ascilite 2011
CHANGING DEMANDS, changing directions.
Wrest Point | Hobart Tasmania Australia | 4–7 December 2011

An Investigation into the Learning Styles and Self-Regulated Learning Strategies for Computer Science Students

Ali Alharbi, **David Paul, Frans Henskens and Michael Hannaford**
School of Electrical Engineering and Computer Science,
The University of Newcastle, Australia

Student-centred educational paradigms place a high level of responsibility on learners to control and self-regulate their personal learning processes. In these new educational paradigms, it is essential to understand students' preferences and the self-regulated learning strategies they use in order to enhance the learning process. This paper examines the different learning styles and self-regulated learning strategies used by students in a core computer science course. An Index of Learning Styles and a Self-Regulated Learning Strategies Questionnaire were administered to second year students studying programming languages concepts and paradigms. Results show that aspects of students' preferred learning styles had a significant impact on academic performance in the midterm examination. Further, consideration of the self-regulated learning strategies used by students provides evidence that metacognitive strategies were the least popular strategies among students. This suggests that students are not aware of important self-regulated learning strategies and may benefit from educational interventions focusing on these strategies. These results have implications for future teaching of the course, and are being used to guide the development of an online collaborative learning objects repository that aims to improve self-directed student learning.

Keywords: learning styles, self-regulated learning, computer science education

Introduction

The recommended educational paradigm has shifted from being teacher-centred to being more student-centred, with each student taking greater responsibility for his or her own learning process (Berglund, et al., 2009). Since every student has different learning preferences, it is important that course material is presented in such a way that no student is unfairly disadvantaged. To ensure an equal experience for all students, it is necessary to understand the learning preferences and strategies of the students being taught. Adopting a specific teaching method without considering the diverse needs of the group being taught can result in an inefficient learning outcome for some students (Pritchard, 2009). Thus, when presenting learning material to students, it is important that all student learning styles are supported. Further, the interaction between the learners and the learning material should be taken into consideration to improve the quality of the learning material over time.

Researchers have only recently started investigating educational aspects to improve the learning and teaching of computer science (Haden, Fincher, & Petre, 2004). In computer science courses, very few students share the same learning styles as their instructors (de Raadt & Simon, 2011). Thus, instructors cannot wholly rely on their own learning styles when developing learning material for their students. However, studies that investigate the learning styles of students in computer science courses are limited (de Raadt & Simon, 2011). Further, these studies focus only on students' learning styles, isolated from other aspects of student-centred educational paradigms, such as the cognitive and social aspects of teaching and learning. Education theories that combine cognitive and social aspects of learning can help provide a framework leading to a greater understanding of students' preferences and introducing a new direction for research and design of learning material in computer science education (Ben-Ari, 2004; Machanick, 2007).

This paper describes the diversity and influence of learning styles and self-regulated learning strategies for students enrolled in the core computer science course entitled "Programming Languages and Paradigms" at The University of Newcastle. This provides a case study for computer science education, and is being used to aid the development of an online collaborative learning object repository that assists students by evaluating their preferred learning style and directing them to the materials that they should find most useful. The aim of the study is to provide a baseline to assist the design and allow the evaluation of the effectiveness of a new online collaborative learning objects repository. This study is guided by the following questions:

1. What aspects of learning styles can be found in a typical computer science course?
2. What is the degree of use of different self-regulated learning strategies by students in the course?
3. What is the influence of students' learning styles on their academic performance in the course?
4. What self-regulated learning strategies have the most influence and need more focus?
5. How can the results of this study be combined with contemporary education paradigms to provide a framework for building a collaborative learning object repository to improve the next iteration of the course?

Theoretical Background

Different students perceive and process information in different ways (Shaw & Marlow, 1999). A student's preferred learning style is one of the main individual differences that effects how the student approaches new knowledge. Another important factor is the student's use of various self-regulated learning strategies. This section provides a brief introduction to learning style theory and self-regulated learning, and relates the theories to education in computer science.

