Oscar: An Intelligent Conversational Agent Tutor to Estimate Learning Styles

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Abstract—**Intelligent tutoring systems are computer learning systems which personalise their learning content for an individual, based on learner characteristics such as existing knowledge. A recent extension to ITS is to capture student learning styles using a questionnaire and adapt subject content accordingly, however students do not always take the time to complete questionnaires carefully. This paper describes Oscar, a conversational intelligent tutoring system (CITS) which utilises a conversational agent to conduct the tutoring. The CITS aims to mimic a human tutor by dynamically estimating and adapting to a student's learning style during a tutoring conversation. Oscar also offers intelligent solution analysis and problem support for learners. By implicitly modelling the student's learning style during tutoring, Oscar can personalise tutoring to each individual learner to improve the effectiveness of the tutoring. The paper presents the novel methodology and architecture for constructing a CITS. An initial pilot study has been conducted in the domain of tutoring of undergraduate Science and Engineering students using the Index of Learning Styles ILS) model. The experiments to investigate the estimation of learning style have produced encouraging results in the estimation of learning style through a tutoring conversation.**

I. Introduction

INTELLIGENT Tutoring Systems (ITS) are computerised learning systems which attempt to imitate human tutors to provide more personalised learning than previous content delivery systems [1]. If human tutors could be mimicked adequately, the effectiveness of online learning would be improved and access to learning widened. The availability of an effective computer tutor would have a positive impact on distance learning as well as offering support for traditional class-based courses. Students attending an online tutoring session are able to learn at their own pace and at a time suited to other commitments. Students could also benefit from personalised learning, with the ability to revisit and delve further into topics they have not fully understood, which cannot be offered in a class of many students. For education establishments, online tutorials are a cost-effective way of offering flexible courses, with the cost fixed and borne at the time of development regardless of the number of students.

ITS are generally designed with a menu-style user interface [2], but a conversational interface would be a more natural mimic of human tutoring, offering constructivist styles of learning as used by human tutors [3]. Only a small number of ITS allow discussion with the tutor [4] due to the time and complexity of development. Like human tutors, ITS adapt the tutorial content for each individual student. Adaptation is normally based on a student's level of knowledge, but a recent enhancement is to present content suitable to a student's learning style [5], [6]. Learning styles describe the way in which groups of people learn most effectively, and are normally assessed by questionnaire [7]. Human tutors often informally pick up cues from students which indicate their understanding of a topic, and adapt the tutoring to aid learning, for example by drawing a diagram or giving a practical example. By assessing the student's reaction to particular styles of tutoring, human tutors then favour the more successful styles in future tutorials. ITS adaptation to learning style normally requires the student to complete a formal questionnaire [5], however students do not always take the time to answer questionnaires accurately, leading to incorrect results and less effective learning. Some ITS model learning style based on historical learning behaviour, however adaptation to learning style cannot then be offered initially. If an ITS could learn and adapt to a student's learning style during a tutoring conversation, such personalised, conversational tutoring would improve the student's learning experience. The novel conversational ITS described in this paper aims to mimic a human tutor by learning and adapting to a student's learning style during the tutoring conversation.

Conversational agents (CAs) are computer programs which interact with users by natural language [8]. There are three main approaches to developing CAs – using natural language processing (NLP) [9], pattern matching [10] or artificial intelligence (AI) techniques [11], which will be outlined in section II. The Oscar CITS presented in this paper adopts the pattern matching approach, which may be more reliable as patterns can cope with grammatically incorrect user utterances [11], as often used by students. Conversational agents require scripting for particular domains, a time-consuming and complex task, however to replicate human tutoring, a conversational interface is important.

This paper describes Oscar, a novel CITS which estimates

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student learning styles by picking up cues from students during tutoring conversations. By learning and adapting to a student's learning style during a tutoring conversation, Oscar can intelligently personalise tutoring at an early stage and without additional burden on the learner. Oscar is a web-based CITS with a CA interface which leads the tutoring session, asking questions, showing visuals and movies and offering intelligent feedback to students. A novel architecture has been designed which will facilitate the development of a CITS in any domain. For the purpose of this paper Oscar has initially been developed to offer online SQL revision tutorials. The results of the initial pilot study are presented which analysed student interaction with Oscar during an SQL revision tutorial to assess the accuracy of learning style predictions.

