditional multimedia learning applications.

To move toward the ‘next generation’ of educational games, a significant community of researchers addresses the field of a sensible adaptation to the learner/player; undoubtedly, “balancing” computer games according to certain (presumed) preferences and needs of the players in an autonomous and adaptive manner is an important feature. To be enjoyable, a computer game must be balanced well (Tins, Brokken, & Ijsselsteijn, 2008, 2009), meaning the game must match an individual player’s playing preferences, playing styles, and playing capabilities in a suitable way in order to avoid too one-sided gameplay. So far there is almost exclusively a tradition of adaptively balancing recreational games. Main goal is to avoid undesired player emotions such as frustration (because the game is too hard) or boredom (because the game is too easy; cf. Koster, 2004). Adams and Rollins (2007) list a number of requirements for well-balanced games are for example:

• meaningful choices;
• chance should not make player capabilities irrelevant;
• players must perceive the game to be fair;

Specifically in serious games, an appropriate adaptation is of crucial importance in order to reach and maintain fun and enjoyment on the one hand and effective, successful learning on the other hand (a review can be found in Kickmeier-Rust, Mattheiss, Steiner & Albert, 2011). Of course, the idea of (and the need for) a smart educational personalization is not only valid for educational games. Originally, the concept was developed in the field of conventional adaptive/intelligent educational and tutorial systems; an overview about adaptation techniques in e-learning can be found, for example, in Brusilovsky and Peylo (2003) or De Bra (2008).

The Origins of Educationally Intelligent Systems

Along with the industrial revolution and the invention of assembly-lines, a new view of learning and teaching emerged. Standardized tests emerged during World War I, teaching machines were invented in the 1920s, instructional films came up in the 1940s, or programmed instruction came up in the 1950s, in the 1960s and 1970s the educational television was invented and educational computer technology became popular in the 1980s and 1990s. (cf. Wulfeck, 2009).

The modern approaches to adaptive educational technology can be traced back to Lee Cronbach and Richard Snow (1977) and their Aptitude-Treatment Interaction model, which mirrors the idea that different aptitudes (abilities or prior knowledge) require different treatments (i.e., instructional methods, designs, or conditions). Further work in the area was also leveraged by Benjamin Bloom (1984) who posed the two-sigma problem that, essentially,
states that tailored tutoring results in performance superior by 2 standard deviations in comparison to regular teaching. Ultimately, the idea is that learners are not overburdened by the educational demands and therefore quickly frustrated but, at the same time, not under-challenged and therefore bored. Insofar, the concept is closely related to the portrayed ideas of game adaptation. Commenced by Bloom, psychologists, educationists, and technicians attempted to develop technology that is able to take the role of a private teacher and to intelligently provide individual learners with suitable tutoring (cf. De Bra, 2008).

**Assessment**

Naturally, balancing a conceptually complex environment such as a computer game (including visual, environmental, gameplay, game mechanics, narrative, and educational features), requires a robust, psychologically meaningful yet simple assessment that can be realized in real time in the background of the gaming and in addition to the computational demands of the game itself. Assessment, therefore, must be based on simple identifiable indicators and it must be based on valid heuristics; the indicators, thereby, may be divided into performance related aspects, emotional-motivational as well as personality related aspects. The performance related aspects include measuring, gathering, analyzing, and interpreting:

- scores;
- task completion rates;
- task completion times;
- task success rates (e.g., number of individual strikes in a shooting game);
- task success depth (the quality or degree to which a task has been accomplished);
- distances covered / progress in the game world;
- exhibited knowledge, competence states, or skills;
- incongruent behaviors as indicator for succeeding by chance (e.g., alternately exhibiting success and failure);

According to Wulfeck (2009), who delivered a comprehensive summary the present state-of-the-art, important dimensions of assessment are:

- individual preferences;
- progress/results/scores;
- traits/aptitudes;
- prior knowledge/ability;
- prior achievements;