Learning Style Theory

Learning is the process by which individuals acquire new knowledge. Each individual is different, so every student approaches the learning environment in a different way. A learning style is "the characteristic cognitive, affective and psychological behaviours that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment." (Keefe, 1988). Learning styles are not fixed, and learners can adopt a different learning style depending on the subject matter and current learning environment (Pritchard, 2009). However, students do typically have one learning style that is preferred over others and can be motivated by learning material compatible with this preference (Larkin & Budny, 2005). Knowledge of their preferred learning styles can be used to help guide students to choose the best learning strategies, and allow teachers to modify their instructional strategies to provide the greatest opportunity for all students to learn.

This paper uses the Felder-Silverman Learning Style model (Felder & Silverman, 1988), a popular model to identify learning styles in science and engineering education. It is used for both traditional and technology-supported learning, and consists of the following four dimensions:

Perception (Sensing or Intuitive) describes the ways in which learners tend to perceive information. Sensing learners prefer to learn facts, are comfortable with details, and tend to solve problems using well-established methods. Intuitive learners prefer abstract concepts, theories, and mathematical formulas, and seek innovation and new ideas when solving problems.

Input (Visual or Verbal) distinguishes between learners based on their preferred medium for the presentation of information. Visual learners prefer to learn using visual medium of presentations, such as pictures, charts, and diagrams. Verbal learners prefer spoken or written materials. Both types of learners benefit when material is delivered using a combination of visual, verbal, and written forms (Mills, Ayre, Hands, & Carden, 2010).

Processing (Active or Reflective) evaluates learners based on the way they process information. Active learners prefer to learn material by using it, whereas reflective learners prefer to think about how things work before actually trying them out. Active learners are typically more comfortable working in groups than reflective learners.

Understanding (Sequential or Global) looks at how users understand new information. Sequential learners like to follow a step-by-step linear approach that focuses on the connections between the different parts of the learning material. Global learners prefer to grasp the full picture before narrowing into the details.

Self-Regulated Learning

In student-centred educational paradigms, it is essential for learners to control and regulate their individual learning processes (Chen, 2002). Self-regulated learning is an educational theory influenced by constructivism theory (Ben-Ari, 1998) and social learning (Bandura, 2001). Self-regulated learners are characterized by their ability to be “metacognitively, motivationally, and behaviourally active participants in their own learning process” (Zimmerman, 1986). Metacognition refers to an individual’s awareness and control of the cognition process and includes processes such as goal setting, planning and self-evaluation used to control and monitor the individual’s learning process (Pintrich, 1999). While there are various models of self-regulated learning (Curry, 1983), they all share some main assumptions (Pintrich, 2004). Firstly, the learner is considered to be an active participant in the learning process rather than a passive receiver of knowledge. Secondly, it is possible for the learner to control, monitor and self-regulate some of the learning process. Finally, the learner has a goal and the learning process can be evaluated to determine whether the current learning process will reach that goal, or whether a change is required. Learners can improve their learning strategies through a variety of different techniques. These techniques fall into the following categories (Pintrich & De Groot, 1990):

Cognitive learning strategies are methods used by the learner to deal with the actual learning material. Elaboration methods, such as summarizing, paraphrasing and relating new information to existing knowledge is one cognitive strategy that has a positive impact on the academic performance of students (Pintrich & De Groot, 1990). Other examples are organisational strategies, which involve creating hierarchies of presented information to make it easier for the learner to connect related concepts, and critical thinking, which evaluates the creditability of the learning material and attempts to apply the concepts under study to new situations.

Metacognitive learning strategies are based around the learner’s knowledge and self-regulation of their own cognition through planning and monitoring of their cognitive learning activities (Pintrich, 1999). Planning involves setting goals and generating questions to guide study and make the learning process easier. Monitoring strategies include self-assessment to verify the learner’s understanding of the material.

Resource management strategies require the learners to take control of their learning environment. This includes management of time and study environment. Another important aspect is the management of who to include in the study environment; being able to seek help and learn from peers are important characteristics of a self-regulated learner (Ryan & Pintrich, 1997).