This paper is organised as follows: Section II will describe conversational agents, Section III introduces learning styles, Section IV will outline ITS, Section V introduces the Oscar CITS, Section VI describes the experimental methodology of the pilot study and Sections VII and VIII include the results, discussions and conclusions.

II. Conversational Agents

Conversational agents allow people to interact with computer systems using natural language dialogues. There are three main approaches to developing CAs. The natural language processing approach [9] seeks to understand the user input by studying the constructs and meaning of natural language, applying rules to process important parts of sentences. Pattern matching systems [10] use an algorithm to match key words and phrases within an utterance, and so do not require grammatically correct or complete input. The AI method [11] compares the semantic similarity of phrases to decide on the meaning of the input.

CAs usually rely on a knowledge base containing a set of rules. User utterances are matched to pattern-based rules in the knowledge base and an algorithm decides which is the best fitting rule to fire, producing the CA response. A rule normally consists of an identification, a set of stimulus patterns, the rule's current status and a response pattern [11]. The Oscar CITS uses a pattern matching CA, which is most reliable in coping with student utterances including grammatically incorrect or incomplete language.

III. Learning Styles

Learning styles describe the way in which groups of people learn most effectively, for example by trial and error, or by observation [12]. There are numerous models of learning styles, which are generally assessed using self-assessment questionnaires. Most models of learning style describe dimensions along which a value is placed to represent the tendency for learning style. For example, on a visual/verbal dimension, learners who are more comfortable with discussion and verbal explanation tend towards the verbal end, whereas learners who prefer to study diagrams and pictures would tend towards the visual end.

Learning styles are thought to be a subset of personality [12] and there is much discussion in the literature about whether and how learning styles can be of use to teachers and learners [13], [14]. Pask concludes "It seems evident that distinctive learning strategies exist. ... There are also certain distinct styles, or dispositions to adopt classes of strategy" [14].

An early learning styles model was Kolb's Experiential Learning Model (ELM) [7], which is a four-stage learning cycle which can be entered at any point. ELM was developed further to produce the *Learning Style Inventory* (LSI), a 12 item questionnaire requiring the ranking of sentence endings [7]. Honey and Mumford's *Learning Style Questionnaire* (LSQ) was developed for management trainees and defines four learning styles which are similar to the stages of learning in ELM [15]. The LSQ model has been used in some ITS [1].

The *Index of Learning Styles* (ILS) [16], [17] was developed to describe the learning styles in engineering education and suggest different pedagogical styles to address learners' needs. The ILS model defines four dimensions of preferred learning style: perception (Sensor/Intuitor), input (Visual/Verbal), processing (Active/Reflective) and understanding (Sequential/Global). The ILS uses a self-assessment questionnaire with 11 questions per learning style dimension, which results in a score for each of the four dimensions. Each learning style dimension represents an axis with the opposite learning styles at each end (e.g. Visual versus Verbal), and the ILS questionnaire score places each learner on the axis according to the strength of their preferred learning style. The ILS has been adopted by a number of ITS [18], [5], [19], [20]. The ILS model was chosen for the Oscar CITS as it was designed for engineering students, who will make up the initial experimental groups. However, Oscar's modular structure means it is not restricted to ILS and can be adapted to use other learning style models.

IV. Intelligent Tutoring Systems

Computer-assisted learning systems were traditionally information-delivery systems developed by converting tutor or distance-learning material into a computerised format. The popularity of the Internet has enhanced the opportunities for e-learning, however most online systems are still teacher-centred and take little account of learner needs [21]. [22] identified two main groups of adaptive and intelligent web-based educational systems - Adaptive Hypermedia Systems (AHS) and Intelligent Tutoring Systems (ITS). AHS are akin to interactive books which adapt the navigation and content of hyperlinks to the knowledge of the user [1], [6]. ITS personalise teaching according to individual student characteristics, such as knowledge of the subject. A student model is built, including personal details and learning history, and teaching is adapted to the student. Such systems are now being extended to adapt to other student information, such as mood and emotion [23], [24] and