In general, classifying the learners was subject of a large body of research (see Sampson, Karagiannidis, & Kinshuk, 2002 for an overview) and has a very long tradition. In fact, classifying goes back to the first attempts of assigning grades to students. An early example perhaps is Joachim Heinrich Campe, a German writer, linguist, and pedagogue who rewarded students with diligence cards and golden nails assigned to the name lists on the wall, as reported back in 1776 (cf. Kersting, 1992). In recent times, Sloane, Wilson, and Samson (1996) of the Berkeley Evaluation and Research Center established four principles of assessment: (i) the developmental perspective (viewing learning as a longer process that cannot
be assessed by one shot), (ii) instructional fidelity (match between objectives for assessment and important learning objectives), (iii) teacher management and responsibility (valid for classroom assessment), and (iv) quality of evidence (e.g., standards of fairness, etc.).

In the context of autonomous intelligent, adaptive tutorial systems (ITS / ATS), classifying and modeling the learner plays a crucial role and bears one of the most substantial challenges to research. The cognitive aspects are in the center of most attempts and frameworks, for example in the CTM, the *Cognitive Trait Model*, which enables student modelling on the basis of cognitive abilities and resources (cf. Kinshuk, Lin, & Patel, 2006).

A well-elaborated and validated framework for assessing in particular cognitive aspects comes also from Kickmeier-Rust and colleagues (e.g., Augustin, Hockemeyer, Kickmeier-Rust, & Albert, 2010; Kickmeier-Rust et al., 2011), utilizing the ideas of *Competence-based Knowledge Space Theory* (CbKST).

Most concisely, CbKST is an extension of the originally behavioural *Knowledge Space Theory* by Doignon and Falmagne (1999) where a knowledge domain is characterized by a set of problems or test items / tasks. The *knowledge state* of a learner is identified on the subset of problems s/he is capable of solving. Due to mutual dependencies between the items captured by *prerequisite relations*, not all potential knowledge states are supposed to occur. The set of all possible states is called a *knowledge structure*. To account for the fact that a problem might have several prerequisites (i.e., and/or-type relations) the notion of a *prerequisite function* was introduced. Recent updates of this rigorous mathematical approach are described by Falmagne and Doignon (2010).

The principle idea of CbKST is to separate the observable behavioural aspects, i.e., whether a learner masters a problem or test item, from the not directly observable construct of aptitude/ability/knowledge behind the performance. The entities of aptitude matching the concept of problems or items are called skills or competencies. Equal to knowledge structures, prerequisites between competencies establish competence structures that include only meaningful sets of competencies a person can have. To give an example, having the competency to multiply integers but, at the same time, not having the competency to add integers are not meaningful or plausible. The relationships between the competencies and problems/items are established by a *skill function*. Such function assigns a collection of subsets of competencies (i.e., *competence states*) to each problem that are relevant for solving it. By associating competencies with the problems/items of a domain, a knowledge structure on the set of problems is induced. The latent competencies can be uncovered on the basis of a person’s observable performance.

To account for the specific needs of educational games and to achieve a non-invasive, unobtrusive assessment, Kickmeier-Rust and Albert (2010) developed a formal model of the problem solving behaviour in game-based learning situations (LeS). Basically, LeS are characterized by a large degree of freedom and complex problem solving demands. The problem solution process is considered to be a meaningful sequence of *problem solution states* establishing a *problem space*. Stochastic process models are applied in order to estimate the likelihood of certain state transitions and to estimate the probability of reaching a solution state (within a specific time interval). In other terms, a LeS is segmented into a set of possible problem solution states, each mapped to one of a set of possible competence states. By this means, the educational AI of a game can interpret the behaviour of the learner in terms of available knowledge, un-activated knowledge, or missing knowledge, simply by mapping the actions of the learner to competence states.
Practically speaking, the global framework, termed micro adaptivity, attempts to analyse a learner’s progress in the game environment (e.g., if s/he passes through a door or is making use of a specific tool) and to associate a probability of available or lacking competencies on a probabilistic level. Depending on an increase (what actually is desired) or a decrease of the probability of specific competencies, pedagogical/didactic meta-rules are utilized to select a specific intervention and feedback (e.g., ‘if the probability of a competency v involved in a LeS decreases below a threshold w, and the probability of a competency x is above a value y, then trigger an educational hint z’).