Computer Science Education

Teaching and learning of computer science concepts are challenging tasks for both teachers and students (Ben-Ari, 1998). Computer science involves studying dynamic and abstract concepts that are difficult for students to understand using traditional teaching and learning methods. Further, computer science is a rapidly changing area, which is driven by newly emerging technologies rather than the pedagogy (Holmboe, McIver, & George, 2001). “Only recently have CS educators begun to explore important issues and methodologies in computer science teaching” (Haden, et al., 2004). Computer science education research is still in its infancy and there are many initiatives to apply different learning theories to improve computer science education.

In the last few years, student-centred approaches to learning have received some attention in computer science education. These approaches focus on the role of the learners to discover and construct knowledge through active participation in the learning process. This new view of learning is related to some extent to the theory of constructivism (von Glasersfeld, 1997). Constructivism theory has particularly influenced mathematics and science education, and in the last few years computer science education research has investigated the role of constructivism as a theoretical basis of computer science education (Ben-Ari, 1998).There have been a number of educational approaches and software proposals based on the theory of constructivism. Problem-based learning, in particular, is a technique based on constructivism that has been found useful in computer science education. However, constructivism accounts only for cognitive aspects of learning and neglects, to some extent, the social dimension of learning. Cognitive-based models are not enough to describe the learning process (Machanick, 2007), so new models are required for computer science education. In particular, there is a need for models that include the social aspects of learning.

There have been some previous studies to investigate the learning styles of computer science students. Thomas et al. (2002) investigated the learning styles of students enrolled in an introductory programming course. The majority of students in the study were assessed as sensing, visual, reflective and sequential. The result of the study indicated that, in the exam portion of the course, significant differences were detected in students' performance between reflective and active learners in favour of reflective learners, and between verbal and visual learners in favour of verbal learners. One interesting result of the study was that although the majority of students were visual learners, verbal learners had the highest performance in the course. This result is consistent with the results reported in (Chamillard & Karolick, 1999) and (Allert, 2004). In a recent study, de Raadt and Simon (2011) stated that there is a scarcity of research in the exploration of learning styles in computer science education. Motivated by this, they conducted a study to investigate students' learning styles, again in an introductory programming course. The study found that the majority of students preferred practical applications and concrete information connected to reality and were comfortable with details. They prefer to learn using simulation and case studies. The study concluded that learning materials do not have to cover all possible learning styles but "at least provide one usable thing for each student" (de Raadt & Simon, 2011).

The existing studies of learning styles in computer science education have investigated aspects of learning styles independently of other pedagogical factors, such as the strategies used by students when presented with learning material. While the results are interesting, they do not suggest how they can be integrated with other contemporary learning theories to improve the learning process. Further, the studies mentioned do not indicate the strength of the students' learning style preferences, making it difficult to determine which aspects of learning styles require greater focus. Self-regulated learning models can explain not only cognitive aspects of learning but social aspects as well. Thus, an investigation into the learning styles and self-regulated learning strategies of students can be combined to help provide a framework upon which educational interventions can be built. This study presents an investigation into the learning styles and self-regulated learning strategies of computer science students to assist with the design of a collaborative learning object repository for use in future iterations of the course, and to provide a baseline to test the effectiveness of the new system.

Research Method

The purpose of this study was to evaluate the learning styles and self-regulated learning techniques used by computer science students as a necessary step towards the improvement of teaching and learning methods of a computer science course. This required the collection and analysis of data from computer science and software engineering students. In this section we describe the participants used in the study, the data collected from them, and how the data has been analysed.

Participants

Participants were 38 students enrolled in the "Programming Languages and Paradigms" course taught at the University of Newcastle, Australia, in the first semester of 2011. This is a compulsory second year course for undergraduate students enrolled in the computer science and software engineering programs. The course covers the theory behind the design and implementation of programming languages, recognised as an integral part of any computer science or software engineering degree (IEEE/ACM, 2005). The course follows a traditional teaching method consisting of weekly lectures and workshops. The instructor covers the theoretical concepts of the course in the lectures using PowerPoint slides that have been prepared based on cumulative experience from teaching the course for the last few years. The workshops provide hands-on exercises to show students how the concepts covered in the lectures are applied in practice. Interaction between students and instructors outside of the formal face-to-face sessions is supported through the Blackboard learning management system. Students have to complete three individual practical assignments throughout the course, as well as written midterm and final exams. This study uses the midterm exam as a way to measure students' performance in the course.

