Oscar: An Intelligent Adaptive Conversational Agent Tutoring System

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Abstract. This paper presents an adaptive online intelligent tutoring system called Oscar which leads a tutoring conversation and dynamically predicts and adapts to a student's learning style. Oscar aims to mimic a human tutor by using knowledge of learning styles to adapt its tutoring style and improve the effectiveness of the learning experience. Learners can intuitively explore and discuss topics in natural language, helping to establish a deeper understanding of the topic and boost confidence. An initial study into the adaptation to learning styles is reported which produced encouraging results and positive test score improvements.

Keywords: Intelligent Tutoring System, Conversational Agent, Learning Style

Introduction

The widespread use of the Internet has presented opportunities for the delivery of learning, both in terms of distance-learning and in supporting traditional classroom activities. Intelligent Tutoring Systems (ITS) extend traditional content-delivery computerised learning systems by adding intelligence which aims to improve the effectiveness of a learner's experience. This usually involves personalising the tutoring by adapting the learning material presented according to existing knowledge Brusilovsky, P., Peylo, C.: Adaptive and Intelligent Web-based Educational Systems. Int. J. Artificial Intelligence in Education 13, pp. 156-–169 (2003) or student affect such as emotion D'Mello, S., Lehman, B., Sullins, J., Daigle, R., Combs, R., Vogt, K., Perkins, L., Graesser, A.: A Time for Emoting: When Affect-Sensitivity Is and Isn't Effective at Promoting Deep Learning. In Proc. ITS 2010, LNCS, vol. 6094, pp. 245-254, Springer (2010).. ITS which build in some social awareness, such as personalising tutoring to the individual, offer a more familiar and comfortable learning experience. Most ITS are menu-based and offer student-directed study and support at a time and pace to suit individuals, but offer an experience more akin to a computerised textbook than a classroom tutorial. Conversational Intelligent Tutoring Systems (CITS) incorporate more human-like natural language interfaces which allow learners to explore and discuss a topic, supporting the constructivist style of learning used by human tutors. However, creating a CITS which can converse naturally with a learner is a complex and time-consuming task, which is why only a few CITS exist Graesser, A., Chipman, P., Haynes, B.C., Olney, A.: AutoTutor: An Intelligent Tutoring System With Mixed-Initiative Dialogue. IEEE Trans. Education 48 (4), pp. 612--618 (2005)Popescu, E.: Adaptation provisioning with respect to learning styles in a Web-based educational system: an experimental study. Journal of Computer Assisted Learning 26, pp. 243--257 (2010). Human tutors adapt their tutoring style and content based on cues they pick up from students, such as their level of existing knowledge and their learning styles. Learning styles describe the way groups of people prefer to learn, for example by trial and error or by observation Felder, R., Silverman, L.K.: Learning and Teaching Styles in Engineering Education. J. Engineering Education 78 (7), 674--681 (1988). A CITS which can mimic a human tutor by leading an adaptive tutorial conversation offers students a familiar format which can help improve confidence and motivation, leading to a better learning experience. There are no tutor-led CITS which can predict and adapt to learning styles during a tutoring conversation.

This paper describes a novel CITS which dynamically predicts and adapts to a student's learning style during a tutor-led conversation. The research focussed on mimicking a face-to-face tutorial and building in knowledge of learning styles rather than designing an interface specifically to pick up learning style behaviour, as in Cha, H. J., Kim, Y. S., Park, S. H., Yoon, T. B., Jung, Y. M., Lee, J. H.: Learning styles diagnosis based on user interface behaviours for the customization of learning interfaces in an intelligent tutoring system. In: Proc. ITS 2006, LNCS, vol. 4053, Springer (2006).. The adaptation algorithm employed recognises the importance of providing a coherent learning experience, and so considers both the student's learning style preferences and the opportunity for adaptation in tutoring questions.

In this paper, section 2 introduces the background concepts of Intelligent Tutoring Systems, the Index of Learning Styles and Conversational Agents. Section 3 describes the Oscar CITS and the methods used to incorporate adaptivity. Section 4 outlines the experimental methodology and two sample learner dialogues. Section 5 reports the results and discussion, and Section 6 describes the conclusions and future work.

