

A Psycho-Pedagogical Framework for Multi-Adaptive Educational Games

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ABSTRACT

One of the trump cards of digital educational games is their enormous intrinsic motivational potential. Although learning game design is often understood on a one-fits-all level, the actual motivational strength of an educational game strongly depends on the individual learners, their very specific goals, preferences, abilities, strength and weakness, personality, and experiences with gaming. Considering motivation being a fragile and constantly changing state, it is important to continuously assess learning and gaming processes and the oscillations of motivation and immersion within a game. With this premise in mind, we developed a psycho-pedagogical approach to a non-invasive, embedded assessment of motivational states and learning progress, feeding into a dynamic, ontology-driven learner (and gamer) model. To evaluate the approach, the demonstrator games were subject to intensive quantitative and qualitative experimental research. The results show that a meaningful personalization and an individual support are key factors of the success of learning games.

Keywords: Digital educational games, non-invasive assessment, motivation, micro adaptivity, macro adaptivity, adaptive storytelling

INTRODUCTION

Computer games are an incredibly successful genre that captivates children as well as adults and that instantly mirrors the spirit of a time and the state-of-the-art in computer technology. Computer games combine art and technology in a fascinatingly natural and convincing way. The games' success is reflected in enormous sales figures, economic growth, and numbers of users. Particularly, Massively Multiplayer Online Games (MMOGs), brings together millions of players in a single virtual world, and have become a market and technology leader. Thus, it is no surprise that computer games spill over into more serious applications beyond pure entertainment - and the hype over serious games and especially games for learning exists, with a great many initiatives, projects, and even products.

The core strengths of computer games, distilled to their essence, are fun, fantasy, curiosity, challenge, and control (Malone & Lepper, 1987), leading to an enormous intrinsic motivational potential. The idea of utilizing those strengths for educational purposes is amongst the most exciting developments in the area of educational technologies in the past decades. It is thrilling and challenging for educators, researchers, developers, and designers - educators and parents are struck by "*the quality of engagement that stands in stark contrast to the half-bored watching of many television programs and the bored performance exhibited with school homework*" (Kafai, 2006). Of course, the idea is not new. The attempt to utilize technological

trends for education has a long history. Technologies such as radio, television, computers, or the Internet were quickly – and successfully – adopted for fostering learning. The motivational potential along with the high level of interactivity and the large degrees of freedom in computer games for educational purposes may open entirely new horizons for educational technology (de Freitas, 2006).

Playing games, in general, is not only one of the most natural forms of human activity but also one of the most natural forms of learning. Children learn to talk by playing with sounds and learn collaboration and strategic thinking when playing Cowboys and Indians. Already Johan Huizinga in 1938 ventilated the view that the *Homo ludens*, the playing man, develops abilities through play. Thus it is no surprise that educational computer games have a long history. An early example is the educational game *Oregon Trail*, a resource management game released first in 1971 and re-released by the educational publisher *Brøderbund* for the *Apple II* in 1985. So in conclusions, the essence of game-based learning is the attempt to utilise the strengths and educationally beneficial aspects of computer games, for example, the high level of intrinsic motivation to play and proceed in the game, a meaningful yet rich and appealing learning context, immediate feedback, or a high level of interactivity, challenge, and competition. It is clear, digital educational games (DEG) can be way more than just “*chocolate covered broccoli*” (Jacob Habgood, 2009).

According to many researchers in the field of game-based learning, however, DEGs are still in their infancy from a scientific and pedagogical perspective (e.g., Fu, Su, & Yu, 2009; Oblinger, 2006). Major challenges for research, design, and development are seen, for example, in finding an appropriate balance between gaming and learning activities (Van Eck, 2006) or finding an appropriate balance between challenges through the game and abilities of the learner (e.g., Kickmeier-Rust et al., 2007). We see the most important challenges for research on educational games in relation to their core strength, which can be summarized with their enormous intrinsic motivational potential. On the one hand, maintaining a high level of motivation requires an intelligent and continuous real-time adaptation of the game to the individual learner, for example, a continuous balancing of challenge and ability, of problems and learning progress. This adaptation and level of responsiveness must occur in the context of learning progress but also in the context of gaming and story. As important the intrinsic motivation is, equally difficult is it to maintain that level of motivation and equally fragile is a suitable balance between challenges and abilities. Essentially, this idea is covered by the concept of *flow* – a highly immersed experience when a person is engaged in a mental and/or physical activity to a level where this person loses track of time and the outside world and when performance in this activity is optimal (Csikszentmihalyi, 1990).

