Simulated Learners for Testing Agile Teaming in Social Educational Games

Steeve Laberge and Fuhua Lin

School of Computing and Information Systems, Athabasca University, Edmonton, Canada
slaberge@acm.org, oscarl@athabascau.ca

Abstract. This paper proposes an approach for creating and testing an multiagent systems based adaptive social educational game (SEG), QuizMASter, using the concept of simulated learners to overcome experimentation complexity and unpredictable student availability, as is typical with online learning environments. We show that simulated learners can play two roles. First, it can be used for testing the game planning, scheduling and adaptive assessment algorithms. With some degree of success met with our initial experimentation with QuizMASter, advanced planning and coordination algorithms are now needed to allow the game-based assessment platform to realize its full potential. The multi-agent system approach is suitable for modeling and developing adaptive behaviour in SEGs. However, as we have found with our early prototypes, verifying and validating such a system is very difficult in an online context where students are not always available. MAS-based assessment game planning and coordination algorithms are complex and thus need simulated learners for testing purposes. Second, to overcome unpredictable student availability, we modeled QuizMASter as a new class of socio-technical system, human-agent collective (HAC). In the system, human learners and simulated learners (smart software agents) engage in flexible relationship in order to achieve both their individual and collective goals, while simulated learners are selected for serving as virtual team members.

Keywords: social educational agents, multiagent systems, simulated learners

1 Introduction

For decades, educational games have proven to be an effective means to motivate learners and enhance learning. Social (multi-player) educational games (SEGs) offer many opportunities to improve learning in ways that go beyond what a single-player game can achieve because SEGs allow players to be social, competitive, and collaborative in their problem solving. The presence of other players can be used to increase playability and to help teach team-work and social skills. SEGs promote intragroup cooperation and intergroup competition [1]. However, existing SEGs share many of the shortcomings of classroom role-playing. Setting up existing SEGs is logistically challenging, expensive, and inflexible. Furthermore, players become bored after going through existing SEGs once or twice.

To test such a social educational game, we face two difficulties. One is how to test the planning and scheduling algorithms. Another is how to meet the need of agile team formation. In SEGs, group formation has big impact on group learning performance. Poor group formation in social games can result to homogeneity in student characteristic such that the peer learning is ineffective. Thus, there is a need to constitute a heterogeneous group SEGs that constitutes students with different collaborative competencies and knowledge levels. However, without empirical study it becomes difficult to conclude which group characteristics are desirable in the heterogeneity as different game-based learning needs may require different group orientations. Previous research has focused on various group orientation techniques and their impact on group performance like different learning styles in group orientation [2–4]. However, there is need to investigate the impact of other group orientation techniques on group performance like grouping students based on their collaboration competence levels. Furthermore, most of the previous research in group-formation focuses on classroom based learning. Also, it lacks the true experiment design methodology that is recommended when investigating learning outcomes from different game-based learning strategies. Simulated learners methodology [5] has shown a promising way to solve these challenges.

In this paper, we show that simulated learners can play two roles. First, it can be used for testing the game planning, scheduling and adaptive assessment algorithms. Second, working with human learners and forming human-agent collectives (HAC), simulated learners serve as virtual team members to enable asynchronous game-based learning in a context where student availability is unpredictable. This paper is structured as follows: In Section 2 we discuss recent advancements and related work. Section 3 describes QuizMASter. Section 4 presents the proposed architecture for development of QuizMASter. Section 5 explains how we intend to use simulated learners for testing QuizMASter. Finally, Section 6 concludes.