Background

Intelligent Tutoring Systems

Intelligent tutoring systems (ITS) are computerised learning systems which adopt intelligent systems techniques to personalise the learning experience. ITS endeavour to improve the effectiveness of tutorials and boost learners' motivation and confidence by adapting to each individual's characteristics, such as existing knowledge. ITS are normally designed to be student-directed, with a system of menu choices or hyperlinks which are reordered or ranked to recommend a particular sequence to learners Klasnja-Milicevic, A., Vesin, B., Ivanovic, M., Budimac, Z.: E-Learning personalization based on hybrid recommendation strategy and learning style identification. Computers & Education 56, pp. 885--899 (2011). Whilst this design simplifies the analysis of student behaviour, it does not truly teach the students but rather assists in self-learning, and is little different to recommending chapters of a book. Although rarely employed, conversational interfaces allow a more natural, teacher-led learning experience which supports the construction of knowledge used by human tutors Chi, M.T.H., Siler, S., Jeong, H., Yamauchi, T., Hausmann, R.G.: Learning from human tutoring. Cognitive Science 25, pp. 471--533 (2001). Examples of CITS are AutoTutor Graesser, A., Chipman, P., Haynes, B.C., Olney, A.: AutoTutor: An Intelligent Tutoring System With Mixed-Initiative Dialogue. IEEE

Trans. Education 48 (4), pp. 612--618 (2005) and CIRCSIM-tutor Woo Woo, C., Evens, M.W., Freedman, R., Glass, M., Seop Shim, L., Zhang, Y., Zhou, Y., Michael, J.: An intelligent tutoring system that generates a natural language dialogue using dynamic multi-level planning. Artificial Intelligence in Medicine 38, pp. 25--46 (2006) which both help students construct knowledge using conversational agent tutors, however neither consider learning styles during tutoring.

The three main approaches to intelligent tutoring Brusilovsky, P., Peylo, C.: Adaptive and Intelligent Web-based Educational Systems. Int. J. Artificial Intelligence in Education 13, pp. 156-–169 (2003) are curriculum sequencing (presenting material in a suitable sequence Klasnja-Milicevic, A., Vesin, B., Ivanovic, M., Budimac, Z.: E-Learning personalization based on hybrid recommendation strategy and learning style identification. Computers & Education 56, pp. 885--899 (2011)), intelligent solution analysis (giving feedback on incomplete or erroneous solutions Mitrovic, A.: An Intelligent SQL Tutor on the Web. Int. J. Artificial Intelligence in Education 13, pp. 171--195 (2003)) and problem solving support (offering intelligent assistance in finding solutions Melis, E., Andrès, E., Büdenbender, J., Frishauf, A., Goguadse, G., Libbrecht, P., Pollet, M., Ullrich, C.: ActiveMath: A web-based learning environment. Int. J. Artificial Intelligence in Education 12 (4), pp. 385--407 (2001)). Most ITS employ curriculum sequencing based on student knowledge and also more recently user affect factors such as emotion Ammar, M. B., Neji, M., Alimi, A. M., Gouarderes, G.: The Affective Tutoring System. Expert Systems with Applications 37, 3013--3023 (2010), personality Leontidis, M., Halatsis, C.: Integrating Learning Styles and Personality Traits into an Affective Model to Support Learner's Learning. In: Spaniol, M. et al. (Eds.) ICWL 2009. LNCS 5686, 225--234. Springer, Heidelberg (2009) and learning style Popescu, E.: Adaptation provisioning with respect to learning styles in a Web-based educational system: an experimental study. Journal of Computer Assisted Learning 26, pp. 243--257 (2010). Few ITS incorporate all three techniques as they are complex and time-consuming to develop, but the Oscar CITS presented in this paper will incorporate all three intelligent technologies by personalising learning material and discussing problems and solutions with students.

The Index of Learning Styles

The Index of Learning Styles (ILS) model Felder, R., Silverman, L.K.: Learning and Teaching Styles in Engineering Education. J. Engineering Education 78 (7), 674--681 (1988) describes the learning styles in engineering education and their associated teaching styles. In the ILS model a student's learning styles are represented as points along four dimensions to indicate the strength as well as the nature of their learning style preference. Each learning style dimension describes a step in the process of receiving and processing of information, as shown in Fig. 1. The ILS model measures learning style with a 44-question self-assessment questionnaire. There are 16 (2^4) combinations of learning styles, for example intuitive/visual/active/global.

Fig. . ILS Dimensions

For each learning style, the ILS model details typical learner behaviours and teaching styles which address learner preferences. This information is beneficial for lecturers who informally group types of learners to adapt their teaching rather than using the formal assessment questionnaire. Knowledge of learner behaviours and teaching styles is also indispensable when developing a CITS which can adapt its teaching style to individual learner preferences.

