Supporting Low-Performing Students by Manipulating Self-efficacy in Digital Tutees

Betty Tärning (betty.tarning@lucs.lu.se)
Lund University Cognitive Science, Lund University, 222 22 Lund, Sweden

Magnus Haake (magnus.haake@lucs.lu.se)
Lund University Cognitive Science, Lund University, 222 22 Lund, Sweden

Agneta Gulz (agneta.gulz@lucs.lu.se)
Lund University Cognitive Science, Lund University, 222 22 Lund, Sweden

Abstract

Educational software based on teachable agents has repeatedly proven to have positive effects on students' learning outcomes. The strongest effects have been shown for low-performers. A number of mechanisms have been proposed to explore this outcome, in particular mechanisms that involve attributions of social agency to teachable agents. Our study examined whether an expression of high versus low self-efficacy in a teachable agent would affect low-performing students with respect to their learning outcomes and with respect to a potential change in their own self-efficacy. The learning domain was mathematics, specifically the base-ten system. Results were that the learning outcomes of low-performers who taught a low self-efficacy agent were significantly better than the learning outcomes of low-performers who taught a high self-efficacy agent. There were no effects from the manipulation of self-efficacy expressed by the teachable agent on changes of the low-performing students' own self-efficacy.

Keywords: social agency; educational software; teachable agent; math self-efficacy; math performance

Introduction

A *teachable agent* (TA) is a graphical computer character in a tutee role. The basic idea is that *the student* instructs and guides the TA (Brophy, Biswas, Katzlberger, Bransford, & Schwartz, 1999). In essence, TA-based educational software implements the pedagogical approach *learning by teaching*, (Bargh & Schul, 1980).

To date a set of TA-based learning games targeting the STEM areas have been developed and evaluated, and repeatedly proven to have positive effects on students' learning outcomes. Some studies have compared effects of TA-based software with ordinary teaching (regular classroom practice) (Pareto, Haake, Lindström, Sjödén, & Gulz, 2012; Chin, Dohmen, & Schwartz, 2013). Others have compared educational software versions with and without a teachable agent included (Chase, Chin, Oppezzo, & Schwartz, 2009; Pareto, Schwartz, & Svensson, 2009).

An observation from several of the studies is how readily the metaphor of the computer figure as a tutee (*digital tutee*) is accepted by students. They express engagement for the task of teaching the character, although it is in fact nothing but a computer artifact (Chase et al., 2009; Lindström, Gulz, Haake, & Sjödén, 2011.) They also make more effort to learn in order to teach their digital tutee than to learn for themselves (Chase et al., 2009). In effect, students attribute mental states and responsibility to the digital tutee as if it were a social agent (Chase et al., 2009; Lindström et al., 2011). They see the agent as a socio-cognitive actor that can learn (respond to being taught by them) and that can be ascribed traits such as 'brave', 'slow', 'smart', 'forgetful' etc.

TA-systems and Low-Performing Students

Several studies show that the students who benefit most by educational software with teachable agents – whether compared to equivalent software without TA or compared to ordinary classroom teaching – are the low-performing students. When comparing eleven year olds who used an educational game in biology with or without TA, the former spent more time on learning activities and also learned more, with the effects most pronounced for lower performing students (Chase et al., 2009). In a study by Sjödén and Gulz (2015), 9-10 year-olds used a TA-based educational math game in school over a period of eight weeks. Thereafter, the students were divided into two groups, matched according to their pretest scores, and randomly assigned to a post-test with or without the TA present (the TA did not act in order to influence the test but was merely present). Results showed that low-performers (according to the pretest) improved significantly more than high-performers but only when tested with the TA. Pareto et al. (2009), likewise found a considerably stronger improvement for low ability students than for high ability students when they used a math game with a TA feature compared to the math game without the TA.

Mechanisms in TA-Systems that may Support Low-Performing Students

A number of explanations for the pedagogical power of TA-based games have been proposed, including some that also provide possible rationales for why the effect is often larger for low-performers.