Figure 1. Conceptual architecture for micro adaptivity, a framework for an unobtrusive assessment.

From a technical perspective, the architecture consists of three modules (cf. Figure 1). In the centre is a regular game engine which is responsible for rendering the game, providing game mechanics, and the input and output mechanisms. The game engine is connected to a so-called story engine which monitors and controls the spread of the game’s narrative in dependence of specific educational interventions and adaptations. The main task of this module is to assure that no breaks and inconsistencies occur in the virtual game world. Finally, moderated through the story engine, a so-called learning engine is responsible for interpreting the input coming from the game and for informing the story engine in the first instance and subsequently the game engine with educational suggestions or recommendations. Interventions and adaptations are only triggered in accordance with the game’s story and global state. As indicated conceptually in Figure 1, as a foundation for the interpretation and reasoning process as well as the subsequent interventions and adaptations the system utilizes the competence space for a
given domain, a problem space, psycho-pedagogical rules and heuristics as well as a story model, which drives the spread of the game’s storyline.

Entirely different yet highly promising directions for assessment and reasoning are covered by attempts to incorporate machine learning techniques to improve the assessment heuristics gradually during the game play (cf. van Lankveld, Spronck, van den Herik, & Rauterberg, 2010). In addition to mere performance, these approaches account for oscillating psychological states (i.e., emotional states or, maybe more importantly, motivational states) and rather static psychological characteristics (i.e., personality traits). Assessment regarding emotional-motivational aspects includes for example:

- virtual character analyses (e.g., posture, alignment, locations, motions, etc.);
- force exerted on interactive game controllers (if available);
- facial expressions recorded by camera devices (e.g., webcams; if available);
- gestures recorded by camera devices (e.g., Microsoft’s Kinect system; if available);
- speech analyses – natural language processing;
- text chat analyses;

Increasingly important, especially in consideration of the rapidly advancing technological measurement solutions, is also a strong focus on the rich possibilities of various psycho-physiological factors – even if such features and approaches are still in their infancy. Aspects considered by ongoing research are: Heart rate, heart rate variability, respiration rate, coherence between respiration rate and heart rate, blood pressure, blood volume pulse, activity of the corrugator supercilii muscle, activity of the zygomaticus major muscle, activity of the orbicularis oculi muscle, skin conductance level, skin conductance responses, eye movements, pupil size, eye blink rate, brain activity at various frequencies, or evoked response potential (cf. Tijs, Brokken, & Ijsselsteijn, 2008). Meanwhile a growing body of research provides the serious games community with knowledge about the interactions and dependencies between gaming behaviors, experiences, preferences, and psycho-physiological measures. An example is the work of Nacke and Lindley (2010), who investigated the relationships between gaming experience, level design, and psycho-physiological measures (electromyogram and electrodermal activity). Their results yielded that different game level designs effect emotional patterns during game play, which in turn has a high potential as an axis for real-time assessment and adaptation in educational games.

A further example is given by Kickmeier-Rust, Hillemann, and Albert (2011) who demonstrated the use of eye tracking for a real-time identification of motivational states in an educational game. The results of this study revealed that children can effectively learn while gaming; more importantly, a distinct finding presented in this study is that extreme groups such as high and low performers exhibit different visual patterns especially in their fixation duration and saccade lengths. Very concisely, good learners scan the visual field evenly with longer saccades and attend relevant areas on screen more frequently and in a more stable fashion than poor learners do. Furthermore distinct gender differences could be found in the interaction style with different game elements, depending on the demands on spatial abilities concerning navigating in the three-dimensional spaces.