The ILS model was incorporated into the Oscar CITS as engineering students will make up the initial experimental groups. However the flexible modular structure of the Oscar CITS does not restrict the choice of learning style model to the ILS.

Conversational Agents

Conversational agents (CAs) allow people to interact with computer systems intuitively using natural language dialogues. CA interfaces have been used effectively in many applications, such as web-based guidance Latham, A., Crockett, K., Bandar, Z.: A Conversational Expert System Supporting Bullying and Harassment Policies. In: Proc. ICAART 2010, pp. 163--168 (2010)., database interfaces Pudner, K., Crockett K.A., Bandar, Z.: An Intelligent Conversational Agent Approach to Extracting Queries from Natural Language. In Proc. WCE Int. Conf. Data Mining and Knowledge Engineering, 2007, pp. 305-310 (2007). and tutoring Graesser, A., Chipman, P., Haynes, B.C., Olney, A.: AutoTutor: An Intelligent Tutoring System With Mixed-Initiative Dialogue. IEEE Trans. Education 48 (4), pp. 612--618 (2005). CAs are complex and time-consuming to develop, requiring expertise in the scripting of conversations, and are therefore rarely found in ITS. Systems such as Oscar CITS which aim to mimic a human tutor need CA interfaces to support the construction of knowledge through discussion Chi, M.T.H., Siler, S., Jeong, H., Yamauchi, T., Hausmann, R.G.: Learning from human tutoring. Cognitive Science 25, pp. 471--533 (2001).

Textual CAs usually adopt a pattern matching Michie, D.: Return of the Imitation Game. Electronic Transactions on Artificial Intelligence 6, pp. 203--221 (2001) or semantic based Li, Y., Bandar, Z., McLean, D., O'Shea, J.: A Method for Measuring Sentence Similarity and its Application to Conversational Agents. In Proc. FLAIRS 2004, pp. 820—825 (2004),Khoury, R., Karray, F., Kamel, M.S.: Keyword extraction rules based on a part-of-speech hierarchy. Int. J. Advanced Media and Communication 2 (2), pp. 138--153 (2008) approach. Semantic-based CAs seek to understand the meaning of the input by studying the constructs and meanings of natural language Khoury, R., Karray, F., Kamel, M.S.: Keyword extraction rules based on a part-of-speech hierarchy. Int. J. Advanced Media and Communication 2 (2), pp. 138--153 (2008) or by comparing the semantic similarity of phrases Li, Y., Bandar, Z., McLean, D., O'Shea, J.: A Method for Measuring Sentence Similarity and its Application to Conversational Agents. In Proc. FLAIRS 2004, pp. 820—825 (2004). Pattern-matching CAs rely on a knowledge base containing a set of pattern-based rules Pudner, K., Crockett K.A., Bandar, Z.: An Intelligent Conversational Agent Approach to Extracting Queries from Natural Language. In Proc. WCE Int. Conf. Data Mining and Knowledge Engineering, 2007, pp. 305-310 (2007).. During a conversation user utterances are matched to rules in the knowledge base, with the best matching rule (selected by an algorithm) firing to produce a natural language response. In the case of Oscar CITS, a pattern matching approach was adopted as it can cope with grammatically incomplete or incorrect phrases, as are commonly found in text-based chat by students.

Oscar: An Adaptive Conversational Intelligent Tutoring System

Oscar is an online CITS which dynamically predicts and adapts to each individual student's learning style during a tutoring conversation. By adapting the tutoring style to suit individual learners, Oscar aims to provide the most appropriate learning material for their learning style, leading to a more effective learning experience and a deeper understanding of the topic. In addition to delivering tutor material suited to an individual's learning style (known as curriculum sequencing), Oscar provides intelligent solution analysis and conversational problem solving support. Like human tutors, Oscar CITS promotes a deeper understanding of the topic by using a constructivist style of tutoring, giving intelligent hints and discussing questions with learners rather than presenting the answer straight away. Oscar CITS imitates classroom tutorials with human tutors by using a natural language interface and tutor-led tutorial style which aims to help learners feel comfortable and confident during online tutorials.