First, in a TA-based game, the student is positioned as the one that is most able, the one who can teach someone else that knows less. This experience – being someone who is

capable, who knows more than someone else – can potentially affect a student's view on her own competence in a positive way. This will likely benefit low-performers more than high-performers, since the latter are more likely to already have experienced the role of 'teaching someone else' and 'knowing more'. High-performers are more likely than low-performers to spontaneously take a teacher role (or be assigned this role in class). Acting teacher can potentially strengthen the student's belief in her own capability in the domain in question, and this may in turn have effects on performance.

Second, a teachable agent can be a model of learning behaviors (Blair, Schwartz, Biswas, & Leelawong, 2007). A TA is often designed to model fruitful and productive student behaviors, such as being curious, asking questions, reasoning, being explicit about parts of 'knowledge'. It is, however, more likely that high-performing students already have such behaviors on their repertoire compared to low-performing students, and that the latter therefore are more helped by being inspired by productive learning behavior in a TA.

Thirdly and crucially a TA is *teachable.* More specifically a TA models someone who from the beginning has little or no knowledge but learns incrementally or step-by-step. In other words, a teachable agent (re)presents or models an incrementalist theory of competence in contrast to an entity theory of competence according to which some individuals are held to be gifted and others non-gifted. This latter view is quite common among students (Dweck, 2006). Specifically it holds in the domain of mathematics, where it has also been shown that teachers to a larger extent than for other subjects used terms such as 'talented' and 'not talented' (Rattan, Good, & Dweck, 2012). In principle both high- and low-performing students can have an entity view of competence, and potentially benefit from viewing competence (in this study competence in math) as something that can be changed with effort. However, it is more likely that low-achievers with an entity view of competence are trapped in a circle, where they don't think they are talented and see no meaning in making an effort; therefore make little effort; therefore don't achieve and thus confirm they are not talented. In other words, they create a self-fulfilling prophecy.

Fourthly, Chase et al. (2009), propose a mechanism named *ego-protective buffer*. In TA-system it is the TA that is tested for its knowledge. When the TA fails at a test, the failure or non-success does not come as close onto the student as when she takes a test herself. Even if students are aware that the TA's knowledge reflects how the TA has been taught by themselves, the responsibility for failing is not only theirs. Instead of bearing the full burden of a failure, the responsibility of failure can be shared between the TA and student. Even though this may benefit high-performers as well, low-performers are more used at failing at school and thus the *ego-protective buffer mechanism* may explain why in particular low-achieving students perform better when working with a TA.

In sum, there is a set of proposed mechanisms that may explain why low-performers benefit more than high-performers from using teachable agents. All mechanisms involve the tendency of students to attribute social characteristics and agency to the agent, and interact intellectually and socially with it. For instance, to view the TA as someone that it is possible to share a failure with; to view the TA as someone who can accomplish a task (or not), as someone whose knowledge is different from mine and that I can influence by teaching it; to view that TA as someone that can learn – and as learner be slow, quick, smart, forgetful, etc.

In view of the above, we found it plausible that students would also tend to attribute *high or low self-efficacy* to an agent, if designed in an adequate manner. Spelled out, they would tend to attribute to an agent high or low belief in its own capability to learn and be successful – in our case with respect to math and base ten problems. The present study thus approaches the trait of self-efficacy, which to our knowledge has not been studied before in teachable agents.

Does TA Self-Efficacy Matter for Student Progress

Having an ability to learn, i.e. being *teachable*, is the very essence of a digital tutee or teachable agent. However, whether other kinds of properties are attributed to a TA depends in the first place on how the TA is designed and implemented, and also on the student interacting with the TA. For instance, depending on how it is implemented, a TA can be (perceived as) a quick learner or a learner that needs many rehearsals. A TA can be (perceived as) more or less challenging or questioning (Kirkegaard, 2016).