But not only the continuously oscillating (psycho-physiological) states serve as assessment indicators, also the rather stable personality traits offer assessment indicators such as the adaptation and application of well-acknowledged personality inventories, for example, a widely accepted instrument for assessing the 5-factor model of personality is the NEO-PI-R
personality questionnaire (van Lankveld, Schreurs, Spronck, & van den Herik, 2011). Just as an example, the factor “extraversion” involves:

- **Activity**: Active, energetic people have high pace and powerful movement. They need to be busy and radiate a feeling of energy. They have a busy and hasty life.
- **Assertiveness**: Assertive people are dominant, self-content, and controlling. They talk without hesitation and often lead groups.
- **Excitement-seeking**: Excitement seekers desire adventure, stimulation, and action. They like bright colors, noisy environments, and aculeate sensations.
- **Gregariousness**: Gregarious people prefer the company of others. They seek out others and like crowds and group activities.
- **Positive emotion**: People with positive emotion have fun and feel happy and joyful. They laugh easily and are often cheerful and optimistic.
- **Warmth**: Warm people desire to form emotional bonds with others by showing warmth and action. They are friendly and show that they genuinely like others.

The work of van Lankveld, Schreurs, Spronck, and van den Herik (2011) indicates, for example, that gaming behavior in specific situations (e.g., being forced to wait) can reveal personality traits, in their particular case extraversion, to a certain extent.

Highly interesting and most forward-looking approaches to assessment are the so-called brain-computer interfaces. In essence, these approaches are utilizing EEG and functional brain imaging techniques to directly interface the human brain with the game. This means that the player can control the game more or less directly through thoughts. For example Krepki, Blankertz, Curio, and Müller (2007) used motor imagery to play Pacman, Pong, or Tetris games. Finke, Lenhardt, and Ritter (2009), as another example, moved a character through a virtual scene by measuring the so-called P300 potential in the EEG.

Physiological computing systems that employ real-time measures of psycho-physiology to inform an adaptive system are at an early stage, of course. Fairclough (2009) argues that physiological computing has enormous potential to innovate human–computer interaction by extending the communication bandwidth, fundamental issues for research are the complexity of the psycho-physiological inference, representing the psychological state of the user, ways of designing explicit and implicit system interventions, or defining the “biocybernetic loop” that controls system adaptation.

In conclusion, in contrast to traditional forms of teaching (either in real or virtual environments), where the assessment occurs by test items, questions, or tasks, DEGs require an assessment that does not destroy or impair motivation, immersion, flow experience, or the game’s storyline (Kickmeier-Rust & Albert, 2010). This “protection” is important from two perspectives. On the one hand, there is a large body of evidence concerning the negative impact of interruptions and attention splits on (problem solving) task performance and learning (e.g., Chandler & Sweller, 1992 in the context of cognitive load theory; Foerde, Poldrack, & Knowlton, 2007 in the context of cognitive neuroscience; or Gillie & Broadbent, 1989 in the context of computer tasks). On the other hand, from the perspective of fun and immersion, it is important not to compromise a fluent progress of game play and/or narrative (e.g., Jennett, Cox, Cairns, Dhoparee, Epps, Tijs & Walton, 2008).
Adaptation – Personalization – Balancing

Assessment is the one thing in successful adaptation. The next thing is enabling the system to respond educationally meaningful and effective to the conclusions drawn from the assessment procedures, still protecting immersion and flow. Feedback and interventions can be interpreted as one mechanism that takes over the actions of a teacher, i.e., providing advice, explanations, and evaluations (Vasilyeva, Pechenizkiy, & De Bra, 2007). In game-based learning situations, adaptations on the micro level may occur through embedded feedback (e.g., through a non-player character), by guiding or hinting, or by adjusting the complexity/difficulty of a learning situation. Such kind of adaptation may indicate gaps between current and desired performance level and may enhance motivation and task strategies, it is able to reduce learners’ cognitive load, and it can provide information that is useful for correcting inappropriate task strategies, errors, and misconceptions (Shute, 2008). Existing strands of research (e.g., Steiner, Kickmeier-Rust & Albert, 2009) also focused on equipping the game with a set of psycho-pedagogically inspired adaptive intervention categories and types which are aligned with the non-invasive assessment procedures of a learner’s competence and motivation. Broadly speaking, these interventions strive to enhance cognitive abilities and to support the learners adaptively according to their behaviour and underlying available or lacking skills (cognitive and meta-cognitive interventions) and are supposed to enhance and retain learners’ motivation and engagement on a high level (motivational interventions).