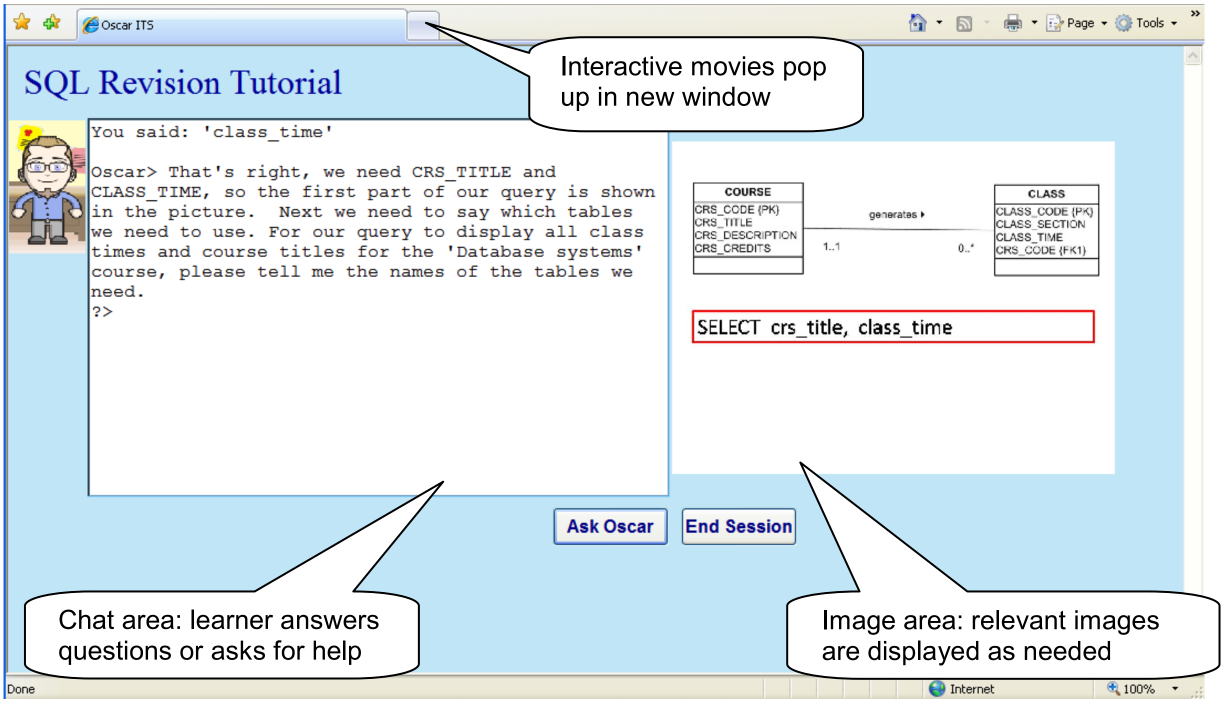

Fig. 1. Oscar CITS learner interface.

learning style [19].

Three approaches to intelligent tutoring are curriculum sequencing, intelligent solution analysis, and problem solving support [22]. Curriculum sequencing involves presenting each student with learning material in a sequence and style best suited to their needs [25]. Intelligent solution analysis aims to provide detailed feedback to the student on incomplete or erroneous solutions [2], and problem solving support techniques offer intelligent help in arriving at a solution [26]. Curriculum sequencing alone is little better than personalising a book, but by incorporating intelligent solution analysis and problem solving support an ITS can get close to mimicking a human tutorial. Few ITS incorporate all three intelligent approaches as they are complex and time-consuming to develop. However, combining all three technologies adds benefits by offering a more effective learning experience and intelligent support which can help to build confidence and motivation. The Oscar CITS presented in this paper will include all three intelligent technologies by personalising the learning material and helping the student to construct knowledge and learn from their mistakes.

A. Conversational ITS

Conversational interfaces have rarely been incorporated into teaching and learning systems, however the benefits of constructivist styles of learning (as used by human tutors) are widely accepted [27]. To mimic a human tutor, ITS should support the construction of knowledge: "*it seems necessary for future generations of ITSs to incorporate natural language capabilities.*" [31]. The complexity of developing conversational tutors means where CAs are included in ITS, it is often to interact or help with the learning management system (e.g. how to use the system) rather than conduct the tutoring [28], [29]. Two conversational ITS which do adopt CA tutors are AutoTutor [4] and CIRCSIM-tutor [30]. AutoTutor allows students to construct knowledge about computer literacy and physics through conversations. CIRCSIM-tutor incorporates a CA to allow students to solve physiology problems by discussion. Neither of these CITS take learning styles into consideration during tutoring.