2 Related Work

Researchers have found that learning can be more attractive if learning experiences combine challenge and fun [6]. As social networks have become popular applications, they have given rise to social games. This kind of game is played by users of social networks as a way to interact with friends [7] and has become a part of the culture for digital natives. Social games have unique features that distinguish them from other video games. Those features are closely linked with the features of social networks [8]. Social games can make a contribution to social learning environments by applying game mechanics and other design elements, 'gamifying' social learning environments to make them more fun and engaging. For games to be effective as a learning tool, a delicate balance must be maintained between playability and educational value [9, 10], and between game design and learning principles. Methods have been proposed for making valid inferences about what the student knows, using actions and events observed during gameplay. Such methods include evidence-centered-design (ECD) [11, 12]; the learning progressions model [13], the ecological approach to design of e-learning environments [14], stealth assessment [15], game analytics [16], and learning analytics [17]. Most of the new concepts target an ever-changing learning environment and learner needs, as today's education moves toward a digital, social, personalized, and fun environment. Moreover, as is the case for all competitive games, an equal match between players is essential to self-esteem and to maintain a high degree of player interest in the game. Hence, we need mechanisms and models that can aggregate the current performance and preferences of players, and accurately predict student performance in the game. Software agents have been used to implement consistent long-term intelligent behaviour in games [18], multi-agent collaborative team-based games [19], and adaptive and believable non-player character agents simulating virtual students [20]. The use of agent technologies leads to a system characterized by both autonomy and a distribution of tasks and control [21]. This trend has two aspects. First, game-based learning activities should be carefully orchestrated to be social and enjoyable. Second, game scheduling and coordination should be highly adaptive and flexible. However, nobody has yet developed models, algorithms, and mechanisms for planning, scheduling, and coordination that are suitable for creating and testing SEGs.

3 QuizMASter

QuizMASter is designed to be a formative assessment tool that enables students to be tested within a multi-player game [22]. Two or more students simultaneously log in remotely to the system via a Web-based interface. Each student is represented by one avatar in this virtual world. Students are able to view their own avatar as well as those of their opponents.

Each game has the game-show host who is also represented by an avatar visible to all contestants [22]. The game-show host poses each of the game questions to all the contestants. The students hear the voice of the host reading each question and view them displayed on their screens. They individually and independently from one another answer each question by, for instance, selecting an answer from available choices in a multiple-choice format. Each correct answer would receive one mark. Figure 1 shows a screen shot of QuizMASter.

3.1 Characteristics of QuizMASter

The environment for QuizMASter has the following characteristics:

Flexibility. The environment for QuizMASter needs flexibility for game enactment, to be able to cope with dynamic changes of user profiles, handle fragmentation of playing and learning time needed to accomplish activities and tasks,

Fig. 1. QuizMASter in Open Wonderland

adequately handle exceptional situations, predict changes due to external events, and offer sufficient interoperability with other software systems in educational institutions. Individual learners have particular interests, proficiency levels, and preferences that may result in conflicting learning goals.

Social ability and interactivity. The environment for QuizMASter should encourage interaction and collaboration among peers, and should be open to participation of students, teachers, parents, and experts on the subjects being taught. Web 2.0 has had a strong influence on the ways people learn and access information, and schools are taking advantage of this trend by adopting social learning environments. One way to engage learners in a collaborative production of knowledge is to promote social rewards.

User control. One of the most desirable features of social education games is to empower players with control over the problems that they solve. For example, in QuizMASter, students, parents, and teachers can design new rules to create their own games and modify the game elements to fit different knowledge levels.

Customization. Customization is a core principle that helps accommodate differences among learners [23]. Teachers could build a QuizMASter that has its own style and rules to determine the game's level of difficulty, to gear the game for specific goals or a specific group of learners. Some teachers may be interested in sharing collections of rules to fit the learning and play styles of their students. Like teachers, learners/players can be co-creators of their practice space through building new game scenarios, creating their own rules, sharing their strategies and making self-paced challenges [23].

4 The Proposed Architecture

Multi-agent technologies are considered most suitable for developing SEGs as it will lead to systems that operate in a highly dynamic, open, and distributed environment. In an MAS-based SEG, each learner/player is represented as an autonomous agent, called learner agent. MAS technologies, such as goal orientation and the Belief-Desire-Intention (BDI) paradigm, is used as the foundation for the agent architecture. These learner agents are able to reason about the learning goals, the strengths and weaknesses of learners and update the learner models.