The architecture and methodology for developing the original Oscar CITS is described in Latham, A.M., Crockett, K.A., McLean, D.A., Edmonds, B., O'Shea, K.: Oscar: An Intelligent Conversational Agent Tutor to Estimate Learning Styles. In Proc. IEEE World Congress On Computational Intelligence 2010, pp2533—2540 (2010). Results of two initial experiments which investigated the prediction of learning styles show that Oscar CITS was successful in dynamically predicting several learning styles Latham, A.M., Crockett, K.A., McLean, D.A., Edmonds, B., O'Shea, K.: Oscar: An Intelligent Conversational Agent Tutor to Estimate Learning Styles. In Proc. IEEE World Congress On Computational Intelligence 2010, pp2533—2540 (2010),Latham, A.M., Crockett, K.A., McLean, D.A., Edmonds, B.: Predicting Learning Styles in a Conversational Intelligent Tutoring System. In X. Luo et al (eds.), Proc. ICWL 2010, LNCS, vol. 6483, pp. 131-140, Springer (2010).. For the initial studies, Oscar delivers an online tutorial in the domain of the database Structured Query Language (SQL). Oscar draws on knowledge bases of learning styles (the ILS model), tutor material and conversation scripts to deliver a conversational tutorial to a student. To support the tutoring conversation, diagrams, images and interactive movies may be displayed. Aspects of the student's behaviour and understanding inform the dynamic prediction of learning style, allowing the tutoring style to be personalised to best suit the student.

Throughout tutoring the Oscar CITS records and logs information about the behaviour of the student, for example the timing of interactions and the type of tutor resource accessed. The tutoring conversation is also recorded, along with information about the student knowledge of the topic being discussed.

The first implementation of Oscar CITS successfully incorporated human-like intelligence into a conversational tutorial which improved student test results and dynamically predicted their learning styles. The next section will outline the extension of Oscar CITS to include the ability to adapt a tutorial to a student's learning styles.

Methods for Including Adaptivity

The Index of Learning Styles model Felder, R., Silverman, L.K.: Learning and Teaching Styles in Engineering Education. J. Engineering Education 78 (7), 674--681 (1988) was analysed and a table of learner behaviour for each learning style drawn up. The characteristics were evaluated to establish whether they could be incorporated into a CITS. The subset of learner behaviour considered to be most important for an adaptive CITS was then assigned the appropriate teaching styles described in the ILS model. The breakdown of behaviour and teaching styles was examined further to develop several domain-independent categories of tutor material required for developing an adaptive CITS. Each tutor material category was mapped to the appropriate learning style, for example, Category 4: Practical Examples maps to the Sensor, Active and Sequential learning styles. The standard categories were designed from the point of view of the tutor and intend to make the development of tutoring material for an adaptive CITS as simple and consistent as possible. The standard organisation of tutor material also facilitates modular development, as additional materials can be expanded and added without the need for a total redesign of the tutoring session.

The next stage was to consider how the Oscar CITS would adapt tutoring according to a student's learning style. The ILS model indicates that students who have no strong learning style preference in a dimension (i.e. they are placed at the centre of the ILS scale with a score of 1 or 3) should be given learning material including a mixture of styles. An additional *Neutral* learning style category was introduced to group those students and a Neutral adaptation style included.

There are a number of possible ways to adapt to learning styles, the simplest of which would be to adapt to the student's strongest learning style. However, a tutorial is made up of a number of tutorial questions, and this approach would require incorporating every category of tutor material into every tutorial question. This may not be possible in real life, as it is important to construct a coherent tutorial and learning experience. Consequently the adaptation strategy needed to consider not only the strength of the student's learning style but also the strength of adaptation available for each individual tutorial question. This method was adopted and a complex, domain-independent adaptation algorithm was developed which combined the strengths of the student's learning style with the tutorial adaptations to select the best fitting adaptation for each question in the student's learning path.

For the initial study an SQL revision tutorial was developed for the Oscar CITS. The adaptive SQL learning material extended the tutorial delivered in previous experiments Latham, A.M., Crockett, K.A., McLean, D.A., Edmonds, B., O'Shea, K.: Oscar: An Intelligent Conversational Agent Tutor to Estimate Learning Styles. In Proc. IEEE World Congress On Computational Intelligence 2010, pp2533—2540

(2010),Latham, A.M., Crockett, K.A., McLean, D.A., Edmonds, B.: Predicting Learning Styles in a Conversational Intelligent Tutoring System. In X. Luo et al (eds.), Proc. ICWL 2010, LNCS, vol. 6483, pp. 131-140, Springer (2010).. This was achieved by adding different resources covering the standard categories of tutoring material. This involved creating several versions of the learning material, each suited to a different learning style. Next, each tutorial question was assigned a score for every learning style which represented the number (or strength) of opportunities for adaptation to that learning style. Where no adaptation existed for a learning style (i.e. the question score was zero) the Neutral adaptation was assigned by the algorithm. The initial study will now be described.

