Agent-Based Approach for Game-Based Learning Applications: Case Study in Agent-Personalized Trend in Engineering Education

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Abstract This article presents the effectiveness of agent-based approach in computer learning games. There are a lot of intelligent agents that are successfully used for educational purposes. However, some of them are very interesting because they can demonstrate behaviors that agents may possess; on the other hand they are used to display a set of requirements that must be met during their creation and design. Some of these requirements are similar to those used in the ITS, while the second type of behavior is quite different from them, and may even be unique. Based on this re-search, the effectiveness of games is illustrated in detail with regard to three current perspectives on agent-based approach to games: design game-based learning environment with agent, the process decisions of agent interaction and the reflection of agent recommendations and learning outcomes. Although, all perspectives are connect with the hope of better learning through games, it is criticized that the effectiveness cannot be simply answered by one of the three alone. The goal of the article is therefore to clarify the different views in case agent-personalized trend in engineering education.

Keywords Game-based learning · Pedagogical agent · Personalized agent system · Engineering education

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1 Introduction

Educational research has shown that by discerning how one learns, one can become a more efficient and effective learner. There is no one single method of learning and the most effective approach depends upon the task, context and learner's personality. The learning will be more effective if learners can choose from a wide range of possible learning methods, if they know when to apply them and which approach is the best for them. Honey and Mumford [1] identify four distinct styles or preferences that people use while learning. Kolb et al. [2] suggest that in order to learn effectively one need to keep moving around the following cycle: *Experiencing* – doing some-thing; *Reviewing* – thinking about what has happened; *Concluding* – drawing some conclusions and *Planning* – deciding what to do in the future.

To become a more effective learner one should engage in each stage of the cycle, and that may imply resorting to activities and styles that one would not normally choose.

On the other hand, anthropologist Levi-Strauss predicates that brain uses a story oriented structure to store and recall life experiences [3]. Furthermore, Heo has asserted that even facts, ideas, and theories are learnt more effectively if these are linked as a narrative [4]. Storytelling provides a powerful model of effective communication because it links with a basic human need: to create emotional engagement and movement [5]. According to Hassenzahl and Tractinsky, "User experience is a strange phenomenon: readily adopted by the human – computer interaction (HCI) community – practitioners and researchers a like – and at the same time critiqued repeatedly for being vague, elusive, and ephemeral". However, they attempt to convey the experience to users by considering the following three aspects [6]: the experiential (dynamic, complex, unique, situated, and temporally bounded), beyond the instrumental (holistic, aesthetic, and hedonic) and emotion and affect (subjective, positive, antecedents and consequences).

Regardless of delivery medium, any training development process must identify key skills that promote organizational goals and build training around the tasks that constitute those skills. Be it games, virtual worlds, or social media, technophiles gravitate toward the latest cool trends—sometimes without considering whether and how best to leverage them in ways that support relevant learning. Effective guided discovery forms of e-learning, including simulations and games, engage learners both behaviorally and psychologically. Today, there is an impressive arsenal of instruction-al technologies that can be used, ranging from educational games played on mobile devices to virtual reality environments to online learning with animated pedagogic agents and with video and animation [7].

Interactive animated pedagogical agent provides a simple learning environment that allows users to gain knowledge, adapting to their own pace. These agents are trying to achieve a certain balance in relation to the factors of good human tutor and good aspects of computer intelligent tutoring systems. For example, it is human to encourage students as they learn well, as it is human that the student should not feel embarrassed if he needs repeated explanation of materials. This paper reports a case study that proposes the use of pedagogical agents in a Graphics Algorithm unit in the IT Fundamentals Course built under the agent-based approach in computer learning games. Its main purpose is to discuss how agent's recommender can be used to improve students' cognitive preferences and level of recommender with agent's content realized as a text message.

2 Related Work

A pedagogical agent is not a human teacher but is a computer-based animated interface character. Consequently, students might have different perceptions and expectations of a human teacher as compared to a pedagogical agent. Findings from research on the effect of animated pedagogical agents on learning achievement are not consistent. The study of Kim et al. [8] tested strategies incorporating change management, motivational, and volitional characteristics in order to facilitate positive attitudes toward engineering. In an introductory engineering course, the strategies were distributed via email to two groups: one received the strategies with an animated pedagogical agent (Agent-MVM) and the other received the strategies in a text-only format (Text-MVM). The independent variable was type of message with three levels. The first consisted of motivational and volitional messages (hereafter, the acronym MVM will be used for convenience) delivered by an animated pedagogical agent, the second was MVM delivered in a text-only format, and the third was a control group that received innocuous information in text. The effects of the strategies on attitudes were compared with the control group which received neither formats of the strategy message. Contrary to expectations, the results indicated that the attitudes of the Agent-MVM group were not significantly more positive than the Text-MVM group or the control group.