On the other hand, another challenge is the enormous quality of today’s commercial, non-educational computer games and, associated with that, the skyrocketing development costs. Modern triple-A games have a development budget of tens of millions of Euros. Unfortunately, the target audience for a non-educational computer game is way larger than the target audience of an educational game that is usually developed in a specific language, for a specific limited target age, and according to a specific curriculum.

PERSONALIZING LEARNING AND GAMING

As outlined above, one of the most crucial factors for successful educational games can be seen in the game’s ability to maintain an individual learner’s motivation and interest by adapting the individual learning and gaming experiencing the this very learner’s needs, preferences, goals,

and abilities. On the one hand, this certainly is a matter of a suitable and creative learning game design. But sheer design cannot cover individual differences, thus we need mechanisms to assess we the learners need and what they want and, subsequently, to adjust the learning game accordingly. This attempt is not trivial.

Generally, the idea comes from the field of *adaptive/intelligent tutoring* in conventional technology-supported teaching and learning, basically inspired by Benjamin Bloom in 1984 who stated that students who received one-to-one tutoring performed on average as well as the top two percent of those receiving classroom instructions. Ever since psychologists, instructors, 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. The spectrum of approaches, methods, frameworks, and applications is quite broad (De Bra, 2008; Kinshuk, Lin, & Patel, 2006). Adaptivity refers to three major concepts: (a) *Adaptive presentation*, which means adjusting the look and feel of a learning environment according to individual preferences or needs; for example, different colour schemes, layouts, or amount of functionality; (b) *adaptive curriculum sequencing*, which means providing the learner with learning tailored to individual preferences, goals, learning styles, or prior knowledge; (c) *adaptive problem solving support*, which means providing the learner with feedback, hints, or solutions in the course of problem solving processes.

Generally speaking, those rough classes of adaptation have in common that they require an assessment of knowledge and learning progress and that adaptation significantly influences the presented learning objects. While in conventional learning environments such approach works well, in game environments it is not applicable. On the one hand, conventional assessment methods such as popping up queries or multiple choice items would most likely destroy immersion and flow experience. On the other hand, it is not possible to add or skip specific learning objects because this substantially harms the story and red thread through the game.

In the framework of the ELEKTRA project a new approach was introduced, addressing those problems. The new concepts, which are tailored to learning environments with large degrees of freedom, are adaptivity on macro and micro levels (Kickmeier-Rust & Albert, 2010). Macro adaptivity refers to rather traditional techniques of adaptation such as adaptive presentation and adaptive navigation on the level of learning objects (or *learning situations* in an educational game). Generally, macro adaptive interventions are based on a fixed learner model (e.g., traits) or adaptation model (e.g., pedagogical implications) and on typical (knowledge) assessments (via test items). Micro adaptive interventions, on the other hand, are non-invasive (meaning that an overall narrative is not compromised) and affect the characteristics of a specific learning object or learning situation. Techniques of micro adaptive interventions are, for example, adaptive hinting, adaptive feedback, or an adaptive adjustment of the environment.

Micro Level Adaptation

Non-invasive Assessment of Cognitive and Motivational States

In the first instance, micro adaptation relies on an embedded method to the assessment of learning progress, cognitive as well as motivational states. The basic idea is to monitor and interpret the learner's behavior in the game. To achieve this, we utilize the formal framework of *Competence-based Knowledge Space Theory* (CbKST), which is a cognitive framework, extending the originally behavioural *Knowledge Space Theory* (Doignon & Falmagne, 1999), where a knowledge domain is characterised by a set of problems and prerequisite relations