Experimental Methodology

A controlled study was conducted to test the hypothesis that students who are presented with learning material matched to their learning styles perform better than students presented with learning material which is unsuited to their learning styles. 70 final year undergraduate science and engineering students were asked to refresh their SQL knowledge by completing the Oscar CITS SQL revision tutorial. This involved each student registering with the Oscar CITS anonymously and completing the formal ILS questionnaire before beginning the tutorial. Next, students completed a pre-tutorial multiple choice question (MCQ) test to assess existing knowledge before starting the conversational tutorial. The tutorial was led by the Oscar CITS tutor who conversed in natural language with students and guided them through the ten tutorial questions, showing images, movies and examples as necessary. The conversational SQL revision tutorial took on average approximately 43 minutes, with each learner following an individual learning path depending on their knowledge and learning styles (see section 4.1 for example dialogues). After the tutorial conversation, students completed the same MCQ test and were then presented with a comparison of their test results and some feedback from Oscar. Finally, students were asked to complete a user evaluation questionnaire.

After completing the ILS questionnaire, participants were unknowingly assigned to one of three experimental groups. Students whose learning styles were at the centre of all ILS scales (i.e. there was no strong preference) were assigned to the *Neutral* group. These students followed the neutral adaptation learning path, with tutor material including different aspects of all learning styles (e.g. describing theory as well as examples). Students who had at least one preferred learning style were randomly assigned to either the *Adapt* or *Mismatch* groups using a 2:1 ratio. These students followed an adaptive learning path assigned by the algorithm, and were given tutor material favouring particular learning styles (e.g. containing explanations of theory rather than practical examples). Students in the Mismatch group were deliberately presented with learning material unsuited to their learning styles, e.g. if a student was Sequential, they were presented with material suited to a Global learner.

For each completed tutorial, log files which recorded the dialogue, timings, knowledge and other behavioural factors were analysed to assess each learner's performance during the tutoring session. During the SQL Revision tutoring session, ten questions were posed, requiring eighteen answers (as some questions incorporated multiple steps or questions). Learning gain was calculated by counting the number of correct answers given to tutorial questions, and an average score was calculated for each experimental group. The experimental group averages were then compared to determine whether there was any difference in learning gain related to the type of adaptation to learning style. In addition, the learner experiences in using Oscar CITS were evaluated by analysing the user feedback questionnaires.

Examples of Adaptive Learner Dialogues

Examples of the Oscar CITS tutoring style adaptation can be seen in the dialogue snippets logged during the experiment (Tables 1 and 2). Both snippets are taken from the same tutorial question where students are asked to write an SQL query, and both students were assigned to the Adapt experimental group (i.e. the adaptation matched their learning style). The student dialogue in Table 1 is an example of the tutoring style adapted to a Sequential learner, where Oscar guides the student through the steps of the query. Table 2 in contrast shows a student dialogue with tutoring adapted for a Global learner, where the student writes a query without initial guidance and learns from the feedback given about errors in their solution.

Table . Dialogue snippet logged during the experiment adapting to a Sequential learner.

Utterance	Dialogue
87. Oscar>	Now let's see if you can remember how to write a query which chooses values between a range. Look at the employees table. We need a query which displays the first and last names of all employees hired between 1 January 1994 and 1 January 1995. The first step in writing a query is to state the information you need. For our query to display the first and last names of all employees hired between 1 January 1994 and 1 January 1995, which columns do we need?
88. Student>	dont know
89. Oscar>	Look again at the columns in the EMPLOYEES table. If we want to display the first and last names of all employees hired between 1 January 1994 and 1 January 1995, which columns do we need?
90. Student>	first_name, last_name, hire_date
91. Oscar>	That's right, we need FIRST_NAME and LAST_NAME, so the first part of our query is shown in the picture. The next step in writing a query is to state which table the information is retrieved from. For our query to list the first and last names of all employees hired between 1 January 1994 and 1 January 1995, type in the name of the table our information will be taken from.
92. Student>	employees
93. Oscar>	That's right, the table is EMPLOYEES. The last part of writing a query is the WHERE clause, which lets us restrict the rows selected to only those satisfying one or more conditions. We want to restrict the employees displayed to only those hired between 1 January 1994 and 1 January 1995. There are a number of ways to write this restriction in ORACLE SQL as dates can be represented in different formats. Type in the WHERE clause which limits the employees in this way.
94. Student>	where hire_date in('01-01-1994' && '01-01-1995')