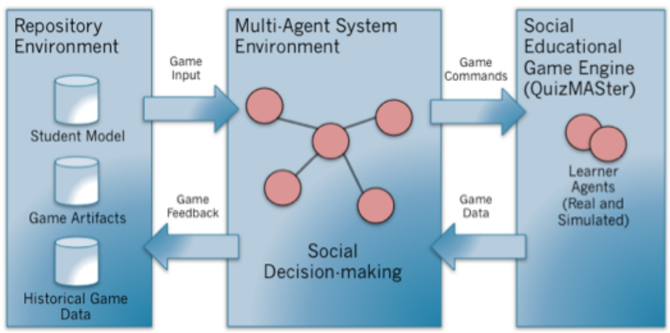

Fig. 2. Architecture for MAS-Based Social Educational Game Environment

Whenever a learner enters the system to play a social educational game, the learner agent will retrieve her/his learner model and acquire preferences about the current game-playing, and then send to a game management agent (GMA) of the system. The GMA is designed for setting up and maintaining teams for the system. The GMA will assign the learner to participate in a most suitable team that is undermanned according to the profile and preferences of the learner. The team will be configured in accordance with the game model by the GMA. Once the team has been completely formed, the GMA will create a game scheduling agent (GSA), a game host agent (GHA), and an assessment agent (AA) for each team. The GSA will continuously generate a game sequence dynamically adapted to the team's knowledge level (represented as a combined learner model [24]. The GHA will receive the game sequence from the scheduling agent and execute game sequence with the learners in the team. It will also be responsible for capturing data about learner/player performance. The AA will receive and interpret game events and communicate with the learner agents to update the learner model as necessary.

The GSA will dynamically schedule the game on the fly through interacting with other agents with a coordination mechanism, considering both the current world state and available resources, and solving conflicts in preferences and learning progression between the agents. The goal of the GSA is to optimize the playability and educational values. We will model the game elements as resources. To solve the distributed constraint optimization problem, we are developing multiagent coordination mechanisms and scheduling algorithms to be used by the GSA.

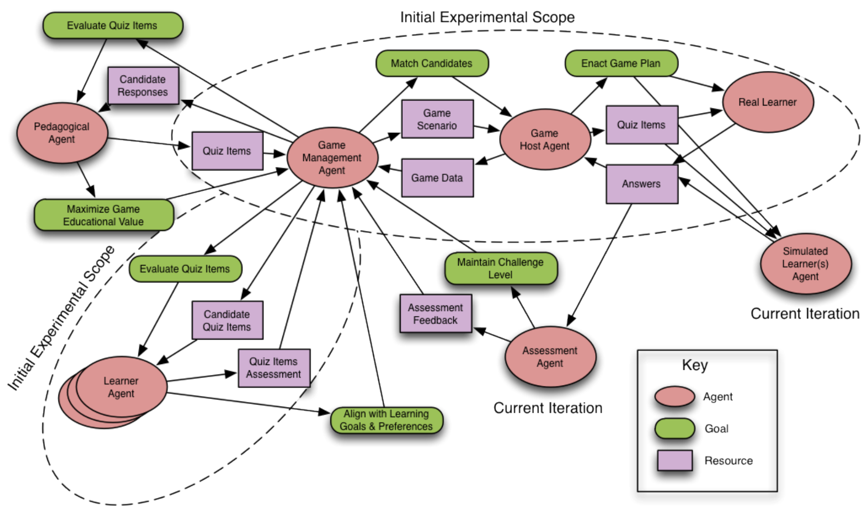

Fig. 3. MAS-Based SEG Agent Interaction Model

4.1 Planning and Scheduling Algorithms

The planning algorithms refer to the (local) planning algorithm of learner agents. To develop planning algorithms for learner agents, the following supporting models have been taken into consideration: (i) Learner models that accumulate and represent beliefs about the targeted aspects of skills. They are expressed as probability distributions for competency-model variables (called nodes) describing the set of knowledge and skills on which inferences are to be based. (ii) Evidence models that identify what the learner says or does, and provide evidence about those skills that express how the evidence depends on the competency-model variables in a psychometric model. (iii) Task/action models that express situations that can evoke required evidence. To design an action model, we adopt a model called Fuzzy Cognitive Goal Net [25] as the planning tool by combining the planning capability of Goal Net and reasoning ability of Fuzzy Cognitive Maps (FCMs). These FCMs give the learner agent a powerful reasoning ability for game context and player interactions, giving the task model accurate context awareness and learner awareness. We are developing coordination mechanisms for the GMA and the GSA to solve the problem of team formation, scheduling and coordination in a highly flexible and dynamic manner. We considered the following concepts or methods:

(i) Contract-net protocols (CNPs) are used as a coordination mechanism by the GMA with a game model repository to timely form a team from all available players, using mutual selection and exchanging information in a structured way to converge on assignments. Each involved learner can delegate the negotiation process to its agent. These agents will strive to find a compromise team-joining decision obeying hard learning constraints while simultaneously resolving individual conflicts of interest.