among them, establishing a knowledge space. The basic idea of CbKST is to separate observable performance and underlying latent skills or competencies (e.g., Albert & Lukas, 1999; Korossy 1999). The relationships between the skills and problems (or learning objects) are established by skill and problem functions. By associating skills with the problems of a domain, a knowledge structure on the set of problems is induced. CbKST provides an internal cognition-based logic that is quite similar to the logic of ontologies: well-defined entities (the skills) are in a well-defined relationship (a so-called prerequisite relation). The domain model, the set of meaningful skill states, and the resulting set of meaningful learning paths are combined with a model of tasks and problems within certain parts, so-called learning missions, of the game (equivalent to conventional “learning objects”), the so-called problem space (cf. Newell, 1990; Newell & Simon, 1972). A simple example for such mission might be the task to fly with the space ship to a certain city and to take a picture. The learning objective of this task might be (among others) to learn about the location of the city on the map. In this situation are various manipulable objects, for example the space ship. The learner can perform certain actions to achieve the goal, in this example primarily changing the directions of the flying space ship or controlling speed and altitude. The aim of micro level assessment is in the first instance to assign a problem solution state from the problem space to each action (e.g., pressing an arrow key). This mapping is done by classifying actions according a set of rules. An example for such rule might be “the distance between space ship and target location is increasing”. The second aim is to assign a set of available and a set of lacking skills to each problem solution state; for example, flying in the right direction indicates that the learner knows the wind direction towards the city. Of course, a single observation is not very convincing. Thus, CbKST provides a probabilistic approach to assessment. We have a probability distribution over all possible skill states and with each action we update the probabilities of those states that include the relevant skills and we decrease those states that include the lacking skills (for details on the probabilistic updating procedure refer to Falmagne & Doignon, 1988). Recently Augustin, Hockemeyer, Kickmeier-Rust, and Albert (2010) have elaborated and most importantly simplified the probability update procedure to reduce the computational load in the real-time assessment context. At the end of this procedure stands a more or less well-founded assumption about the skills the learners have, the skills they don’t have, and their position in the problem solving process.

Similarly, we can assign specific motivational assumptions to specific classes of actions, again based on a set of rules. The rules were derived from the large body of research in the area of motivation psychology and aggregated into a novel framework to motivational assessment. In essence, the framework builds upon the expanded model of motivation to learn (Heckhausen & Heckhausen, 2006) attribution theory (Weiner, 1974) and the concept of self-efficacy (Bandura, 1977), and Keller’s ARCS model (Keller, 1987). Motivational interventions may provide the learner with information about the learning progress or the game, provide or announce incentives or rewards, may address attention or confidence, but may also involve emotionally focused feedback. An example is to interpret the density of actions, that is, the number of actions performed in a specific time interval. The continuously gathered and updated assumptions on the skills and motivational state throughout the game serve the provision of adaptive psychopedagogical interventions tailored to the learner’s current needs.

Interventions on the Micro Level

It is important to avoid comprising the game's flow by assessing learning progress or motivational state, but it is equally important to interventions be convincingly embedded in the game and, more importantly, suitable for the individual learners in their very gaming situations. Micro level interventions may be hints, suggestions, warnings, or feedback. We propose the following general types of interventions:

- Educational interventions provide the learner with specific information (i.e., skills) if the system concludes that the related skills are lacking. In the game context such interventions can come for example from non-player characters.
- Problem solving support provides the learner with information about his/her current state in the game-related problem solving process. To give an example, if the system detects that a number of actions did not decrease the distance between the present problem solution state and the target state, the system can trigger a hint that perfectly suits the present problem solving state.
- Meta-cognitive interventions are supposed to foster reflection about the learner's own abilities, confidence, or self-esteem. A typical realization of such intervention type is to let a non-player character ask specific questions like "are you sure?" or "why did you do that?".
- Assessment interventions are a special form of intervention. If the probabilistic assessment (of either learning progress or motivation) does not lead to clear results after a certain number of actions, the system can trigger interactions to improve the assessment. Typically this can be realized by providing the learner with different problems/tasks or by specific questions through a non-player character.
- Dissolving interventions are a further form to provide the learner with specific information. The purpose of this intervention type is to provide the learner with the solution of a problem/task if the learner wasn't able to do so within a reasonable number of actions. Such interventions, ultimately, shall assure that the game can continue even if the learner is not able to solve a problem/task. Of course, for didactical reasons, this intervention type might not be used for all problems/tasks.
- Motivational interventions are supposed to retain the learner's motivation on a high level or to intervene when the system detects that the motivational states (potentially) decreases. Forms of such interventions are feedback, praise, incitation, encouragement, or directing attribution of success or failure (from a motivational point of view the learner should attribute success to his/her own abilities and failure to external components such as bad luck).