B. Adaptation to Learning Style

Most ITS personalise learning by adapting to a student's existing knowledge of the subject. The extension of ITS to adapt to other student characteristics, such as learning style, is a new area of research. A small number of ITS which adapt to learning style use formal questionnaires completed by students during registration [5], [21]. However, students may not complete the questionnaire accurately as it is time consuming, therefore producing an unreliable student model [19]. There have been some attempts to detect learning style by analysing a student's behaviour history within the ITS [19], [20], [32], [33]. Whilst removing the need to complete a questionnaire, such ITS are not able to adapt to learning style until a number of learning modules are complete. Estimating learning style dynamically and continually updating the student model allows an ITS to adapt to changes in learning style over time. The EDUCE [34] and WELSA [35] adaptive educational systems both dynamically estimate learning style for curriculum sequencing, however they do not include a conversational interface or incorporate other intelligent tutoring technologies. The Oscar CITS reported in this paper will dynamically estimate learning style during a tutoring conversation, and then adapt the tutoring to suit that learning

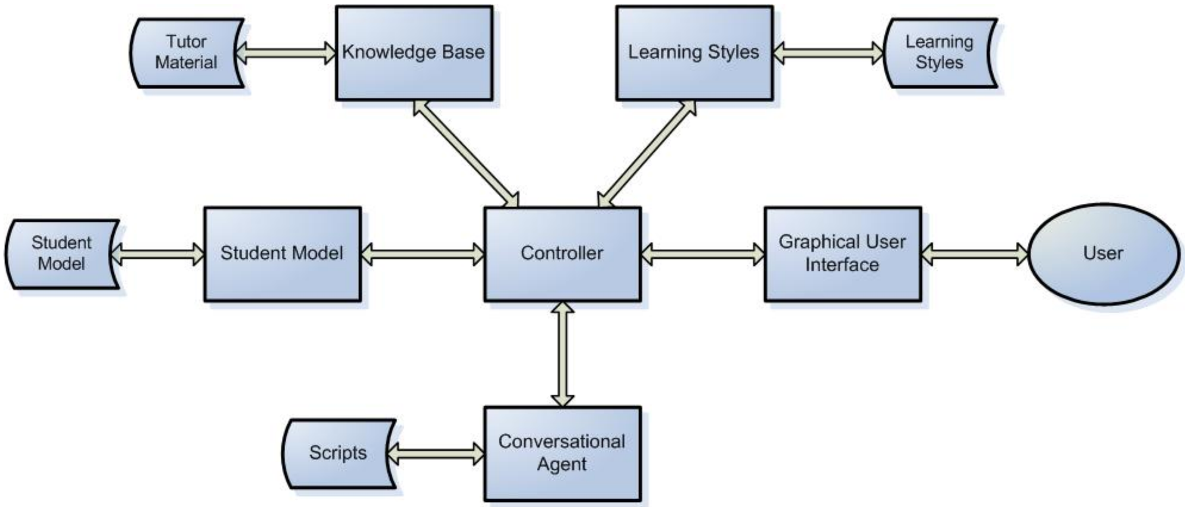

Fig. 2. Oscar CITS structure.

style whilst offering intelligent solution analysis and problem solving support.

V. OSCAR CITS

The Oscar CITS is a conversational intelligent tutoring system which can dynamically estimate and adapt to a student's learning style during a tutoring conversation. In addition to curriculum sequencing, Oscar aims to mimic a human tutor in offering intelligent solution analysis and conversational problem solving support in the domain of the database Structured Query Language (SQL). The ILS model was adopted, which describes different learning characteristics and identifies associated pedagogical styles for engineering students. Oscar draws on a knowledge base of 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 estimation of learning style, allowing the tutoring style to be personalised to best suit the student.

Fig. 1 shows the Oscar CITS graphical user interface (GUI) during a tutoring session, where a diagram is visible and a tutoring conversation is taking place. The student is being asked to write a query with four main parts, and has chosen to be guided through each step by Oscar. The image shows a Unified Modelling Language (UML) diagram of the relevant database tables and the first part of the query written so far. In the chat area, Oscar has responded to confirm that the learner's previous answer was correct and has stated the next step in writing the query. Oscar then reminds the learner of the main query question and asks for information required for the next stage.