(ii) The problem of scheduling and customizing a social educational game can be solved through social-choice-based customization. We view the SEG gameplay design as an optimization problem. Resources must be allocated through strategically scheduling, and coordinating a group of players according to their preferences and learning progressions. The constraints include key learning principles that inform the design of mechanics: challenge, exploration, risk taking, agency, and interactions [26-27]. The objective of the GSA is to maximize the learnability and engagement of the learners in the group. Social choice theory in MAS concerns the design and formal analysis of methods for aggregating preferences of multiple agents and collective decision-making and optimizing for preferences [28-29]. For example, we use a voting-based group decision-making approach such as Single Transferable Voting [30] to aggregate learner preferences and learning progression because it is computationally resistant to manipulation [31]. The purpose is to take information from individuals and combine it to produce the optimal result.

(iii) To support the need for dynamic decision making in the MAS-based SEG architecture, our current line of investigation is the concept of social choice Markov Decision Process (MDP) as recently proposed by Parkes and Procaccia [32]. In a social choice MDP, each state is defined by "preference profiles", which contain the preferences of all agents against a set of alternatives for a given scenario. The course of action from any given state is determined by a deterministic social choice function (the policy, in the context of the MDP) that takes into account the likelihood of transitions and their rewards. However, a preference profile is subject to change over time, especially in a live SEG context. For example, a learner that unexpectedly answers a question initially deemed beyond the learner's perceived level of comprehension would likely trigger a change of belief in the agents and potentially alter their ranking of alternatives. And since the number of alternatives in a SEG can be very large, the state space for any given SEG is huge, making the computation of optimal decision-making policies excessively difficult. We solve this problem by exploiting symmetries that exist in certain game types (e.g. in a quiz game SEG format, using a reduced set of question types that share common characteristics as a basis for alternatives as opposed to individual questions).

5 Simulated Learners

It is our view that the Belief-Desire-Intention (BDI) model is ideally suited for modeling and simulating learner behaviour. According to Jaques and Vicari (2007) [33], intelligent agents based on Bratman's Belief-Desire-Intention model, or BDI agents, are commonly used in modeling cognitive aspects, such as personality, affect, or goals. Píbil et al. (2012) claim BDI agent architecture is "a currently dominant approach to design of intelligent agents" [34]. Wong et al. (2012) describes the suitability of the BDI agent model for applications where both reactive behavior and goal-directed reasoning are required [35]. Soliman and Guetl (2012) suggest that BDI maps well onto models for pedagogically based selection of sub plans within a hierarchical planning strategy – "apprenticeship learning model" given as example [36]. They also talks about advantage of breaking plans down into smaller plans to allow for different "pedagogical permutations" allowing the agent to adapt to different learning styles, domain knowledge, and learning goals. Norling (2004) attributes the successful use of BDI agents for modeling human-like behavior in virtual characters to BDI's association to "folk psychology" [37]. This allows for an intuitive mapping of agent framework to common language that people use to describe the reasoning process. Of particular importance to this study is the way that implementations of the BDI architecture model long-term or interest goals. We have selected the Jason™ [38] platform for providing multi-agent BDI programming in AgentSpeak.

A shortcoming of the BDI paradigm is that although it is intended to be goal-driven, in most implementations this means/amounts to using goals to trigger plans, but does not support the concept of long-term goals or preferences [39], such as a student's long term learning goals, or the pedagogical goals of a CA. They feel that these types of goals are difficult to represent in most BDI systems because they signify an ongoing desire that must be maintained over a long period of time compared to relative short goal processing cycles. It is left to the developer to implement this type of preference goal through the belief system of the agent, modifications to the platform or environment, or other methods of simulating long-term goals.