Data Collection Instruments

Data was collected from participants immediately before they sat the midterm examination for the course. The Index of Learning Styles (Felder & Soloman, 1997) was used to identify each student's learning style according to the Felder-Silverman model. This was followed by a questionnaire based on the Motivated Strategies for Learning Questionnaire (Pintrich, Smith, Garcia, & McKeachie, 1991) to evaluate the self-regulated learning strategies used by the participants.

The Index of Learning Style comprises 44 items that present the participant with a situation and two possible options, asking the participant to choose the option that best represents him or her. There is a total of 11 items for each of the four dimensions of the Felder-Silverman model; these rank participants as either sensing or intuitive, visual or verbal, active or reflective, and sequential or global learners. The self-regulated learning strategies questionnaire consists of 30 items that ask the participant to indicate the extent to which a certain statement applies to the participant using a seven-point Likert scale ranging from “Very true of me” to “Not at all true of me”. The questionnaire determines the extent to which the participant utilizes the six self-regulated learning strategies of elaboration; organization; critical thinking; metacognition; peer learning and help seeking; and e-learning resource management. Students’ academic performance was measured using the midterm exam scores. The exam is a traditional paper-based assessment in which students have to respond to different questions that cover a number of modules studied in the course.

Data Analysis

Descriptive analysis was conducted using the mean, standard deviation, and charts to examine the study variables. A correlation analysis between the study variables was then performed using Pearson’s product moment correlation coefficient. Finally independent samples t-tests were used to investigate the difference in midterm exam scores between students with different learning styles.

Results

This section describes the analysis of the data collected for this study. The results for the various learning styles used by the students are presented first, followed by an investigation of the relationships between the reported self-regulated learning strategies.

Student Learning Styles

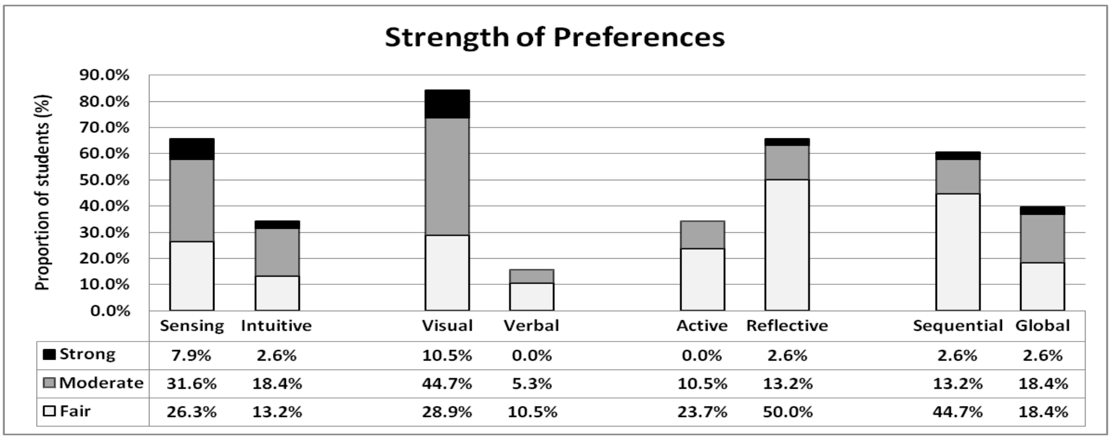

Figure 1: Distribution of students based on the strength of their learning style preferences.