Other studies show that use of pedagogical agents has a positive impact on near and far knowledge transfer Atkinson (2002) conducted a study on helping undergraduate students solve word problems using a computer program [9]. 50 undergraduate students were randomly assigned to one of five conditions: voice plus agent, text plus agent, voice only, text only, or control. Students in the voice-plus-agent condition outperformed their counterparts in the control condition on both near and far transfers.

Paradoxically, in experiment by authors Hershey et al. [10] students detected higher degrees of social presence in both the text only and the fully animated social agent conditions than students in the voice only and the static image of the agent with voice conditions. Furthermore, students had more positive perceptions of the learning experience in the text only condition. The results support the careful design of social behaviors for animated pedagogical agents if they are to be of educational value, otherwise, the use of agent technology can actually detract from the learning experience.

3 Theoretical Background

Practical experience has shown that active participation of the learners is an important part of the learning process and that can be enabled by means of personalization. The learning process has to enable active work by learners, to allow learners to share knowledge in groups, and to enable teachers to cooperatively develop learning content. To accommodate differences between learners: different learning objectives, different prior knowledge and past experiences and different cognitive preferences to the learning experience, the personalization of the learning experience towards the individual requirements has to be supported. The personalized e-learning systems have to include variations in students' intellectual profiles, the influence of the ability theories, Gardner's theory of multiple intelligences, cognitive controls, and in turn, cognitive styles and the learning styles with the aim to provide the highest degree of education efficiency.

An interesting design of service-oriented reference architecture for personalized e-learning systems (SORAPES) and validation of the architecture is described in [11]. The SORAPES is designed by re-using web services and learning objects with layered architecture and highly-scalable personalized e-learning system. The work described in [12] present part of the open learning project, where business practitioners and university researchers aim to combine the most frequently used e-learning technologies with the benefits of customized systems to develop an innovative personalized learning content delivery system.

Systems like My Online Teacher (*MOT*) [13] assist in developing rich adaptive hypermedia but are technically complex and offer little pedagogical support. The Adaptive Course Construction Toolkit (*ACCT*) [14] provides pedagogy, activity, subject matter, personalization and learning re-source based support to the course developer in addressing some of the key barriers to the main-stream adoption of personalized e-learning.

A recommendation module of a programming tutoring system - *Protus*, which can automatically adapt to the interests and knowledge levels of learners, is described in [15]. Personalized approaches based on the technology of intelligent agents means that each student has his pedagogical agent who represents him in the system of agents. Readapting learning objects to different categories of learners constitutes a challenge for intelligent agents in their effort to provide a large scale of collaboration between different e-learning organizations. In order not only to have efficient access to learning objects, but also to offer to learners tutoring and mentoring help, collaborative and cooperative learning strategies, learning advancements, and social interactions, intelligent agents have been highly recommended by a number of researchers. Intelligent-agent strategies and learning objects were successfully joined together in Learning Management Systems (*LMS*). For the purpose of providing more flexibility in *LMS*, Santos et al. [16] introduced the concept of intelligent LMS (*iLMS*) through using an intelligent-agent strategy. van Rosmalen et al. [17] discussed the main tendencies of Instructional Management Systems (IMS).

In paper [18] authors described *InCA*, a modular agent-based architecture framework, which integrates a set of interactive features allowing personalized and adaptive curriculum generation. They present an e-learning framework, named Intelligent Cognitive Agents (*InCA*).

4 Relationship Between Computer Games and Learning

Upon An impact of visual design quality on the learning is relevant to the design of computer games-based learning. Graphics can support learning in a variety of ways, such as drawing attention to key elements, providing links to existing mental models and supporting the creation of new models, simplifying presentation to minimize mental effort, and supporting the transfer of knowledge. The field of visual design is complex and encompasses many areas. Vanderdonckt [19] describes a detailed taxonomy for understanding visual design, including physical techniques such as balance and symmetry.

4.1 Game-Based Learning Model in Engineering Education

Prior to creating a game, an outline for accomplishing educational objectives and tasks compliant to the *Bloom's Taxonomy* has to be drafted. Opposite to the linear sequence that makes Bloom's Taxonomy useful for curriculum planning, the approach based on the game is reflected in perceiving different directions, such as, for example how players acquire or utilize knowledge in the game. In the context of the environment based on the game, model known as *GBL* – Game Based Learning [20] is used. This model represents the experience integration process between game cycles and accomplishing learning results. The link between simulation and the real world labelled as "experience integration" shows link between events in the game and real events, and at the same time it merges experience acquired in the game and learning process. The first step in designing a game-based learning model in the field of computer engineering represents defining start-up values. Following steps of creating games and learning elements should be taken into consideration:

- To establish educational approach,
- Set the model task, to create the game context, respectively,
- Develop details between game and education,
- Insert basic educational back up,
- Create learning activity map as a link between game events, and
- Create learning concept map a link between objects in the game.