All interventions of a game require a manifestation in form of game assets (e.g., a sound file with a specific sentence). Of course, not all possible interventions can be realized. In general, we propose an approach of using interventions conservatively and sparsely. One must be aware that repeated inadequate interventions due to misinterpretations of a situation (e.g., assuming a lack of motivation on the basis of no actions for longer period of time while the learner just has gone to the fridge) are a significant harm to motivation, engagement, and the game flow. The conditions under which a certain adaptive intervention is given are to be developed on the basis of psycho-pedagogical rules, as briefly referenced above.

Macro Level Adaptation

So far our concept of personalization and adaptation for adaptive educational computer games just concerned assessment and interventions within specific limited and pre-defined learning situations. Educationally important techniques for personalization and adaptation such as adaptive sequencing of learning units (curriculum sequencing) or adaptive presentation, however, cannot be addressed reasonably. To extend and enrich the approach to in-game personalization and adaptation, we conceptualized a fusion of the micro adaptivity concept with techniques of interactive digital storytelling. In that way, we can realize a personalized sequencing of learning situations and units according to educational aspects as well as personalized adjustments of the game according to individual needs and preferences. In other words, we can shift in-game adaptation to the *macro level*.

In the literature several techniques for interactive or adaptive storytelling are described, varying in the openness of story generation and in their operational reliability. The approaches range from a recombining of self-contained story elements to an open-ended automated generation of “new” stories. For our goal of adaptation we rely on a robust approach based on the specification of atomic story-related entities (ranging from single spoken sentences to self-contained story units). In this context, a crucial aspect of interactive storytelling is to find an appropriate storyline on the basis of a pool of given atomic story or game elements. These entities can be compared to the rooms of a house and the furniture in those rooms, each entity has a specific goal (e.g., providing the learner with information, assessing internal states, or contributing to story and gameplay), specific characteristics and properties. During a gaming episode the single game entities must be adaptively re-combined and re-assembled into a meaningful storyline and a meaningful environment. The assembly is driven by specific sets of rules which refer to aspects of the game genre, the story model, educational aspects, and individual aspects.

The story model underlying our approach relies on a formalization of the classical *three-act structure* of *Aristotle* providing an arc model with ‘exposition’, ‘rising action to climax’, and ‘denouement’. The related set of rules, in combination with additional annotations such as importance for the game or the educational aim, establishes a set of meaningful paths through the story. This story space can be overlaid with the domain model on the basis of CbKST (the competence structure). This combination generates so-called *game paths* possible and educationally meaningful paths through the game accounting for story model, learning objectives, and pedagogical interventions (cf. Figure 1; see also Göbel et al., 2009 for details). Interventions on the macro level now can be either system-driven adjustments to the overall storyline or adjustments to the game’s pace or intensity (for example, a mission can be accomplished calmly without any time pressure or, on the other hand, driven and fast and with time pressure (e.g., because being chased by virtual opponents).

THE REALIZATION

The introduced approach was developed and realized in two European project, ELEKTA (www.elektra-project.org) and 80Days (www.eightydays.eu). From a technical perspective, the realization is based on a complex interplay of various specialized software components and engines.

The game is traditionally realized with a state-of-the art game engine (Nebula 2 engine by Radon Labs in this case). The learner interacts solely with this game engine. The game passes

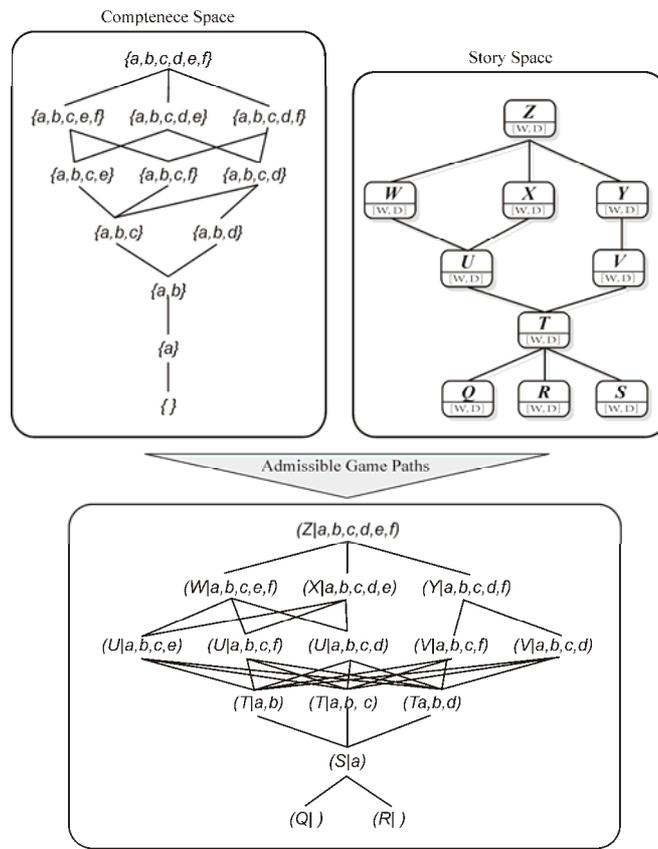


Figure 1. A combination of knowledge and story paths as a basis for adaptation.