The columns in Figure 1 show the students’ learning styles in the four dimensions of the Felder-Silverman Learning Styles model. In the perception dimension (sensing/intuitive), the majority of students (65.8%) were sensing learners, while 34.2% were intuitive learners. The input dimension (visual/verbal) showed an even greater one-way preference with 84.2% of students being identified as visual learners, and only 15.8% as verbal learners. In the processing dimension (active/reflective), 65.8% were reflective learners and 34.2% were active learners. Finally, in the understating dimension (sequential/global), the proportions of sequential and global learners were 60.5% and 39.5% respectively.

A deeper analysis, also depicted in Figure 1, examined the strength of a student’s learning style preference. Each dimension was subdivided into three levels: fair, moderate and strong. In the perception dimension (sensing/intuitive), 26.3% had a fair preference towards a sensing learning style and 13.2% had a fair preference towards an intuitive learning style. Together, this means that 39.5% of students were fairly balanced between the two learning styles. Of the remaining students, 39.5% had a moderate or strong preference towards a sensing learning style and 21.0% had a moderate or strong preference towards an intuitive learning style.

In the input dimension (visual/verbal), visual learners were dominant with 55.2% of students having either a moderate or strong preference towards using visual representations of the learning material. In contrast, only 5.3% of students had a moderate preference, and no students had a strong preference, towards a verbal learning style. In the processing dimension (active/reflective), the majority of students (73.7%) had a fairly balanced preference between the two learning styles, though reflective learning was more popular. Finally, in the understating dimension (sequential/global), while the majority of students were sequential learners, 63.1% had a fairly balanced preference between the two learning styles.

A correlation analysis to measure the relationship between learning style and academic performance is provided in Table 1, and t-tests that provide further insight are presented in Table 2. Two students were excluded from this part of the study because they did not complete the midterm examination. The correlation analysis shows that only the perception dimension had a significant impact on the students' results in the examination, with the t-tests confirming that sensing students (M=47.16, SD=15.50) were significantly outperformed by intuitive students (M=60.27, SD=14.94), t (34) = 2.364, $p < 0.05$.

Table 1: Correlation between learning style dimensions and midterm exam results (N=36).

Dimension	Pearson Correlation (r)	Significance (2-tailed) (p)
Perception (Sensing/Intuitive)	-0.349	0.037*
Input (Visual/Verbal)	-0.078	0.650
Processing (Active/Reflective)	-0.053	0.760
Understanding (Sequential/Global)	0.170	0.323
* Correlation is significant at the 0.05 level (2-tailed).		

Table 2: Mean comparison between different learning styles in midterm exam results.

Descriptive Statistics for exam results (Max=80)				Independent T-test		
Learning Style	**N**	**Mean**	**SD**	**t**	**df**	**Sig.**
Sensing	25	47.16	15.491	-2.364	34	.024*
Intuitive	11	60.27	14.940			
Visual	31	50.42	15.461	-.679	34	.501
Verbal	5	55.80	22.410			
Active	13	50.54	18.338	-.171	34	.865
Reflective	23	51.52	15.465			
Sequential	22	52.68	16.811	.694	34	.493
Global	14	48.79	15.788			
* Correlation is significant at the 0.05 level (2-tailed).						

In the other learning style dimensions, visual learners (M=50.42, SD=15.46) had slightly lower performance than verbal learners (M=55.80, SD=22.41), reflective learners (M=51.52, SD=15.47) slightly outperformed active learners (M=50.54, SD=18.33) and sequential learners (M=52.68, SD=16.81) did better than global learners (M=48.79, SD=15.79). However, in all of these dimensions, the difference was not statistically significant.

Student Self-Regulated Learning Strategies

Student's reported use of self-regulated learning is summarized in Table 3.

Table 3: Students' use of self-regulated learning strategies (N=38)

Self-Regulated Learning Strategies	Mean (Max=7)	Std. Deviation
Elaboration Strategies	4.55	0.91
Organizational Strategies	3.94	1.26
Critical Thinking Strategies	4.32	1.20
Metacognitive Strategies	3.92	0.90
Peer Learning and Help Seeking Strategies	4.02	1.53
E-Learning Resource Management Strategies	4.45	1.10

Students show a moderate use of each of the self-regulated learning strategies with elaboration and e-learning resource management strategies being the most popular. In contrast, metacognitive and organizational strategies were the least popular among the students.