Deducing a game-based learning model in the field of computer and electrical engineering - *GBLm4CE* model [21] created out of learners' profile and teaching methodology. Deployment of start-up values with compliance to the given suggestions for creating *GBLm4CE* model shows the method and pathway of implementing computer games into curricula – in the field of IT Science. Game implemented in the learning curricula in the field of IT Science, created by *GBLm4CE* model application should rely on constructive and collaborative learning approach. Players shall learn to understand and combine various aspects. Abstract and multidimensional spaces in combination with various colors according to the aforementioned aspects could be easier to understand as per *GBLm4CE* model rather than image to be conceived before the eyes or that could be visible during the learning process. Hence, this model application enables easier approach to analyze and com-pare existing solutions, especially its ability of visualization and simulation to be translated to the game.

5 Pedagogical Agents

Pedagogical agents are on-screen characters who help guide the learning process during an e-learning episode. Agents can be represented visually as cartoon-like characters, as talking-head video, or as virtual reality avatars; they can be represented verbally through machine-simulated voice, human recorded voice, or printed text. An important primary question is whether adding on-screen agents can have any positive effects on learning. Even if computer scientists can develop extremely lifelike agents that are entertaining, is it worth the time and expense to incorporate them into e-learning courses? In order to answer this question, researchers began with an agent-based educational game called Design-A-Plant, described previously [22].

Moments in which is necessary to prevent the appearance of an interactive agent are those when the user is focused on solving tasks. Also, it should be done in situations when customers are introduced with global information, or direct access to the raw data is performed. Complex visual information provided by the agent, may interfere with clear presentation of basic information. In addition, when working with children there is a fine line between pedagogical agent and fun. Younger users may be too amazed by interacting with the image of the agent, instead of to be focused on the problem [23]. In the digital world, pedagogical agents most commonly used type of human teaching “one on one”. This technique is a traditional form of learning and it is realized through three models [24]:

– Guided Learning - teacher has a didactic role in presenting the teaching material and training of students;
– Learning by discovery - it is a way of teaching where the student has complete control over the learning environment and control the progress of his knowledge;
– Guided detection - is a combination of the previous two ways. The teacher provides learning and progress, acting as a guide on the way to solving the given problem.

Pedagogical agents can be very useful for teaching forms such as guided learning and guided discovery. Learning by discovery is still an underdeveloped area in the domain of knowledge, since it is beyond the current capabilities of artificial intelligence. The pedagogical agent is increasingly popular in the process of training and teaching of younger age students.

In academic circles, many institutions slowly adopt pedagogical agent technology because of their expensive and complex implementations. The technology of intelligent intermediaries (agents), also known as "*Knowbots*" technology, shows an example of the use of pedagogical agents in academic institutions. However, most of the universities are still very far from the application of agents in laboratories. As this technology becomes more available, and numerous studies [25, 26] demonstrate strong positive beliefs about their application in the learning process, it indicates the willing-ness of many institutions to invest in them.

Numerous discussions in the field of feedback information provided by intelligent agents are based on the fact that the agent should not provide too much to them because it would thus burdening the students. In addition, Negroponte [27] suggests that in the process of waiting in the execution of the student's actions is better to give more simple instructions than not to have any instruction. To avoid giving too much instructions, a good knowledge and familiarity in dealing with pedagogical agents is necessary. To resolve this issue, part of the pedagogical task is to keep track of time and the number of shown information in the form of notice. With the principle of minimal assistance as defaults, the student should be allowed to choose the type of feedback depending on the amount of information, interaction and feedback when solving a given problem.

The basic terms that explain the principle of operations functioning are reached by selecting the Help option in modules. When a student starts learning with the use of the game or faces a difficulty during solving a task generated by the application, Help serves to accelerate finding the right solution [28]. This means that formulation of definitions and theorems within Help is the key moment in designing the entire application. Quality evaluation whether an operation is acquired or not is performed through visual indication of the number of successful and unsuccessful tasks (score) with the same operation, and comparison with preset criteria. In some educational application, through the Help window, realized as a text message, and generated by a pedagogical agent, student is given a 'piece of knowledge', in the form of a theoretical theorem or a definition [29], necessary for successful solving the problem given in the game-based application.