information about the game progress to a central adaptation control engine. This engine passes the relevant data to engines for the real-time assessment of the present knowledge state and for the motivational assessment. The results coming from those engines are analyzed. On the one hand, the results are transcribed into recommendation regarding micro adaptive interventions, as described above. The ultimate decision about triggering micro level interventions comes from the game engine and includes information about the intervention history and the game progress (in order to avoid annoying repeated or similar interventions or interventions in inappropriate situations). On the other hand, the results are considered for macro adaptive adjustments of the entire narrative (including the alteration of the game's speed and intensity). The relevant information for the engines comes from an OWL ontology that serves as a comprehensive database (cf. Kickmeier-Rust & Albert, 2007).

Case Study 1: ELEKTRA

The ELEKTRA project (www.elektra-project.org), funded by the European Commission, ran from 2006 through 2008 and had the ambitious goal to utilize the advantages of computer games and their design fundamentals for educational purposes and to address and eliminate the disadvantages of game-based learning as far as possible. Nine interdisciplinary European partners contributed to the development of a sound methodology for designing educational games and the development of a comprehensive game demonstrator based on a state-of-the-art

3D adventure game teaching physics according to national curricula. In this context the approaches to non-invasive assessment and embedded interventions were developed. The research efforts were realized in form of a compelling demonstrator game which was realized as a classical 3D adventure game in first-person view and it is supposed to teach physics (see Figure 2 for screenshots).

Very briefly, the aim of the ELEKTA game is to save the girl Lisa and her uncle Leo who have been kidnapped by the evil Black Galileans; moreover, the learner has to stop the evil forces from taking over the entire world. During this journey, the learner needs to acquire specific, curriculum-related knowledge, concretely, the learner learns about 8th grade optics. The learning occurs in different ways, ranging from hearing or reading to freely experimenting. After finding a magic hour glass, the learner is in company of the ghost of Galileo Galilei, who is the learner's (hidden) teacher. In addition, the learner can interact with Lisa via a headset, which is indicated in the upper left corner of the screen. Those non-playing characters also play a significant role for intelligent, non-invasive educational and motivational interventions. For example, Galileo tells the learner specific facts, which are needed for certain events in the game, or he intervenes by providing the learner with hints or feedback.

A concrete example for a LeS is the so-called "slope device" situation (Figure 2). In this LeS the students experiment with a machine where several balls of different materials (solid and hollow iron, wood, and plastic) are running down a slope and also a laser can beam down this slope. This machine has a fan and a strong magnet. The learners' task is to make the balls fall into a hole by setting appropriate values for fan and magnet. In addition they should estimate the trajectory of the laser beam in dependence fan, gravity, and magnetic force. This experiment is supposed to visualize the effects of fan, gravity, and magnet on different material and, in the first instance that the laser beam is not influenced by such external forces and independently propagates in a straight line. The *approach to solution* value indicates how fast a learner finds the correct settings of fan and magnet and how well s/he can estimate the trajectory of the laser beam.

Experimental Results

The demonstrator game was evaluated in-depth with children from French schools. In this context a large amount of empirical quantitative and qualitative data were recorded. The most



Figure 2. Screenshots from the ELEKTRA demonstrator game. The right image shows the so-called slope device learning situation.

essential results concern the learning and the impact of micro adaptive interventions. Prototypically we present the results for the slop device learning situation. In this context we distinguished two dependent variables, first, the so-called ‘approach to solution’ (ATS) variable, which states how many action were performed following a certain type of intervention/feedback that were (a) closer to the final solution, (b) farther from that, or (c) without an effect. The value of this variable depends on the number of interventions of a type each learner received. For the analyses we used an ATS value relative to the base line o receiving no interventions. Second, we analyzed the response time that is, the time the learners needed after receiving an intervention/feedback to perform their next actions in the experiments. Since this type of analysis compares intervention/feedback types and not participants (each of them got several of different types), the total experimenting time is not a meaningful measure.