Hübner, Bordini, and Wooldridge (2007) describe plan patterns for implementing declarative goals, with varying levels of commitment in AgentSpeak [40]. Bordini et al. (2007) expand on this in their chapter on advanced goal-based programming [38]. While AgentSpeak and Jason support achievement goals, these patterns are intended to address the lack of support for "richer goal structures", such as declarative goals, which they feel are essential to providing agents with rational behaviour. Pokahr et al. (2005) point out that the majority of BDI interpreters do not provide a mechanism for deliberating about multiple and possibly conflicting goals [41]. It is worth noting that there are "BDI inspired" systems that are more goal-oriented, such as Practionist and GOAL [42]. The Jason multi-agent platform for BDI agents was selected for this project because it is a well-established open-source project that is being actively maintained. It supports both centralized and distributed multi-agent environments. Píbil et al. (2012) describes Jason as "one of the popular approaches in the group of theoretically-rooted agent-oriented programming languages" [34]. A major advantage of Jason is that it is easy to extend the language through Java based libraries and other components. Internal actions can allow the programmer to create new internal functionality or make use of legacy object-oriented code [38]. However, Píbil et al. (2012) caution that the use of such extensions, if used too heavily, can make the agent program difficult to comprehend without understanding the functionality of the Java code [34]. They raise the concern that novice programmers have few guidelines for choosing how much to program in AgentSpeak, and how much too program in Java. The usefulness of being able to extend Jason can be demonstrated by two examples of current research into integrating BDI with Bayesian Networks. Modeling of some student characteristics requires a probabilistic model; Bayesian Networks (BN) being a popular choice in recent years [43-44]. Recent work by Kieling and Vicari (2011) describes how they have extended Jason to allow a BDI agent to use a BN based probabilistic model. Similarly, Silva and Gluz (2011) extend the AgentSpeak(L) language to implement AgentSpeak(PL) by extending the Jason environment. AgentSpeak(PL) integrates probabilistic beliefs into BDI agents using Bayesian Networks [45]. Experimentation with QuizMASter to date has enabled the modelling of simulated learners in virtual worlds with an initial focus on their appearance, gestures, kinematics, and physical properties [46]. Recent related research work in that area has been on the creation of engaging avatars for 3D learning environments [47]. Employing the theory of Transformed Social Interaction (TSI) [48], simulated learners were designed with the following abilities:

(i) Self-identification: The self-identification dimension of TSI was implemented using facial-identity capture with a tool called FAtiMA. Each of the users' face were morphed with their default avatar agent's face to capitalize on human beings' disposition to prefer faces similar to their own and general preference of appearing younger (see Fig. 4).

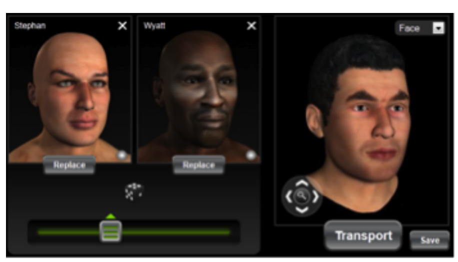

Fig. 4. Transformed Social Interaction – Image Morphing Technique

(ii) Sensory-abilities: Sensory-abilities dimension of TSI were implemented using a movement and visual tracking capability. The general challenge of sensory abilities implementation lies in two areas: the complexity of human senses and the processing of sensory data of different modality and historicity. For the reason of simplicity, only visual tracking capability was exploited.

(iii) Situational-context: The situational-context dimension of TSI was implemented by using the best-view feature of Open Wonderland, whereby the temporal structure of a conversation can be altered.