6 Case Study: Agent-Personalized Approach in an Educational Game

In starting from the point that two genres cover all levels of *Bloom's Taxonomy* we have created simple educative game with shooting effects within action genre. Since we have already decided about the game genre we have decided to integrate physics and smart enemies – (bots) that will be run by the computer as per artificial intelligence algorithm. In order to make the game more interesting for students, we have decided to place the game in Victorian Era, and the ground story is to be based on the clash of the gangs from that Era. The action of the game is located in the high street of imagined town from Victorian Era (Fig. 1).

The task of the game is to run a soldier who is fighting on two different fields under diverse conditions and situations. Two different scenarios were selected so that students could associate with two basic principles of *Z-buffer* algorithm performance red within Graphics Algorithm unit in the IT Fundamentals Course. The objective of the player is to recognize in the enemy who is running after the player and shooting at him recognize proper combination of enemy soldiers. Enemy soldier wears a badge implying which algorithm it is about. Also, the enemy outfit implies to the player if it is about real enemy or not, so the player has to decide whether to destroy the enemy or not. In that manner of the game, students should keep alive enemies that represent proper formation of the pixel colors recorded in Depth buffer of *Z-buffer* algorithm. In case that student as a player eliminates the enemy that should have stayed alive, the error information will be displayed together with the text message of wrongdoing. In this way the role of pedagogical agent that follows up the player giving him/her the instructions is generated.

Fig. 1 A screenshot of the educational game

Usually, the computer tutor needs to provide human educators' teaching strategies such as observing students' progress and giving appropriate feedback. The main reason for applying a pedagogical agent is to reduce the learner's feelings of isolation towards an instructor and to provide encouragement towards the content. Providing encouragement allows learners to feel as if the learning is more personalized like it would be with a human instructor or a one on one tutor. Because of pedagogical agents appearing in the same display with learning contents, the learner's attention to detail may be split between both objects (agent body and recommender content). Although the purpose of a pedagogical agent system in game-based learning contents is fostering a learner's motivation and eventually enhancing learning outcomes, sometimes the pedagogical agent is blamed for distracting learner's efficiency. From this rationale, we have designed three types of recommender contents, and tested them in various ways including measurement techniques of cognitive load to observe learners' help points by measuring agent recommender efficiency. Three types of pedagogical agent contents have been designed incorporating recommender. The recommender includes only theorem, help with text and figures, and introduction. The recommender views are shown in Fig. 2. Different types of content delivered by a pedagogical agent in recommender window are:

- **Type 1** - content from help option in formal style. In formal style important information (theoretical theorem or definition) are presented;
- **Type 2** - content from help option in conversational style. Use conversational style to present theorem or definition content based guide the personalization principle by Clark and Mayer [30];
- **Type 3** - content from interdiction. Interdiction has much important information about gaming and global goal in game.

Fig. 2 Designed contents in recommender window

Among the measurement techniques of cognitive load such as physiological measurement, double task, and questionnaire survey, we have applied the questionnaire test of self-reporting style for allocation after the gaming period. The questionnaire was originally designed by authors. Questions covered the following basic concepts relevant to understanding agent interaction and recommender content:

1. *Is the help from agent was at the right time?*
2. *Is the content of assistance was appropriate to proceed successfully completing the game?*
3. *The content of help from agent is affected to better understand the whole task of the game?*
4. *The content of help from agent is affected to better understand only the current level task in the game?*
5. *The content of help from agent is affected to better understand the theoretical knowledge needed to successfully play the game?*

The cognitive load factor survey was implemented. It consists of 5 factors with twenty items, and 7 points Likert scale. As an effort of developing cognitive load measures, 2 sub factors of cognitive load measures were identified: (1) self-evaluation of learning, and (2) usability of learning material. The cognitive load sub factors and their reliability are given in Table 1.

The goal of this study was to examine how agent recommender with different content difficulties and levels of student knowledge affects learners' subjective judgment of cognitive load measures. Thirty-three college students are participated in experiments with different agent recommender and levels of student knowledge. The current knowledge level a student possesses after playing the education game is given with the following formula [31]:

$$P_i(X = \text{Mastered}) = \left(\mathbf{a} \times \frac{A_i}{N} - \mathbf{h} \times \frac{H_i}{N} - \mathbf{t} \times \frac{t_a \cdot (A_i - H_i) - t_h \cdot H_i}{T_{max}} \right) \times 100 \qquad (1)$$

where values of coefficients a, h, and t are set 0.50, 0.30, 0.15. The number of correct answers of i-th student, A_i is present as right kill an enemy.