The results (on the basis of 40 students, 17 female, 23 male, with an average age of 13.08 years (SD = 1.08)) of these analyses are summarized in Figure 3. Appropriate interventions resulted in an average relative ATS of 0.33, neutral in an average relative ATS of .06, and inappropriate in a relative ATS of 4.00 (SD = 15.21), and not receiving any interventions or feedback resulted in an average approach of -.01. These differences are statistically not significant. However, they clearly indicate that appropriate interventions/feedback result in a quicker problem solving progress that needs fewer steps. Interestingly, neutral interventions resulted in a slightly better performance while – quite reasonably – inappropriate interventions (interventions that did not fit to the situation) reduced the performance in comparison to the no intervention baseline. Somewhat different results were found for the response times after each intervention/feedback. Appropriate interventions/feedback resulted in an average response time of 3.90s (SD = 1.16), neutral in an average response time of 4.03s (SD = 1.08), inappropriate in an average response time of 3.94s (SD = 0.84), and not receiving any interventions or feedback resulted in an average response time of 3.06s (SD = 0.90). An analysis of variance (ANOVA) yielded that receiving no interventions or feedback resulted in statistically significant shorter response times ($F(3)=33,86$; $p<01$) than receiving interventions or feedback; the type of feedback, however, did no influence response times.

The evaluation of a highly adaptive system is difficult in general since each learner potentially receives different interventions at different points in time. Thus, we performed analyses on the learner level by comparing ATS and the average response time for participants

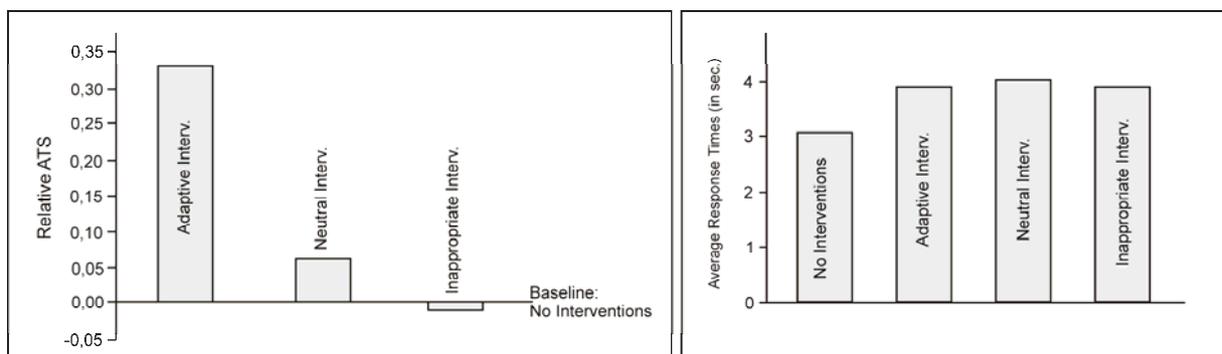


Figure 3. The left panel shows the relative approach to the correct solution of the slope device problem, the right panel shows the corresponding response times.

who received (i) (almost) no inappropriate interventions and feedback with such participants who received a (ii) large portion of inappropriate interventions. These extreme groups included 10% of participants who had received the most inappropriate interventions and the least inappropriate interventions respectively. The results are summarized in Figure 4. The average relative ATS was 0.38 in the appropriate intervention extreme group and 0.01 in the inappropriate intervention extreme group. This means that tailored interventions increased the learners' performance while inappropriate interventions did not affect performance in comparison to the no interventions baseline. Similarly, the average response times were 3.99s (SD = 0.91) in the appropriate intervention extreme group and 3.64s (SD = 1.02) in the inappropriate intervention extreme group. According to an ANOVA, the differences between the extreme groups were statistically significant for both approach to solution ($F(1)=0,31$, $p<0,01$) and response time ($F(1)=5,05$; $p<0,05$).

Finally, we analyzed overall learning performance with the demonstrator game with and without interventions/feedback using a 34 item knowledge test before and after playing the demonstrator. The results are summarized in Figure 4 (right panel). The group with adaptive interventions clearly performed better in the knowledge test than the group without any interventions although these results yielded no statistically significant difference.