Research on adaptation in game environments involves also the macro aspect of storytelling; the challenge is integrating interactive storytelling with the demands of educational and psycho-pedagogical adaptation (e.g., a well-planned sequence of learning events). A fundamental phenomenon, commonly encountered in the creation of (educational) games is the tension between the control over the game by the author and the control exerted by the player over the continuation of the game during play. This phenomenon, referred to as the “narrative paradox” due to the seemingly incompatible interests of author and player, shows the interconnection of two challenges: the composition of an exciting game by an author (authoring) and the continuation of a game at a certain moment during play, ideally adapted to the player’s needs (macro adaptation). A possible solution for highly adaptive games is an open, adaptive storytelling, tailored to the needs and actions of a player, based on more or less abstract rules defined by the author. As briefly introduced in the preceding section, the idea is, in principle, to develop a formal story model (e.g., the Hero’s Journey, cf. Campbell, 2008) and link it, as a formal representation, to problem spaces, competence structures, and ultimately to game elements and assets. Göbel, de Carvalho Rodrigues, Mehm & Steinmetz (2009) describe an approach where atomic and modular game elements, the so-called Narrative Game-Based Learning Objects (NGLOBs), are re-assembled adaptively in accordance with educational adaptations.

Under the conceptual cloak of micro and macro adaptation, there is a broad range of dimensions and techniques to respond or intervene in order to balance a game and tailor its manifestation to the individual learners (Kickmeier-Rust, 2007). A very common technique is the so-called dynamic difficulty adjustment (DDA; van Lankveld, Spronck, van den Herik, & Rauterberg, 2010; Wong, 2008). This technique is widely used in entertainment games but also increasingly enters the AI of serious, in particular educational games. In simple terms, the idea is to increase the difficulty of the game or of game elements along with the increasing capabilities of the players. A similar approach is the so-called speed adjustment which actually focuses on racing-like games, where the speed of artificial opponents is adjusted with the player’s speed and racing abilities. In terms of learning, there exists ground-breaking work to adjust the difficult of learning materials (in mutual dependence with the global game difficulty
and game characteristics; Kickmeier-Rust, Göbel, & Albert, 2008). Also related to this type of balancing is the so-called rubber banding (Pagulayan, Keeker, Wixon, Romero & Fuller, 2002), which means artificially boosting performance (of a race car, for example) when falling behind.

A more sophisticated method, particularly when it comes to a learning-related adaptation and balancing, is problem solving support. This method attempts to identify where in a problem solving process (which is characteristic for many in-game tasks and quests) a player or learner is, to interpret whether support or guidance is required, and which type of support or guidance is the most appropriate one in the given situation (cf. Kickmeier-Rust & Albert, 2010).

In summary, prototypical techniques and methods of adaptation are:

- procedural and adaptive level and content generation (Nitsche, Ashmore, Hankinson, Fitzpatrick, Kelly & Margenau, 2006)
- strategy formulation (e.g., adaptive behavior of agents; Avery & Michalewicz, 2008);
- adaptive and interactive storytelling (Göbel et al., 2009);
- guidance, problem solving support, hinting (Kickmeier-Rust & Albert, 2010);
- motivational interventions; cheer, praise, critiquing (Kickmeier-Rust & Albert, 2010);
- adaptive presentation (Brusilovsky & Peylo, 2003);
- adaptive curriculum sequencing (Brusilovsky & Peylo, 2003);
- navigation support (Brusilovsky & Peylo, 2003);
- intelligent solution analysis (Brusilovsky & Peylo, 2003);

In general, each computer game has some elements of adaptation. The attempt to realize game balancing in a game-related as well as education-oriented sense are crucial still not trivial. To combine both worlds is clearly more than the sum of it.