The main idea of this research has been to explore the methodology for developing simulated learners for simulating and testing SEGs. That is, behind a simulated learner is an agent. Or we can say a simulated learner is an agent's avatar. All avatars, including real students' avatars and agent-based simulated learners, live in the virtual worlds, while the agents live in the multi-agent system. The integration of multi-agent systems with virtual worlds adds intelligence to the SEG platform and opens a number of extremely interesting and potentially useful research avenues concerning game-based learning. However, the advanced algorithms that support game planning, coordination and execution are difficult to test with real subjects considering the overhead involved is seeking authorization and the unpredictable availability of real life subjects in an online environment. This where an expanded view of simulated learners comes into play. The advantages of a simulated environment that closely approximates human behaviour include: (1) It allows for rapid and complete testing of advanced algorithms for game based adaptive assessment as well as SEG planning, coordination and execution in a simulated environment. The efficiency of the algorithms can be measured without first securing the availability of students; (2) With proper learner modeling and adaptive behaviour, simulated learners can engage with real life learners in friendly competitive games for the purpose of formative assessment, again working around the issue of availability of real students in an online learning environment.

6 Conclusions

As our recent experimentation suggests, many outstanding challenges must be addressed in developing intelligent SEGs. As we get closer to real world testing of our experimental game based assessment framework, we are faced with the complexity of enrolling real life learners in an e-learning environment and the variability that human interactions introduce in the measurement of adaptive algorithm efficiency. This is where we see the value of simulated learners. At this stage of our research, simulated learners have been rendered as Non Person Characters (NPCs) controlled by BDI agent running in the multi-agent system based virtual world. Our medium term goal is to extend the existing system to a particular learning subject (e.g., English language learning) to verify the effectiveness of the proposed virtual assessment environment and the benefit that students perceive from interacting with the proposed NPCs.

For simulated learners to be successful in our experimental framework, they must closely approximate the performance of real learners. The simple, pre-encoded behaviour we have implemented so far in the NPCs for QuizMASter will not suffice to demonstrate the efficiency of our adaptive algorithms and allow for simulated learner agents to act as virtual players in our game based assessment framework. Current outstanding research questions within our group are:

1. How do we add intelligence and adaptive behaviour to the simulated learner agents while preserving our ability to obtain predictable and repeatable test results from our adaptive MAS framework?
2. How much autonomy can we afford to give to simulated learners in terms of independent thought and action, and to which degree should a simulated learner be able to adjust its behaviour as a function of its interactions with other agents, including real life learners?
3. How do we incorporate modern game, learning and assessment analytics in the supporting adaptive MAS framework in order to maximize the value of simulated learners as a means to perform non-intrusive, formative assessment?

References

1. Romero, M., Usart, M., Ott, M., Earp, J., de Freitas, S., and Arnab, S.: Learning through playing for or against each other. Promoting Collaborative Learning in Digital Game Based Learning. ECIS 2012 Proceedings. Paper 93 (2012)
2. Alfonseca, E., Carro, R. M., Martin, E., Ortigosa, A., and Paredes, P.: The impact of learning styles on student grouping for collaborative learning: a case study. User Modeling and User-Adapted Interaction, 16(3–4), 377–401 (2006)
3. Deibel, K.: Team formation methods for increasing interaction during in-class group work. In ACM SIGCSE Bulletin (Vol. 37, 291–295). Caparica, Portugal (2005)
4. Grigoriadou, M., Papanikolaou, K. A., and Gouli, E.: Investigating How to Group Students based on their Learning Styles. In In ICALT, 2006 1139–1140 (2006)
5. McCalla, G. and Champaign J.: AIED Workshop on Simulated Learners. AIED 2013 Workshops Proceedings, Volume 4 (2013)
6. Vassileva, J.: Toward social learning environments. IEEE Transactions on Learning Technologies, 1(4), 199–213 (2008)
7. Klopfer, E., Osterweil, S., and Salen, K.: Moving learning games forward: obstacles, opportunities and openness, the education arcade. MIT (2009)
8. Jarvinen, A.: Game design for social networks: Interaction design for playful dispositions. In Stephen N. Spencer (Ed.), Proceedings of the 2009 ACM SIGGRAPH Symposium on Video Games (Sandbox '09), 95–102. ACM, New York, NY, USA (2009)
9. Van Eck, R.: Building Artificially Intelligent Learning Games. In V. Sugumaran (Ed.), Intelligent Information Technologies: Concepts, Methodologies, Tools and Applications, 793-825 (2008)
10. Augustin, T., Hockemeyer, C., Kickmeier-Rust, M. D., and Albert, D.: Individualized Skill Assessment in Digital Learning Games: Basic Definitions and Mathematical Formalism. IEEE Trans. on Learning Technologies, 4(2), 138-147 (2011)
11. Mislevy, R. J., and Haertel, G. D.: Implications of evidence-centered design for educational testing. Educational Measurement: Issues and Practice, 25(4), 6–20 (2006)
12. Mislevy, R. J., Steinberg, L. S., and Almond, R. G.: On the structure of educational assessments. Measurement: Interdisciplinary Research and Perspectives, 1, 3-67 (2003)