In our study the TA was designed to express either high or low belief in its own capacity to learn and perform in a math game. We will soon present our predictions but first discuss the phenomenon of *self-efficacy* in real human students. For human learners we know that there is a relation between self-efficacy and actual performance (Bandura, 1997) in that self-efficacy predicts subsequent performance. Low self-efficacy predicts low performance, and high self-efficacy predicts high performance. Proposed mechanisms are that student's self-efficacy influences how much effort she puts into a task, her tendency to persist, how high she sets her aspirations and her tendency to persevere when being challenged by the task. Individuals with high self-efficacy often achieve more in intellectual terms (Bandura, 1997). Importantly, however, the relations are correlational and on a group level. There are no causal or absolute relations between individual's self-efficacy and her performance; students may over-estimate as well as under-estimate their own capacity.

We now return to self-efficacy in teachable agents. The central research question in the present study was whether a teachable agent expressing low or high self-efficacy,

respectively, would have different impact on low-performing students in terms of their learning and progress. In addition we explored whether there would be any effects on students' own self-efficacy in either of the conditions.

Research Questions and Predictions

Research Question 1 (RQ1) Will learning and progress differ between low-performing students who teach a TA expressing low self-efficacy (**lowSE-TA**) and low-performing students who teach a TA expressing high self-efficacy (**highSE-TA**)?

As a basis for our predictions we used two different theories: (i) role-modeling theory by Bandura (1977) and (ii) the theory of the TA protégée effect by Chase et al. (2009). This resulted in two alternative predictions that point in opposite directions. As such this is not surprising since the predictions are generated from theories not related to one another.

The first, alternative, prediction in line with Bandura´s idea of role modeling focuses on teachable agents as behavioral models, as discussed in the introduction. A **highSE-TA** models a learner with a strong belief in her own abilities to learn, a willingness to persist and not give up, etc. Together with the TA:s incremental progression (given that it is reasonably taught by the student) this is likely to be a positive model for low-performers, that often themselves have low self-efficacy. Thus we predict that low-performers will make larger progress if they teach a **highSE-TA** than if they teach a **lowSE-TA**.

The second, alternative, prediction is based on the protégée-effect mentioned above: in general, students seem to take responsibility for a TA and make an effort to teach it. Now, a **lowSE-TA** expresses uncertainty in its own capacity, and seems in considerable need for support and engagement from the teacher (i.e. student), whereas a **highSE-TA** expresses confidence in its own capability to learn and manage and seems in less need for help from the teacher. Therefore low-performers may be more motivated to take responsibility and make an effort to teach a **lowSE-TA** compared to a **highSE-TA**. Consequently they will also themselves make more progress. Thus we predict that low-performers will make larger progress if they teach a **lowSE-TA** than if they teach a **highSE-TA**.

There is also third possible result, namely that whether the TA expresses low or high self-efficacy will not matter for low-performers progress.

Research Question 2 (RQ2) Will a potential change in self-efficacy in low-performing students differ between those students who teach a TA expressing low self-efficacy and those who teach a TA expressing high self-efficacy?

If the TA functions as a behavioral model with respect to self-efficacy, low-performers are more likely to increase their own self-efficacy if they teach a **highSE-TA** than if they teach a **lowSE-TA**. The reason is that they may be inspired to model the TA along the line "*If this character, my digital tutee, believes strongly in its capability, why shouldn't its teacher, that is me, do so too?*"

From the protégée effect no straightforward prediction can be derived on potential self-efficacy change in students, depending on TA self-efficacy. As discussed under RQ1, if the protégée effect is at work, participants will put particularly large effort into teaching a **lowSE-TA**, since such a TA signals a greater need of help and support than a **highSE-TA** that signals that can learn on its own. But whether students that take more responsibility and make a larger effort to teach their TA also change their belief in their own capacity to learn is not obvious. On the one hand, an interplay between performance and self-efficacy is likely but such influences may take time.