Table 4: Correlation matrix of self-regulated learning strategies (N=38)

		1	2	3	4	5	6
1. Elaboration Strategies	Pearson Correlation (r)		.722**	.297*	.428**	.247	.286*
	Sig. (1-tailed)		.000	.035	.004	.067	.041
2. Organizational Strategies	Pearson Correlation (r)	.722**		.134	.472**	.158	.180
	Sig. (1-tailed)	.000		.210	.001	.172	.140
3. Critical Thinking Strategies	Pearson Correlation (r)	.297*	.134		.477**	.084	.291*
	Sig. (1-tailed)	.035	.210		.001	.308	.038
4. Metacognitive Strategies	Pearson Correlation (r)	.428**	.472**	.477**		-.067	.151
	Sig. (1-tailed)	.004	.001	.001		.345	.183

5. Peer Learning and Help Seeking	Pearson Correlation (r)	.247	.158	.084	-.067		.214
	Sig. (1-tailed)	.067	.172	.308	.345		.098
6. E-Learning Resource Management	Pearson Correlation (r)	.286*	.180	.291*	.151	.214	
	Sig. (1-tailed)	.041	.140	.038	.183	.098	

** Correlation is significant at the 0.01 level (1-tailed).

* Correlation is significant at the 0.05 level (1-tailed).

Table 4 presents the correlation matrix between the self-regulated learning variables used in this study. Results reveal a significant positive relationship between elaboration strategies and organizational strategies (r=0.72, p<0.01). This indicates that, as use of elaboration strategies increases, so too does the use of organizational strategies. There is also a highly significant positive relationship between metacognitive strategies and critical thinking strategies (r=0.48, p<0.01) and between metacognitive strategies and elaboration strategies (r=0.43, p<0.01) and between metacognitive strategies and organizational strategies (r=0.47, p<0.01).

Discussion

This section discusses implications of the results presented in the previous section.

Student Learning Styles

The majority of students in the study (65.8%) were sensing learners, with 39.5% having a moderate or strong preference to that learning style. However, 21.0% of students have a moderate or strong preference to intuitive learning over sensing learning. This suggests that there is a need for learning material for both types of learners, but the greater emphasis should be placed on reducing abstraction to better meet the requirements of the sensing learners, especially when it is seen that intuitive learners performed significantly better on the midterm examination.

In contrast, only 5.3% of students had more than a fair preference to a verbal learning style over visual learning. This suggests that there is less need for more verbal learning material than for more diagrams and visualizations. Results of the midterm examination, where verbal learners slightly outperformed visual learners, further support this idea.

In the processing dimension 73.7% of students have only a fair preference to either active or reflective learning, with the majority preferring reflective learning. Therefore, the learning material should be balanced to meet the requirements of both learning styles. This could be achieved by incorporating some interactive simulations and self-assessment questions with customized feedback as well as giving time for students to reflect on their learning experience.

Similarly, most students in the study are sequential learners, with 63.1% of students having only a fair preference to either sequential or global learning. Still, while not statistically significant, global learners performed slightly worse on the midterm exam than sequential learners. Thus it may be possible to improve the performance of global learners by offering more of a “big picture” view of the course. This could be achieved, for example, by comparing the concepts under study with other related concepts and applying them to different situations to show how the concepts interconnect.

Overall, the results indicate that increasing support for sensing and visual learners will have the greatest benefit for the course. Interactive animations provide one possible technique to achieve this. Such animations engage students visually and reduce the level of abstraction in the concepts under study (Naps, et al., 2003). Dynamic questions with immediate feedback allow students to monitor their understanding as they interact with the animation (Malmi, et al., 2004).