13. Corcoran, T., Mosher, F. A., and Rogat, A.: Learning Progressions in Science: An Evidence-Based Approach to Reform (Research Report No. RR-63). Center on Continuous Instructional Improvement, Teachers College—Columbia University (2009)
14. McCalla, G.: The Ecological Approach to the Design of E-Learning Environments: Purpose-based Capture and Use of Information About Learners. Journal of Interactive Media in Education. (7), 1-23 (2004)
15. Shute, V. J.: Stealth assessment in computer-based games to support learning. Computer games and instruction. Charlotte, NC: Information Age Publishers, 503-523 (2011)
16. Long, P., and Siemens, G.: Penetrating the fog: analytics in learning and education. Educause Review Online 46 (5): 31–40 (2011)
17. El-Nasr, M. S., Drachen, A., and Canossa, A.: Game Analytics: Maximizing the Value of Player Data, Springer (2013)
18. Oijen, J., and Dignum, F.: Scalable Perception for BDI-Agents Embodied in Virtual Environments, Web Intelligence and Intelligent Agent Technology (WI-IAT), 2011 IEEE/WIC/ACM International Conference on, Vol. 2, 46-53, 22-27 (2011)
19. Patel, P., and Hexmoor, H.: Designing BOTs with BDI agents, Collaborative Technologies and Systems, 2009. CTS '09. International Symposium on, 180-186 (2009)
20. Lim, M., Dias, J., Aylett, R., and Paiva, A.: Creating adaptive affective autonomous NPCs, Autonomous Agents and Multi-Agent Systems (AAMAS), Springer, 24(2), 287-311 (2012)
21. Sterling, L. S. and Taveter, K.: The art of agent-oriented modeling, MIT Press (2009)
22. Dutchuk, M., Muhammadi, K. A., and Lin, F.: QuizMASter - A Multi-Agent Game-Style Learning Activity, EduTainment 2009, Aug 2009, Banff, Canada, Learning by Doing, (eds.), M Chang, et al., LNCS 5670, 263-272 (2009)
23. de Freitas, S. and Oliver, M.: How can exploratory learning with game and simulation within the curriculum be most effectively evaluated? Computers and Education. 46(3), 249-264 (2006)
24. Shabani, S., Lin, F. and Graf, S.: A Framework for User Modeling in QuizMASter. Journal of e-Learning and Knowledge Society, 8(3), 1826-6223 (2012)
25. Jennings N. R., L. Moreau, D. Nicholson, S. Ramchurn, S. Roberts, T. Rodden, and A. Rogers: Human-agent collectives. Commun. ACM 57, 12 (2014), 80-88 (2014)
26. Cai, Y., Miao, C., Tan, A.-H., and Shen, Z.: Fuzzy cognitive goal net for interactive storytelling plot design. In Proceedings of the 2006 ACM SIGCHI Int. conf. on Advances in comput. entertainment technology. ACM, NY, USA, Article 56 (2006)
27. Gee, James P.: Good Video Games + Good Learning. New York: Peter Lang (2008)
28. Gee, James P.: Learning by Design: Games as Learning Machines, Interactive Educational Multimedia, Vol. 8, April Ed. 2004, 13-15 (2004)
29. Brandt, F., Conitzer, V., and Endriss, U.: Computational Social Choice, Chapter 6 of book edited by Weiss, G., Multiagent Systems (2nd edition), 213-283 (2013)
30. Conitzer, V.: Making Decisions Based on the Preferences of Multiple Agents, Communications of the ACM, 53(3), 84-94 (2010)
31. Bartholdi, J. J. and Orlin, J. B: Single Transferable Vote Resists Strategic Voting. Social Choice and Welfare, 8, 341-354 (1991)
32. Parkes, D. C. and Procaccia, A. D.: Dynamic Social Choice with Evolving Preferences. In M. desJardins and M. L. Littman (eds.), AAAI : AAAI Press (2013)
33. Jaques, P. A., Vicari, R. M.: A BDI approach to infer student's emotions in an intelligent learning environment. Computers & Education, 49(2), 360–384 (2007)