Again there is a third possible result, namely that whether the TA expresses low or high self-efficacy does not matter with respect to low-performers potential self-efficacy change.

To sum up, the present study made use of a learning game in math including a TA, where we manipulated the TA:s expressed belief in its own capability to perform and learn math as expected in the game. Our two research questions were: RQ1: Would the manipulation of TA self-efficacy have an effect on low-performing students' progress in the game (i.e. their learning math)? RQ2: Would the manipulation of TA self-efficacy have an effect on potential change in self-efficacy in the low-performing students?

Method

Participants

Participants were 166 students (83 girls and 83 boys) aged 10-11 years from 4 schools and 9 classes in Southern Sweden from areas with relatively low socio-economic status and school performance below average. Students were randomly assigned one of the conditions: teaching a digital tutee that expressed high self-efficacy (**highSE-TA**) or teaching a digital tutee that expressed low self-efficacy (**lowSE-TA**). Out of the initial set of participants, 24 were excluded due to missing data points or low attendance. Next, out of the 142 remaining students, the 62 students who performed below the median on a math performance test were selected for further analysis. The math test was based on a representative part of the national tests in mathematics and consisted of 21 problems relating to place value. Thus, in the final data set, there were 28 students in the **lowSE-TA** condition and 34 in the **highSE-TA** condition.

The Educational Game

The TA math game, developed by Lena Pareto (Pareto, 2014), targets basic arithmetic skills related to the place value system, where the student teaches a digital tutee

named Lo, so that Lo can compete against other students' digital tutees or against a computer actor in different digital board games. Lo's knowledge – based on the system's knowledge domain (Pareto, 2014) – develops entirely on the basis of what the student teaches her (and if taught wrong, Lo will learn wrong).

A central part of the student's teaching consists of answering questions from the digital tutee about the math content, specifically regarding place value, via multiple-choice for answering (see figure 1). The other main interaction between student and digital tutee takes place via a free text chat (Silvervarg & Jönsson, 2011). This is also where Lo, the TA, expresses her self-efficacy (see figure 1).

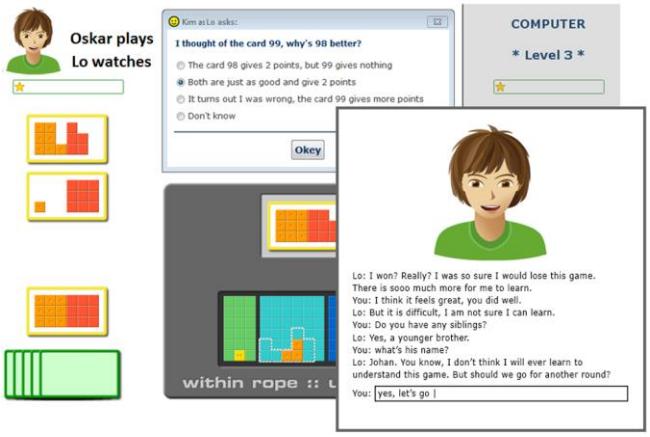

Figure 1: The math game with multiple choice conversation and 'free text chat' conversation (overlay).

Self-Efficacy in the Teachable Agent

High or low self-efficacy in or study was defined as high or low belief in ones capability to make progress and perform well in the math game. In turn, this requires making adequate moves and answering questions regarding the place value system correctly. The definition can be compared to a more general definition of self-efficacy in mathematics as the belief in ones capability to successfully learn mathematics (Bandura, 1997).

After each round of the game where Lo (the TA) has been active – observing and posing questions to the student or being guided by student – the chat conversation starts. The chat begins with Lo commenting on the previous round saying for example: "*Awesome! We won! I have a good grip now of tens and hundreds and all that you teach me.*" (reflecting high self-efficacy), "*Oh I won, did I? Nice. But I feel very uncertain about how to play well.*" (reflecting low self-efficacy).