A. *Oscar Architecture*

Fig. 2 shows the overall structure of the Oscar CITS. A *central controller* communicates with all components to manage the user interaction. The *knowledge base* manages course information, such as topics and their breakdowns, related tests and teaching material, which is accessed from a Tutor Material database. All tutor information is categorised according to teaching style (related to learning style). The *learning styles* component receives information from the CA, GUI, knowledge base and student model and accesses the Learning Styles database, to estimate a learning style. The *student model* holds information about the student, such as name, level of knowledge, topics visited, test scores and learning style. The *GUI* (Fig. 1) displays a webpage showing questionnaires, tests, images, documents and interactive movies and sends communication to and from the user. The *conversational agent* receives natural language text and information about topic and learning style from the GUI, knowledge base and learning styles components, and generates a natural language response. The CA accesses a database of scripts in order to match the input and generate a response.

B. *Methodology*

Learning styles are central to the Oscar CITS, so development started by considering the ILS model. The ILS questionnaire contains 44 questions – too many to incorporate into a tutoring session, so a pilot study was done of 103 completed ILS questionnaires to investigate which were the best predictor questions [36]. The study found that 17 questions predicted the overall result in at least 75% of cases, with the top three questions predicting the result in 84% of cases. The subset of the best ILS predictor questions for each learning style dimension was then considered during the development of the Oscar CITS.

The domain of SQL was selected as the target audience for the pilot study would be undergraduate computing students, for whom a Databases course including SQL is compulsory. The ILS model, which was designed to describe engineering students' learning styles, is appropriate to this target group. Several interviews with undergraduate level database course tutors were undertaken. In consultation with database course lecturers, several SQL concepts were identified from an undergraduate Databases course syllabus.

Tutoring revision scenarios were designed, based around the syllabus and the database lecturers' experience of revision tutorials. Each revision question was mapped to the ILS model by incorporating questions from the questionnaire and using the model's descriptions of indicative behaviour, such as a preference for theoretical questions. Table I shows two examples of logic rules used by the system to increment learning style values during tutoring. Learning styles are held in eight values within the student model, representing each pole of the four dimensions. The logic rules are incremental, increasing learning style values where particular behaviour is evident. At the start of the first tutoring session, no initial learning style values exist for a student. During the tutoring conversation, learning style values are incremented depending on the student's tutoring conversation. At the end of the tutoring session, the value pairs of each learning style dimension are compared to reveal the student's overall learning style tendency for that dimension (i.e. the greater value). Learning style values depend on an individual's unique tutoring session, and if no evidence is gathered to suggest a particular learning style dimension, that learning style will remain unclassified. For example, student *x* attended a tutoring session on SQL during which their behaviour was analysed to uncover evidence suggesting a particular learning style. At the end of the tutoring discussion, the student's learning style was estimated to be Intuitor and Verbal, but no evidence was found to categorise the student for the remaining two learning style dimensions (Active/Reflective and Sequential/Global). Student *x* next completes a follow-up tutorial session which favours content to match an Intuitor/Verbal learning style. Incremental evidence from both tutoring conversations estimated the student's learning style to be Intuitor/Verbal/Active but there was no evidence to indicate a value for the Sequential/Global dimension.

TABLE I
EXAMPLE OF LOGIC RULES USED TO ADJUST STUDENT LEARNING STYLE VALUES BASED ON TUTORING CONVERSATION

1. Example rule to test whether presenting information visually helps the student's information perception:

```
IF      student does not know the answer
THEN    show student image/diagram;
IF      student shown image/diagram
AND     student gives correct answer
THEN    increase VISUAL;
```

2. Example rule to test how comfortable the student is with words and with detail:

```
IF      answer is given in the explanation text
AND     student does not know the answer
THEN    increase INTUITOR
AND     increase VISUAL;
```

Tutoring conversations were written based on the SQL revision scenarios, including numerous possible student responses. Additional material such as images, diagrams and movies was incorporated into the tutoring conversations and mapped to learning styles. The resulting tutorial walkthroughs indicated which learning style should be incremented at which point, based on the student's learning path.