Noteworthy are the results of two European projects, as role models of complex game balancing. The first project was ELEKTRA (www.elektra-project.org), which focused on assessment and adaptation on an unobtrusive level and on subtle educational guidance. The ELEKTRA prototype game is realized as a classical 3D adventure game in first-person view, and aims to teach 8th grade (i.e., 12 to 13 years of age) optics. Briefly, the aim is to save a girl, Lisa, and her uncle Leo who have been kidnapped by the evil Black Galileans. Moreover, the learner must stop the evil forces from taking over the entire world. During this journey, the learner must acquire specific, curriculum-related knowledge. The learning occurs in different ways, ranging from hearing or reading to freely experimenting. After finding a magic hourglass, the learner is in company of the ghost of Galileo Galilei, who is the learner’s (hidden) teacher. The non-playing characters play a significant role in intelligent, non-invasive educational and motivational interventions. For example, Galileo tells the learner specific facts that are needed for certain events in the game and intervenes by providing the learner with hints or feedback. Figure 2 displays two screen shots of the game.
The second example, we want to highlight is 80Days (www.eightydays.eu). This project focused on advancing the non-invasive assessment and on appropriate psycho-pedagogical support of learning. The distinct novelty of the project was the integration of adaptive, interactive storytelling (Kickmeier-Rust, Göbel, & Albert, 2008) and adaptive game balancing. 80Days leaves the well-structured domain of physics and produced a demonstrator game that is teaching geography for the age group of 12 to 14 (see Figure 3 for screenshots).

**How Important is Game Balancing?**

We have tried to outline the basic idea of game balancing and illustrate some examples of approaches to an intelligent automatic adaptation to the players and learners in terms of playing and in terms of learning. Of course, this summary is not meant to be complete. Its intention is primarily to raise awareness that mere mixing of learning materials with computer games and game-like features is likely not successful and may lead to, what famous Seymour Papert called a *Shavian reversal*, a chimera that unifies the worst from two worlds.

A smart, perhaps intelligent individual balance and an emphasis on an autonomous, system-driven acknowledgement of individual needs and preferences, both in a game related as well as learning related sense is a key factor of a game’s success. This, again, concerns both the game hemisphere and the educational hemisphere.

To substantiate this claim, we conducted a meta-review in the field of game-based learning literature. We particularly looked into scientific articles presenting results on the educational efficacy, the learning performance, of computer games. In total we analyzed over 300 papers published between 2009 and 2011 in SCI listed journals. One result was that only a small percentage of those papers (i.e., about 10%) reported serious, non-trivial educational benefits from playing the games. Even more impressing was the fact that from those studies reporting
reasonable and statistically significant benefits, 90% share that the investigated games bear some form of educational adaptation or personalization. These results (the details and further aspects will be published in the near future) are in line with experimental findings that explicitly demonstrated that adaptation, personalization and subtle balancing results in superior gaming experience and educational gains (e.g., Kickmeier-Rust et al., 2008).

The European network of excellence GALA (www.galanoe.eu), which stands for Games and Learning Alliance, is a network that is dedicated to bring European leading players in the field of serious/educational games together, to fight fragmentation, and to establish synergies. The involved organizations and companies cover a broad spectrum from research to development and from commercial to educational organizations. Acknowledging the importance of advancing the “educational intelligence” of serious games, GALA established a technical committee dedicated to “serious game AI” involving personalization, adaptation, and game balancing.

Conclusions

In all our experience and on the basis of the recommendations and findings of a broad range of studies and surveys, a key aspect of a successful educational medium, in particular an education game, a smart and appropriate balance of various factors is crucial. The term balance, in essence, refers to an equilibrium of human dimensions, game-related as well as education-oriented dimensions. This complex set of relationships make it difficult to appropriately and successfully find a state of balance which assures immersive gaming and effective learning for a specific student/player. When the key strength of educational games, however, is seen in their intrinsic motivational potential, all success is up to an embedded and targeted assessment of the various factors and dimensions and a suitable adaptation and personalization accordingly. This is, of course, not a trivial attempt. There is a large community of researchers and practitioners working in the field of intelligent and adaptive tutorial systems but, as outlined, the field of games raises additional challenges. In this paper we have tried to give a brief overview of approaches to assess various factors and dimensions and to adapt accordingly in order to establish a promising balance. In our meta-review we mentioned concisely, we attempted to make clear that smart adaptation and personalization – or balance in other terms – is likely the most important factor for future, successful, and widely accepted game-based learning. Many of the techniques and methods, however, are not mature yet. The approaches and ideas, nevertheless, are recommended to be as strong part of designing the next generation of serious games – making serious games serious business.

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