After that, the students are, according to their knowledge, divided into three levels (low-P(X) < 35 %, middle-35 < P(X) « 75 %, and high- P(X) > 75 %). Based on that, three groups of students were created. For first group G1, pedagogical agent, due to the low level of knowledge, is displayed by a recommender window content of help option, e.t. type 1 with formal presentation style theorem. Due to the partial knowledge that is not enough to understand the context (objective) of the game, as well as a lack of understanding of the concept of *Z-buffer* algorithm, for students of the second group G2, recommender window displays introduction which is normally shown at the beginning of the game. The agent is not sure whether students from this group misunderstanding the theory or the game, and it offers them both through the type 3. The group designated as G3 has the required knowledge and students from this group can respond to obstacles in the game in

Table 1 Elements of visual design quality

Factor	Meaning	Item reliability
Self-evaluation of learning (SEV)/the sense of accomplishment after studying	Self-evaluation is a personal perception of how successfully and/or efficiently a learner deals with a given problem to achieve desirable learning outcomes. The learner's subjective judgments are assumed to be an important factor for efficiency of learning. This factor is related to a learner's personal beliefs about his or her capabilities to produce the designated levels of performance. Learners, who measure highly on self-evaluation, tend to show low perceived task difficulty	0.770
Usability of learning material (USE)/ the effect of instructional design to learner's understanding	Usability measures how well the learning content is used towards the learning purpose. If a learner's perception of usability is high, it indicates that the learning content can facilitate learning or at least will not impede the learning process. When a learner is studying with a learning content with low usability, the learning content may hamper cognitive processes by increasing the unnecessary cognitive load. For this reason, this factor has a strong relationship with extraneous cognitive load	0.807

conversational style to. In all three cases, the display content recommender window by pedagogical agent have been fully complied with guidelines *EnALI* (Agent-Enhancing Learner Interaction) for the effective design of pedagogical agents that addresses social, conversational, and pedagogical issues [32].

To check the cognitive load differences of students, according to different types of contents, we have tested cognitive load and analyzed with MONOVA. The highest self-evaluation and usability factors are found in the G2 content with type 3 agent recommender. The technical statistics for each content are given in Table 2.

Significant interactions between agent recommender and levels of student knowledge were found in usability (USE, $F = 5.03$, $p = 0.017$) and self-evaluation (SEV, $F = 5.10$, $p = 0.016$) when an easy content was given in advance of a hard gameplay one. This result indicated that agent recommender interpretation is applied to the subjective scale of cognitive load. Usability and self-evaluation were very dependent on learners' performance.

Table 2 The technical statistics of cognitive load of each type agent recommender

Factor	G1		G2		G3	
	n = 10		n = 16		n = 7	
	Mean	SD	Mean	SD	Mean	SD
Self-evaluation	4.85	1.22	5.10	1.65	4.28	1.57
Usability	3.83	1.20	5.03	1.69	4.00	1.51

7 Conclusion

Pedagogical agents are autonomous software entities that provide support to the process of learning through interaction with students, teachers and other participants in the learning process, as well as cooperation with other similar agents. Similar to other approaches for personalization, also in the case of agents, the entire process is based on a model of student. A significant feature of pedagogical agents is that they have added a number of ontology in the field of personalized learning. The work of pedagogical agents depends not only on the existence of an ontological model of students, but also on the availability of other relevant ontology - domain ontologies, ontology of instructional approach, etc. which allows them to understand the demands of students and answer to them through different ways of personalization.

The learning task is an instructional goal to be learned. The main function of working memory is to integrate new information from the sensor memory and prior knowledge from the long-term memory. However, human can process only limited numbers of information. Because of this limited capacity the amount of learning content should be managed to avoid from being cognitive overload. In proposed approach, we have three types of recommender contents, and tested them in various ways including measuring techniques to observe learners' attention to detail. From the cognitive load analysis, the pedagogical agent helps the user to provide mental connection with recommender content by pedagogical agent. Even though the existence of an image of pedagogical agent's does cause significant differences in learning outcomes and cognitive load compared with recommender content using introduction, theorem and help. This implies that if the image conveyed more human-like feedback, it may contribute positively towards learners' overcoming the sense of isolation associated with an e-learning environment. Also, when considering the outperformance of learning content with pedagogical agents and recommender content, the pedagogical agent itself does not distract a student's attention, but rather can have a positive effect on creating a better e-learning environment.

The use of ontologies for the realization of personalized learning a few years is very actual direction of research in the area of the application of artificial intelligence in education (*AIED*), and our future work will be in that direction.

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