The chat conversation also contains other comments and reflections from Lo on her own learning, for instance: "*I´m learning the rules in the math game slowly. I´m not a very brilliant student.*" (reflecting low self-efficacy), "*It's going to get better and better. I have so quickly learned so many things about how to play the game.*" (expressing high self-efficacy), and "*I am not sure I can learn these things.*" (expressing low self-efficacy).

The chat always ended with a sentence from Lo regarding her thoughts about the upcoming round, for example: "*I have a feeling that the next round will go really well. Let's play!*" (expressing high self-efficacy) or "*It doesn't seem like I understand much really, but let's play another round.*" (expressing low self-efficacy).

Lo's utterances had previously been evaluated with regard to whether they sounded as uttered by someone who was confident, not confident, or neither nor in her ability to learn and perform. The evaluators were 22 fourth graders from a school not participating in the study. The evaluation resulted in the removal of a few sentences and slight modifications of others, resulting in a set of 136 sentences, 68 reflecting a digital tutee with high self-efficacy and 68 reflecting a digital tutee with low self-efficacy.

In addition the manipulation – low and high self-efficacy in the TA – was validated within the present study by participating students. At the end of the last study session they were asked to evaluate Lo's belief in her/his own capability to play the math game on a Likert scale. A Mann-Whitney test showed a significant difference (Z = -4.85, p < .001, r = .39) between the low SE-TA and the high SE-TA, confirming that the manipulation had intended effects on the perception of the TAs self-efficacy.

Procedure

All study sessions took place in ordinary classrooms and lasted about 30 minutes. At the pre-test session, students completed a math pre-test targeting the place value system, and a pre-questionnaire targeting their self-efficacy in math with respect to the place value system. The students' math pre-test scores were used to identify the target group for this study's research questions, i.e. low-performers (in math).

Thereafter students participated during seven game-playing sessions, once a week. At the post-session, students again filled out the questionnaire targeting their self-efficacy in math and the place value system and were debriefed about the two different types of digital tutees and the purpose of the study.

Measurements

Performance During Game Play Students' performance while teaching the digital tutee is a reflection on how well they perform themselves. In line with this we calculated a performance score for each student on the basis of the data-logging. Through the game the digital tutee poses questions to the student that concerns the conceptual model and principles of the place value system. For instance: "*How many orange square boxes are there in the 2 yellow square boxes on the game board?*" and "*How many red square boxes are needed to fill a yellow square box?*" The tutee

posed three such questions during each game session, and the student had to choose one out of four alternative answers (one correct, two incorrect and the alternative "*I don't know.*"). The performance score was calculated as the percentage of correct answers minus the percentage of incorrect answers. Additionally, a study by Pareto (2014) showed that in-game performance in this math game correlated with standard paper-and-pencil tests on the place-value system.

Self-Efficacy Change To measure this we used a self-efficacy pre- and post-questionnaire based on Bandura, Barbaranelli, Caprara, and Pastorelli (1996); for this study translated into Swedish

The seven items targeted the students' self-efficacy with regard to the place value system and the question "*How good are you at solving this type of task?*" Item one to five regarded calculation tasks such as "*1136 + 346*", and item six and seven targeted place value concepts, such as: "*Which digit has the highest place value in the number 6275?*" All items were graded in five steps from "*Not good at all*" to "*Very good at*".

Results

Statistical analyses were conducted in R v3.2.4 (R Core Team, 2016). Of the 142 participants with complete data, the 62 performing below the median on the pre-test in math were included in the analysis.

Effects TA Self-Efficacy on Low-Performing Students' Performance During Game Play

An unmatched two sample *t*-test showed a significant difference ($t(60) = 3.40$, $p = .0012$, Cohen's $d = 0.87$) of TA self-efficacy on student performance with the students in the **lowSE-TA** condition ($M = 54.8$, $SD = 13.7$) outperforming the students in the **highSE-TA** condition ($M = 43.7$, $SD = 12.0$).