Student Self-Regulated Learning Strategies

Students' use of self-regulated learning strategies was moderate. Correlation analysis showed that metacognitive strategies were significantly correlated with elaboration, organizational and critical thinking strategies, indicating that students who use more metacognitive learning strategies are more likely to be aware of the cognitive strategies as well. However, metacognitive strategies were the least popular of the self-regulated learning strategies included in this study. This indicates that students may benefit from further education of possible self-regulated learning strategies which could be achieved by introducing interventions such as new educational software that encourages the use of different self-regulated learning techniques.

Conclusions and Future Work

This paper presented the results of an investigation into students' learning styles and their use of different self-regulated learning strategies in a core computer science course. The main aim of the study was to understand students' preferences and the self-regulated learning strategies they use. The results show a diversity of learning styles among students, with the majority showing a preference towards the visual and sensing learning styles. The influence of students' learning styles on their academic achievement in the course was also discussed, as were some recommendations to make the course more compatible with different learning styles. Intuitive learners, who represent only 34.2 % of the course cohort, significantly outperformed the 65.8 % of students who have a sensing learning style. This is consistent with the observation that most instructors use a teaching method that suits intuitive learners (Layman, Cornwell, & Williams, 2006), suggesting that the teaching strategies being used are not optimal for the majority of learners in the course.

The study included an analysis of the self-regulated learning strategies used by students, and it was discovered that metacognitive strategies, which were the least used by the students, were significantly correlated with many of the other strategies. The results of this study can be combined with the contemporary educational paradigms to provide a framework for improving the teaching of the next iteration of the "Programming Language and Paradigms" course as a pilot course representing computer science.

Based on this work, an online collaborative learning object repository is under development. This provides an environment for students to interact and share different learning objects to support traditional computer science teaching. The system contains a learning style assessment module to allow students to identify their preferred learning styles. Based on the result, students are provided with recommended strategies to follow throughout the course. The students' learning styles are also used by the system to automatically recommend learning objects that are most compatible with each individual student's preferences. New learning objects can be created inside the system through the use of a special template that helps ensure that aspects of different learning styles are taken into consideration.

As well as recommending the most compatible learning objects, the online collaborative system also aims to increase students' awareness of different self-regulated learning strategies. To help increase individual cognitive learning strategies, a collaborative filtering technique provides students the opportunity to rate and comment on existing learning objects. This allows the student to reflect on his or her learning experience, and the feedback enriches the repository for other users. Metacognitive strategies are also supported by the system, with the generation of self-assessment exercises allowing students to better monitor their knowledge of the concepts being studied.

While still in an early stage of development, the new online collaborative learning object repository will be fully operational by the end of the year. The system will be used in conjunction with the traditional teaching of "Programming Languages and Paradigms" in the first semester of 2012. Results of the 2012 course will then be compared to the results presented in this study to help evaluate the new teaching approach. It is hoped that the support offered by the new system will improve equality of teaching for computer science students, by offering the best strategies and objects for their different learning styles.

References

Allert, J. (2004). Learning style and factors contributing to success in an introductory computer science course.
Bandura, A. (2001). Social cognitive theory: an agentic perspective. *Annual review of psychology, 52*, 1.
Ben-Ari, M. (1998). Constructivism in computer science education. *SIGCSE Bull., 30*(1), 257-261.
Berglund, A., Eckerdal, A., Pears, A., East, P., Kinnunen, P., Malmi, L., et al. (2009). Learning computer