TABLE II
EXAMPLE OF INFOCHAT PATTERNSCRIPT SCRIPTING SHOWING AN FAQ RULE

```
<Rule-01>
a:0.01
p:50   *<explain-0> *select*
p:50   *select* <explain-0>*
p:50   *<remind-0> *select*
p:50   *select* <remind-0>*
p:50   *<confused-0> *select*
p:50   *select* <confused-0>*
r:     The SQL SELECT command is used to retrieve data from
       one or more database tables.
```

Several styles of question were included, for example practical problems to create queries and theoretical questions to test knowledge. Standard question formats were represented diagrammatically to speed up development by reuse of the logic and CITS scripts. A list of frequently asked questions (FAQs) about SQL was compiled and an existing multiple choice test was adapted to cover the revision syllabus.

Next began the time consuming and complex task of scripting the CA component. Convagent's InfoChat CA [37], a CA employing natural language pattern matching, was chosen. CA scripts, organised into contexts, were developed to manage the tutorial conversation and respond to student inputs. Overall, there were 38 contexts containing around 400 rules which demonstrates the complexity of developing a CITS. A frequently asked questions (FAQ) layer of scripts was developed to deal with student responses which did not directly relate to the current question. Additionally a lower layer of scripts was designed to pick up abusive language (sessions are ended at this point). An example FAQ rule from one of the InfoChat scripts is shown in Table II. In the rule, *a* is the activation level used for conflict resolution [38]; *p* is the pattern strength followed by the pattern and *r* is the response. Also seen in the example is the wildcard (*) and macros (<explain-0>) containing a number of standard patterns which are each matched separately. Further information about the PatternScript language and InfoChat algorithm is available by contacting http://www.convagent.com.

The student model was designed, which holds the student name and password, level of knowledge, test scores and learning style values. The Oscar CITS components were then developed, producing a framework system which draws on various resources (the conversational agent scripts, tutor material, student model and learning styles) to present an adaptive tutoring session. The CITS student registration includes the completion of the ILS questionnaire and the completion of a multiple choice question (MCQ) pre-test to assess existing student knowledge. The same MCQ test is presented at the end of the tutoring session in order to assess learning.

During tutoring, the CITS records and logs information about the behaviour of the student, such as timing of interactions, the number of words used, the number of times FAQs are asked 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.

VI. Experimental Methodology

An initial pilot study was conducted to assess the Oscar CITS in two ways – firstly Oscar's estimation of learning style and secondly the acceptance of the Oscar tutor by users. Three experiments were conducted, focusing on the perception (Sensor/Intuitor) and input (Visual/Verbal) ILS learning style dimensions. Experiment 1 explored the student's path through the learning material, Experiment 2 examined the number of discourse interactions during tutoring and Experiment 3 investigated reading time.

TABLE III
Experimental Results

	Learning Style	Comparison	Accuracy of Estimation
Experiment 1 – learning path			
	SNS/INT[a]	-	70%
	VIS/VRB[b]	-	50%
Experiment 2 – number of interactions			
	VIS/VRB	Mean	70%
	VIS/VRB	Median	70%
Experiment 3 – reading time			
	VIS/VRB	Mean	60%
	VIS/VRB	Median	70%

[a]SNS/INT is the Sensor/Intuitor dimension
[b]VIS/VRB is the Visual/Verbal dimension

Ten people were chosen whose first language was English and who had previous experience of an undergraduate ORACLE SQL course (but with various levels of expertise). Each person registered for the Oscar CITS, completing the ILS questionnaire and pre-test, and then went through the SQL revision tutorial. Finally each person completed the post-test. At the end of the tutoring session, each person was informally interviewed and asked to complete a feedback questionnaire.

The log files recorded by the Oscar CITS for each person were analysed and compared to the results of the formal ILS questionnaire to assess whether the information being collected could be used to indicate learning style, and whether Oscar had accurately estimated learning style.

For Experiment 1, depending on the student's answers to tutoring questions, learning styles were incremented according to the mappings made to the ILS model which were documented in the tutoring conversation walkthrough. The final learning style scores were then converted into an overall learning style for each dimension, e.g. for the VIS/VRB (Visual/Verbal) dimension if the score for Visual was higher than that for Verbal, the student was considered to be Visual. The learning style result was compared to the ILS questionnaire results for each student.

For Experiment 2, the number of discourse interactions during the tutoring session was counted and compared to the mean and median values across the sample group. The hypothesis was that the more discursive a student is (i.e. the more interactions), the more they tend towards the verbal learning style.