95. Oscar>	One way to tackle this query is to use the BETWEEN keyword to specify a range. Complete the last line of the query shown - type in the WHERE clause to limit the employees displayed to those hired between 1 January 1994 and 1 January 1995.
96. Student>	'01-01-1994' and '01-01-1995'
97. Oscar>	OK, excluding date conversion functions, ORACLE recognises dates in 3 basic formats: '01-JAN-94', '01-January-94' and '01-January-1994'. The picture shows two different ways in which the WHERE clause could have been written to give the right results.

Table . Dialogue snippet logged during the experiment adapting to a Global learner.

Utterance	Dialogue
64. Oscar>	Now let's see if you can remember how to write a query which chooses values between a range. Look at the employees table. Please type in a query which displays the first and last names of all employees hired between 1 January 1994 and 1 January 1995.
65. Student>	select First_name, last_name from Employees where Hire_date between 1-JAN-1944 and 1-Jan-1995;
66. Oscar>	I'm afraid your WHERE clause is not quite right. Check your spelling and type in the last part of our query which displays the first and last names of all employees hired between 1 January 1994 and 1 January 1995.
67. Student>	select First_name, last_name from Employees where Hire_date between 1-JAN-1994 and 1-Jan-1995;
68. Oscar>	No. Excluding date conversion functions, ORACLE recognises dates in 3 basic formats: '01-JAN-94', '01-January-94' and '01-January-1994'. The picture shows two different ways in which the WHERE clause could have been written to give the right results.

Results and Discussion

Of the 70 student participants, 54 fully completed the tutoring session. Table 3 shows the results of the experiment. The group of 8 Neutral students had learning style results which showed no strong preference for a particular learning style (i.e. their styles were balanced in the centre of the scale), and followed a neutral adaptation learning path. The Adapt group contained 32 students who followed a learning path containing learning material in a style adapted to their individual learning styles. The Mismatch group of 14 students followed an adaptive learning path of tutor material which was mismatched to their learning styles.

Table . Experimental results

Experimental Group	No. Students	Average Correct Answers
Neutral	8	72%
Adapt	32	73%
Mismatch	14	61%
Total	54	70%

Students in the Neutral and Adapt groups have similar averages of correct answers given during the tutoring, of 72% and 73% respectively. However, the Mismatch group has a much lower average of only 61% correct answers, which is 12% less than the Adapt group average. The results support the hypothesis that students who are presented with learning material matched to their learning styles perform better than students presented with learning material which is not matched to their learning styles.

In general, the user evaluation results showed that the Oscar CITS was well received, with 95% of learners finding the tutoring helpful and 89% agreeing that Oscar helped them to revise. 91% of the sample said that they would use the Oscar CITS resource, with 86% stating they would use Oscar to support classroom tutoring and 77% saying they would use Oscar instead of learning from a book. A surprising 50% of the sample said they would use Oscar in place of attending face-to-face tutorials. There was a 21% mean test score improvement after tutoring for students who did not achieve full marks in the initial test.

Conclusions and Further Work

This paper has presented a novel conversational intelligent tutoring system called Oscar, which implicitly predicts and adapts to a student’s learning style during a tutoring conversation. Oscar employs a conversational agent to intelligently lead an online tutorial, mimicking a human tutor in offering students learning material adapted to their learning styles, individualised problem solving support and intelligent solution analysis. A CITS which personalises tutoring by dynamically predicting and adapting to learning styles could improve the effectiveness of a student’s learning experience and help to boost confidence. Effective, personalised online tutoring could support class-based courses and widen access through distance learning.

The results of the initial study showed that students whose learning path adapted to their learning styles achieved on average 12% more correct answers than those students presented with learning material not matched to their learning styles. With regards to Oscar’s conversational tutoring, the results have shown that the subjects did value the online Oscar CITS and that Oscar’s tutoring seemed to help learning and improved test scores by 21% on average. It can therefore be concluded that using Oscar has helped provide students with a positive learning experience.

In future, it is planned to incorporate the tutor material categories into a toolkit to speed up the development of an adaptive CITS.

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