34. Píbil, R., Novák, P., Brom, C., Gemrot, J.: Notes on Pragmatic Agent-Programming with Jason. In L. Dennis, O. Boissier, & R. H. Bordini (Eds.), Programming Multi-Agent Systems, 58–73. Springer Berlin Heidelberg (2012)
35. Wong, W., Cavedon, L., Thangarajah, J., Padgham, L.: Flexible Conversation Management Using a BDI Agent Approach. In Y. Nakano, M. Neff, A. Paiva, & M. Walker (Eds.), Intelligent Virtual Agents, 7502, 464–470). Springer (2012)
36. Soliman, M., Guetl, C.: Experiences with BDI-based design and implementation of Intelligent Pedagogical Agents. In 2012 15th International Conference on Interactive Collaborative Learning (ICL) (1–5). Presented at the 2012 15th International Conference on Interactive Collaborative Learning (ICL) (2012)
37. Norling, E.: Folk Psychology for Human Modelling: Extending the BDI Paradigm. In Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems - Volume 1 (202–209). Washington, DC, USA: IEEE (2004)
38. Bordini, R. H., Hübner, J. F., Wooldridge, M.: Programming Multi-Agent Systems in AgentSpeak using Jason. John Wiley & Sons (2007)
39. Bellotti, F., Berta, R., De Gloria, A., Lavagnino, E.: Towards a conversational agent architecture to favor knowledge discovery in serious games. In Proc. of the 8th Int. Conf. on Advances in Comput. Entertainment Technology, 17:1–17:7 (2011)
40. Hübner, J. F., Bordini, R. H., Wooldridge, M.: Programming Declarative Goals Using Plan Patterns. In M. Baldoni & U. Endriss (Eds.), Proceedings on the Fourth International Workshop on Declarative Agent Languages and Technologies, held with AAMAS 2006 (123–140). Springer Berlin Heidelberg (2007)
41. Pokahr, A., Braubach, L., Lamersdorf, W. (2005). A BDI architecture for goal deliberation. In Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems (1295–1296). New York, NY, USA: ACM (2005)
42. Braubach, L., Pokahr, A.: Representing Long-Term and Interest BDI Goals. In L. Braubach, J.-P. Briot, & J. Thangarajah (Eds.), Programming Multi-Agent Systems (pp. 201–218). Springer Berlin Heidelberg (2010)
43. Conati, C., Maclaren, H.: Empirically building and evaluating a probabilistic model of user affect. User Modeling and User-Adapted Interaction, 19(3), 267–303 (2009)
44. Chrysafiadi, K., Virvou, M.: Student modeling approaches: A literature review for the last decade. Expert Systems with Applications, 40(11), 4715–4729 (2013)
45. Silva, D. G., Gluz, J. C.: AgentSpeak(PL): A New Programming Language for BDI Agents with Integrated Bayesian Network Model. In 2011 International Conference on Information Science and Applications (ICISA) (pp. 1–7). Presented at the 2011 International Conference on Information Science and Applications (ICISA) (2011)
46. McClure, G., Chang, M., Lin, F.: MAS Controlled NPCs in 3D Virtual Learning Environment, The International Workshop on Smart Learning Environments at the 9th International Conference on Signal-Image Technology and Internet-Based Systems, Japan, Kyoto, 2013-12-02, 1026 – 1033, DOI: 10.1109/SITIS.2013.166 (2013)
47. Walsh, T.: An Empirical Study of the Manipulability of Single Transferable Voting, Proceedings of the 2010 conference on ECAI, 257-262 (2010)
48. Leung, S., Virwaney, S., Lin, F., Armstrong, A J, Dubbelboer, A.: TSI-enhanced Pedagogical Agents to Engage Learners in Virtual Worlds", International Journal of Distance Education Technologies, 11(1), 1-13 (2013)