Effects of TA Self-Efficacy on Low-Performing Students' Self-Efficacy Change

An unmatched two sample *t*-test showed no significant difference ($t(60) = 0.35$, $p = .73$) of TA self-efficacy on student self-efficacy change between the students in the **lowSE-TA** condition ($M = 1.18$, $SD = 3.81$) and the students in the **highSE-TA** condition ($M = 1.53$, $SD = 4.00$).

Discussion

Teaching a **lowSE-TA** compared to teaching a **highSE-TA** made the participants perform significantly better, as measured by their in-game performance scores. But the two conditions did not differ with respect to whether the participants changed their own self-efficacy. Changes were small and did not differ between the conditions.

These results contribute to our knowledge about mechanisms in a TA-based educational game with respect to why low-performers tend to benefit more than high-performers from these games. First, we showed that a manipulation of expressed self-efficacy in a TA can influence performance for low-performers: a TA that expressed low self-efficacy was more beneficial than a TA that expressed high self-efficacy. The effect as such, regardless of direction, confirms that at least some of the pedagogical power in a TA-based game derives from attributions of social agency to TA:s, in this case attributing to the TA a weak or strong belief in its own capability. Consequently this is one of the traits that a TA designer ought to be aware of; a trait that can explain why low-performers benefit more than high-performers from TA-based games.

With respect to student performance, we based our predictions on two different theoretical models: role modeling according to which a **highSE-TA** should have the most positive influence on the performance of low-performers, and the protégée effect according to which a **lowSE-TA** should have the most positive influence on the low-performers performance. The latter theory was supported and can be further elaborated on by means of the results of our study. According to the protégée-effect students tend to make more effort and take more responsibility for the task of teaching a TA than for the task of learning for themselves (Chase et al., 2009). In our study the outcome was better when low-performers taught a **lowSE-TA** compared to a **highSE-TA**. It is near at hand that they made an even larger effort and took even more responsibility for a TA with low self-efficacy since this TA expresses a low trust in her own ability to learn, and likely comes across as someone who is more in need of help than a TA with high self-efficacy. A **highSE-TA**, on the other hand, indicates that s/he is capable to learn and perform, and is in less need of help.

The lacking effect on students self-efficacy change, depending on high or low self-efficacy in the TA, means that the role-modeling hypothesis proposed above was not supported. Students were not inspired by a **highSE-TA** as a model to increase their own self-efficacy. Neither did teaching a **lowSE-TA** lead to an increase in the students' self-efficacy. However, it did lead to an increase in their performance, and we can thus conclude that the increased performance was not caused by an increased self-efficacy, at least not as measured in our study. It should also be pointed out that an increase in self-efficacy is not always desirable, in particular not for students who overestimate their capabilities. At the same time, given the interactions between self-efficacy and performance, it is often a good thing when students with low self-efficacy in a domain gain more confidence in their abilities to make progress. What is desirable *in general* is that as many students as possible have an incrementalist rather than an entity view of intellectual capabilities – something that the use of TA-

based educational games may contribute to (Chase et al., 2009).

Limitations of the Study and Future Research

The study should be seen as a first examination about how the manipulation of self-efficacy in a digital tutee can influence student performance. Some limitations should be kept in mind when interpreting the results. One is that there was no group of students who taught a digital tutee that expressed a neutral mode of self-efficacy. In future research such a condition should be included. Furthermore, rather than aiming to be conclusive, the present study opens up for associated studies. For instance, one relevant question is whether the results will replicate or not with other age groups than 10-11 year olds. Another interesting line of research could be to explore a TA with adaptive self-efficacy that reflects the rate at which it actually learns, which in turn reflects the proficiency of the student that is teaching it.

Acknowledgments

This research was funded in part by Marcus and Amalia Wallenberg Foundation and the research environment Cognition, Communication and Learning. The authors thank all students and teachers who participated in the study.