In conclusion, the idea of assessing learning performance by monitoring and interpreting the learners' behavior in the context of a game environment with a large degree of freedom and the subsequent personalized support by tailored interventions such as hints or feedback appeared being a promising approach to enrich educational games with adaptive educational measures on an individual level.

Case Study 2: 80Days

The European research project 80Days (www.eightydays.eu) funded by the European Commission and inspired by Jules Verne's novel "Around the world in eighty days" is a direct successor project of ELEKTRA and runs from 2008 through 2010. Basically, the project's endeavors include addressing motivational assessment and adaptation, on the one hand, and the realization of macro adaptation as described above, on the other hand.

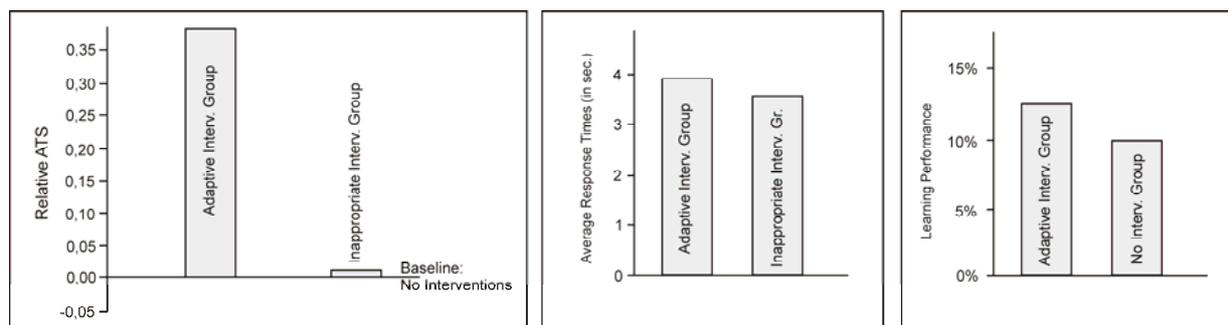


Figure 4. The left panel shows the relative approach to the correct solution in the slope device problem and the middle panel shows the corresponding response times. The right panel shows the absolute learning performance for the slope device problem in dependence of adaptation.



Figure 5. Screenshots from the 80Days demonstrator game.

As in ELEKTRA, the research endeavors of the seven European partner organizations are realized in form of a demonstrator game. The game is teaching geography for a target audience of 12 to 14 year olds and follows European curricula. The game design includes premises, concepts, metaphors, structures, gameplay, learning objectives, contents, background story, game characters, visual design and game props. In concrete terms, an adventure game was realized within which the learner takes the role of an Earth kid at the age of 14. The game starts when a UFO is landing in the backyard and an alien named Feon is contacting the player. Feon is an alien scout who has to collect information about Earth. The player wants to have fun by flying a UFO and in the story pretends to be an expert in the planet earth. He or she assists the alien to explore the planet and to create a report about the Earth and its geographical features. This is accomplished by the player by means of flying to different destinations on Earth, exploring them, and collecting and acquiring geographical knowledge. The goal is to send the Earth report as a sort of travelogue about Earth to Feon's mother ship. Finally, the player sees through the alien's game (of preparing the conquest of the earth) and reveals the "real" goal of the game: The player has to save the planet and the only way to do it is to draw the right conclusion from the traitorous Earth report. Therefore the game play has got two main goals: (1) to help the alien to complete the geographical Earth report, and (2) to save the planet, which is revealed in the course of the story, when the player realizes the true intention of the alien. Figure 5 gives some illustrations of the game.

Experimental Results

The demonstrator game was evaluated in Austrian as well as British school classes. During the ongoing evaluation activities a broad spectrum of questions is addressed. In this work we can only present a minor cutout of the preliminary results. These results are based on 69 Austrian children (27 boys and 42 girls) at an average age of 12 years and 40 British children (36 boys and 4 girls) at an average age of 11. In this regard we want to concentrate on learning performance with the adaptive demonstrator game, similar to the results presented for ELEKTRA.