science: Perceptions, actions and roles. *European Journal of Engineering Education, 34*(4), 327-338.
Capretz, L. (2002). Implications of MBTI in software engineering education. *ACM SIGCSE Bulletin, 34*(4), 134-137.
Chamillard, A., & Karolick, D. (1999). Using learning style data in an introductory computer science course. *ACM SIGCSE Bulletin, 31*(1), 295.
Chen, C. (2002). Self-regulated Learning Strategies and Achievement in an Introduction to Information Systems Course Systems Course. *Information Technology, Learning, and Performance Journal, 20*(1), 11.
Curry, L. (1983). *An Organization of Learning Styles Theory and Constructs*. Paper presented at the The Annual Meeting of the American Educational Research Association
de Raadt, M., & Simon (2011). *My Students Don't Learn the Way I Do.* Paper presented at the Australasian Computing Education Conference (ACE 2011), Perth, Australia.
Felder, R. M., Felder, G. N., & Dietz, E. J. (2002). The effects of personality type on engineering student performance and attitudes. *JOURNAL OF ENGINEERING EDUCATION-WASHINGTON-, 91*(1), 3-18.
Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering education, 78*(7), 674-681.
Felder, R. M., & Soloman, B. A. (1997). Index of Learning Styles Questionnaire Retrieved 20 June, 2011, from http://www4.ncsu.edu/unity/lockers/users/f/felder/public/ILSpage.html
Haden, P., Fincher, S., & Petre, M. (2004). BRACE Yourself: CS Education research is coming. *Proceedings of the 17th NACCQ*.
Holmboe, C., McIver, L., & George, C. (2001). *Research agenda for computer science education*.
IEEE/ACM (2005). Computing Curricula 2005, The Overview Report Retrieved 20 June, 2011, from http://www.acm.org/education/education/curric_vols/CC2005-March06Final.pdf
Keefe, J. (1988). Profiling and Utilizing Learning Style. NASSP Learning Style Series.
Larkin, T., & Budny, D. (2005). *Learning styles in the classroom: approaches to enhance student motivation and learning*.
Machanick, P. (2007). A social construction approach to computer science education. *Computer Science Education, 17*(1), 1-20.
Malmi, L., Karavirta, V., Korhonen, A., Nikander, J., Seppälä, O., & Silvasti, P. (2004). Visual Algorithm Simulation Exercise System with Automatic Assessment: TRAKLA2. *Informatics in Education, 3*(2), 267-288.
Mills, J., Ayre, M., Hands, D., & Carden, P. (2010). Learning About Learning Styles: Can It Improve Engineering Education? *MountainRise, 2*(1).
Naps, T., Rößling, G., Almstrum, V., Dann, W., Fleischer, R., Hundhausen, C., et al. (2003). Exploring the role of visualization and engagement in computer science education. *SIGCSE Bull., 35*(2), 131-152.
Pintrich, P. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research, 31*(6), 459-470.
Pintrich, P. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational psychology review, 16*(4), 385-407.
Pintrich, P., & De Groot, E. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of educational psychology, 82*(1), 33-40.
Pintrich, P., Smith, D., Garcia, T., & McKeachie, W. (1991). A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ). *Ann Arbor. Michigan, 48109*, 1259.
Pritchard, A. (2009). *Ways of learning: learning theories and learning styles in the classroom* (2nd ed.): David Fulton Publish.
Ryan, A., & Pintrich, P. (1997). "Should I Ask for Help?": The Role of Motivation and Attitudes in Adolescents' Help Seeking in Math Class. *Journal of educational psychology, 89*(2), 329-341.
Shaw, G., & Marlow, N. (1999). The role of student learning styles, gender, attitudes and perceptions on information and communication technology assisted learning. *Computers & Education, 33*(4), 223-234.
Thomas, L., Ratcliffe, M., Woodbury, J., & Jarman, E. (2002). Learning styles and performance in the introductory programming sequence. *SIGCSE Bull., 34*(1), 33-37.
von Glasersfeld, E. (1997). Amplification of a constructivist perspective. *Issues in Education, 3*(2), 203-209.
Zimmerman, B. (1986). Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology, 11*(4), 307-313.

Author contact details:
Ali Alharbi Ali.Alharbi@uon.edu.au
David Paul David.Paul@uon.edu.au
Frans Henskens Frans.Henskens@newcastle.edu.au
Michael Hannaford Michael.Hannaford@newcastle.edu.au

Please cite as: Alharbi, A., Paul, D., Henskens, F. & Hannaford, M. (2011). An investigation into the learning styles and self-regulated learning strategies for Computer Science students. In G.Williams, P. Statham, N. Brown & B. Cleland (Eds.) *Changing Demands, Changing Directions*. *Proceedings ascilite Hobart 2011*. (pp.36-46).
http://www.ascilite.org.au/conference/hobart11/procs/Alharbi-full.pdf