References

Bandura, A. (1997). *Self-Efficacy: The exercise of control*. New York, NY: W.H. Freeman.

Bandura, A. (1977). *Social learning theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (1996). Multifaceted impact of self-efficacy beliefs on academic functioning. *Child Development*, *67*(3), 1206–1222.

Bargh, J. A., & Schul, Y. (1980). On the cognitive benefits of teaching. *Journal of Educational Psychology*, *72*(5), 593–604.

Blair, K., Schwartz, D., Biswas, G., & Leelawong, K. (2007). Pedagogical agents for learning by teaching: Teachable agents. *Educational Technology*, *47*(1), 56–61.

Brophy, S., Biswas, G., Katzlberger, T., Bransford, J., & Schwartz, D. (1999). Teachable agents: Combining insights from learning theory and computer science. In S.P. Lajoie & M. Vivet (Eds.), *Frontiers in Artificial Intelligence and Applications, Vol 50. Proc. of AIED 1999*. Amsterdam, The Netherlands: IOS Press.

Chase, C., Chin, D., Oppezzo, M., & Schwartz, D. (2009). Teachable agents and the protégé effect: Increasing the effort towards learning. *Journal of Science Education and Technology*, *18*, 334–352.

Chin, D. B., Dohmen, I. M., & Schwartz, D. L. (2013). Young children can learn scientific reasoning with teachable agents. *IEEE Transactions on Learning Technologies*, *6*(3), 248–257.

Dweck, C. (2006). *Mindset: The new psychology of success*. Random House.

Kirkegaard, C. (2016). *Adding challenge to a teachable agent in a virtual learning environment*. Licentiate Thesis in Cognitive Science, Linköping University. Linköping, Sweden: Linköping University Electronic Press.

Lindström, P., Gulz, A., Haake, M., & Sjödén, B. (2011). Matching and mismatching between the pedagogical design principles of a maths game and the actual practices of play. *Journal of Computer Assisted Learning*, *27*, 90–102.

Pareto, L. (2014). A teachable agent game engaging primary school children to learn arithmetic concepts and reasoning. *International Journal of Artificial Intelligence in Education*, *24*(3), 251–283.

Pareto, L., Schwartz, D. L., & Svensson, L. (2009, July). Learning by guiding a teachable agent to play an educational game. In V. Dimitrova, R. Mizoguchi, B. du Boulay, A. C. Graesser (Eds.), *Frontiers in Artificial Intelligence and Applications, Vol 200. Proc. of AIED 2009* (pp. 662–664). Amsterdam, The Netherlands: IOS Press.

Pareto, L., Haake, M., Lindström, P., Sjödén, B., & Gulz, A. (2012). A teachable agent based game affording collaboration and competition – Evaluating math comprehension and motivation. *Educational Technology Research and Development*, *60*, 723–751.

Rattan, A., Good, C., & Dweck, C. (2012). "It's ok – Not everyone can be good at math": Instructors with an entity theory comfort (and demotivate) students. *Journal of Experimental Social Psychology*, *48*(3), 731–737.

Silvervarg, A., & Jönsson, A. (2011). Subjective and Objective Evaluation of Conversational Agents. In *Proceedings of the 7th Workshop on Knowledge and Reasoning in Practical Dialogue Systems* (pp. 65–72). Barcelona, Spain.

Sjödén, B., & Gulz, A. (2015). From Learning Companions to Testing Companions. In C. Conati, N. Heffernan, A. Mitrovic, & M.F. Verdejo (Eds.), *LNAI/LNCS: Vol. 9112. Proc. of AIED 2015* (pp. 459–469). Berlin/Heidelberg, Germany: Springer-Verlag.

R Core Team (2016). *R: A language and environment for statistical computing* [Software]. R Foundation for Statistical Computing, Vienna, Austria. Available from http://www.R-project.org/.