The most distinct results concern the learning performance; as independent measure we computed the relative average performance increase in a 13-items knowledge test questionnaire covering the knowledge and skills relevant for a terra forming mission (Figure 6, right image), which is supposed to teach the effects of different constructible and cultivation measures on the risk of floods and severity of flood damages. The measure indicates the amount of knowledge gained from playing the game in comparison to a pretest, computed for the entire sample. As

shown in Figure 6, the Austrian children showed an increase of 19.97 (SD = 11.54), the British children an increase of 49.47 (SD = 15.66). The reason for the clearly better performance of the British children is lies in all likelihood in a language disadvantage of the Austrian sample since the demonstrator game is in English language. The performance increase yielded statistical significance for both Austrian ($t=-2.19$, $df=44$, $p<.05$) and British children ($t=-4.93$, $df=27$, $p<.001$). An interesting aspect of evaluation concerns the motivational adaptation and the macro adaptation (as describe above), which is novel to 80Days. We compared, as an example, different adaptation groups, that is, a group with motivational interventions as well as macro adaptation, a group with macro adaptive interventions only, and a group with no interventions at all. As shown in Figure 6, right panel, the combined adaptation group yielded the highest learning performance. Interestingly, macro adaptation only yielded even somewhat weaker results than no interventions at all. For the presented sample, however, the differences are not statistical significant.

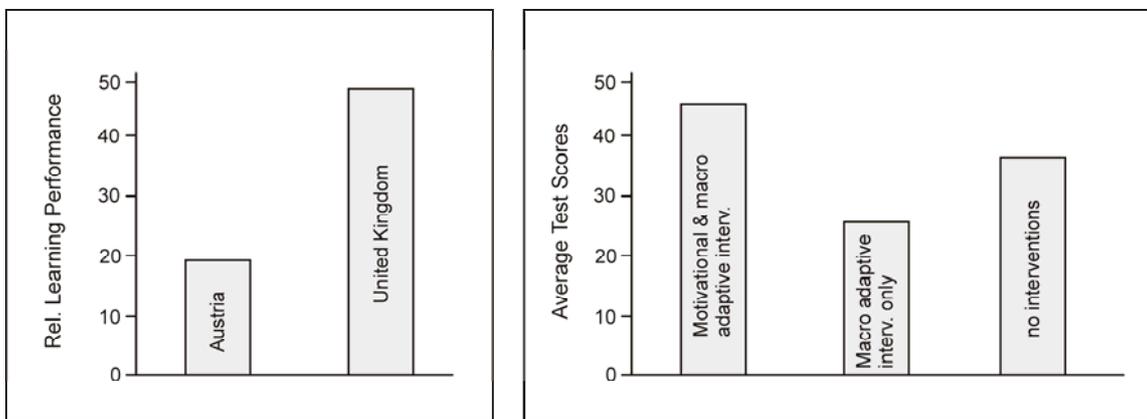


Figure 6. The left panel shows the learning performance in the terra forming problem for Austrian and British children; the right panel shows the mean test scores in a knowledge test in dependence of the adaptation group.

CONCLUSIONS

The key strength of educational computer games is usually seen in their tremendous motivational potential. The motivation to play – and therefore to learn – however, is a fragile construct and heavily relies on the preferences, abilities, the goals, and even the taste of individual players/learners. This holds for commercial, non-serious games and it is even more important for games with a well planned educational purpose. Today, learning game design is often understood on a one-fits-all level, which does not account for the individual learners, their very specific goals, preferences, abilities, strength and weakness, personality, and experiences with gaming. With this idea in mind, in two projects we developed a psycho-pedagogically sound approach to a non-invasive, strongly embedded assessment of motivational states as well as learning progress, feeding into a dynamic, ontology-driven learner (and gamer) model. On this basis, the game system responds to the learners' demands in terms of motivation and in terms of didactical support in a smart way and in real time. To collect empirical evidence on the effects and efficacy of micro and macro adaptive assessment and interventions, we conducted in-depth evaluations with the demonstrator games, focusing on different aspects of game-based learning, assessment,

and particularly interventions and feedback. The results provide some evidence that our idea of personalization is key to a learning game's impact and success. We could show that micro adaptive interventions lead to a faster approach to the correct solution, meaning to a faster problem solving process, in problem solving situation than neutral, inappropriate, or no interventions. In addition, we could demonstrate that providing the learner with appropriate, personalized interventions resulted in a better learning performance with the demonstrator game in comparison to providing no interventions at all. On the basis of 80Days' first results, we could also show that motivational and macro adaptive interventions have a highly positive impact on learning performance.

Future work will not only strengthen the experimental foundations of educational games, important aspects of assessment and adaptation, namely those of the highly successful genre of multiplayer games, must address increasingly.

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