For Experiment 3, the mean time taken to read 10 Oscar words was calculated for each student and compared to the mean and median values across the sample group. The hypothesis was that the longer a student takes to read instructions (i.e. the less comfortable the student is with words), the more they tend towards the visual learning style.

The next section presents and discusses the results of these experiments.

VII. Results and Discussion

Table III summarises the results of the three experiments. It should be noted that, as expected, the split of learning styles assessed by the ILS questionnaire was not equal across the sample. For the SNS/INT (Sensor/Intuitor) dimension, 20% of the sample was Sensory and 80% Intuitive learners. For the VIS/VRB dimension, 80% of the group was Visual and 20% was Verbal learners. Each experiment will now be discussed separately, and then the learner feedback on Oscar CITS will be summarised.

A. *Experiment 1 - Learning Path*

In experiment 1, the estimation of learning style depended on the learner's path through the tutoring material. For the perception dimension (Sensor/Intuitor), Oscar's result agreed with the ILS questionnaire result in 70% of cases. For the input dimension (Visual/Verbal), Oscar's results agreed with the ILS questionnaire in only 50% of cases. Clearly, further work and consideration needs to be given to the effect of visual material (images) versus discussion and explanation on the learner's understanding. As the tutorial is tutor-led rather than student-led, this dimension may be more difficult to estimate by conversation than in, for example, a hyperlink system [35]. However, the results of each experiment are not intended to be taken in isolation, and the development of an algorithm to combine different types of analysis may offer better accuracy.

B. *Experiment 2 – Number of Interactions*

Experiment 2 relates to the input dimension (Visual/Verbal) with the hypothesis that the students who enter into most discussion with Oscar are Verbal learners. The students were categorised as Visual or Verbal learners by comparing the number of discourse interactions to the mean and the median for the sample, and this was compared to the ILS questionnaire result. In 70% of cases for both the mean and median comparisons, there was agreement in the learning style assessment.

C. *Experiment 3 – Reading Time*

The hypothesis for Experiment 3 was that Visual learners take longer to read than Verbal learners. Students were categorised as Visual or Verbal learners by comparing their mean reading time for 10 Oscar words over the whole tutoring session with the group mean and median. Compared to the group mean, Oscar agreed with the ILS in 60% of cases, rising to 70% of cases when compared to the sample median. The mean differed considerably from the median, by 2 seconds, as the duration of the tutoring session also differed substantially, by 37 minutes, 7 seconds. As each individual's learning path is different, different numbers of Oscar words will be presented, however the indication is that the median is the most appropriate measure for comparison in this case.

D. Using Oscar CITS

In general, the user feedback from the initial pilot study showed that Oscar was well received, understandable and helpful. All students showed an improvement in their test scores after the revision tutorial, with the average improvement across the sample of 21%. 90% of the group would use Oscar to support classroom tutoring, with a surprising 20% stating they would use Oscar *instead* of face-to-face tutoring. Only 40% of learners agreed that they would use the Oscar CITS instead of reading a book. When openly asked for comments, half of the group commented that the conversational interface was natural and easy to understand, with one learner remarking "*it encouraged me to think rather than simply giving me the answer".*

VIII. Conclusion

This paper has presented the novel architecture and methodology for developing Oscar, a CITS which implicitly estimates and adapts to a student's learning style. Oscar employs a CA to intelligently lead an online tutorial, mimicking a human tutor in offering students individualised problem solving support and intelligent solution analysis. A CITS which personalises tutoring by dynamically estimating and adapting to learning style could improve the effectiveness of a student's learning experience and help to boost confidence. Effective, personalised online tutoring could offer support for class-based courses and widen access with distance learning.

The results of the initial pilot study are promising, with an accuracy of estimating learning style of 70% in three cases but 50% in the worst case. It is not appropriate to draw firm conclusions with a small initial sample size, and an unequal spread of learning style. Further experiments with a larger group are currently being undertaken. In addition, an algorithm using a fuzzy set representation of learning styles is currently being developed to combine different aspects of behaviour to improve the accuracy of learning style estimation. With regards to Oscar's conversational tutoring, the results have shown that the subjects did value the online Oscar CITS in supporting classroom lessons, and that Oscar's tutoring seemed to help learning and improved test scores in every case. It can therefore be concluded that using Oscar has helped give students a positive learning experience.

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