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Building analytical, mathematical-logical, and problem-solving skills informally in parallel with a formal first-year computer science course

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1 Introduction

Research carried out in 2014 (Halse) at Rhodes University investigated the role of learning styles in the teaching and learning of computer science, using Kolb's Experiential Learning Cycle and accompanying assessment instrument, the Learning Styles Inventory (LSI). Learning Styles as a concept were defined as the preferences or strengths people have in terms of how they take in and deal with experience (Chamillard, & Karolick, 1999; Howard, Carver, & Lane, 1996; Kolb & Kolb, 2005a; Modalfsky & Kwon, 1994). The LSI describes four learning styles: Divergent, Assimilative, Convergent, and Accommodative, with finer-grained distinction in learning profiles given by using Abbey, Hunt, and Weiser's model 01985) to expand Kolb's original four learning styles to nine distinct styles, including five new learning styles categories (Northerner, Easterner, Southerner, Westerner, and Balancing) (Kolb & Kolb, 2005a;0 Abbey, Hunt, & Weiser, 1985).

2 2014 Study

Kolb's LSI version 3.1 (Kolb, 2007) was administered to the first year computer science programming students at Rhodes University, in the second semester of 2014 (July – December) (Halse, 2014). Scores for the four dimensions of the LSI were calculated and analysed and dominant learning styles determined. The relationship between academic performance and learning styles indicated students with Converger or Assimilator as their dominant style were the highest achievers (using Kolb's original four learning styles) and that students with Converger, Southerner, or Assimilator as their dominant learning style (using the nine expanded learning styles) accounted for 74% of the first class passes (22%, 26%, and 26%

respectively) . This distribution mirrored and amplified the dominant pattern identified for computer science students.

3 2016 Study

Many students coming into first year computer science have very weak analytical, mathematical-logical, and problem-solving skills. This impacts negatively on these students' ability to learn to code. Engaging with further programming tasks can trigger significant distress and performance anxiety and further retard skills development. In an attempt to address this problem a programme of informal workshops was run in parallel with a formal first year computer science programming course. The workshops focussed on developing analytical, mathematical-logical, problem-solving and metacognitive skills rather than on content-based learning, in order to assess whether this could support the development of learning styles and approaches shown to correlate with students' academic success in previous research.

As new skills are learned, students' learning styles change (Kolb, 1984), and so LSI results can indicate whether skills have been learned or not. The LSI was administered twice, first in early March at the beginning of the semester and again in early June at the end of the semester shortly before exams. In between the two rounds of LSI administration, the workshops that formed the bulk of the research programme took place weekly.

3.1 Activities for parallel skill-building

For activities to meet the requirements of the programme, they needed to obviate the stressors associated with programming for students, engender positive feelings, and enhance mathematical-logical thinking and analytical capabilities. Literature on Computational Thinking (CT) and Puzzle based Learning (PBL) was consulted extensively in formulating the programme. CT is a term coined by Wing in 2006, explained as thinking that "involves solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science" (p. 33) - essentially thinking like a computer scientist when problem-solving, which is what we wanted our first year students to learn to do. What was drawn from the field of CT in the selection of activities and the framing of classes in the workshop programme was the fundamental idea of "defining, understanding, and solving problems, reasoning at multiple levels of abstraction... and analyzing the appropriateness of the abstractions made" (Lee et al., 2011), but without a focus on automation, algorithmics, or programming for the reasons explained previously involving programming anxiety. PBL is an approach that is often in both engineering and computer science to encourage student to "think about how they frame and solve problems using educational puzzles to support problem-solving skills and creative thinking" (Falkner, Sooriamurthi, & Michalewicz, 2010, p. 21). Falkner et al. suggest a number of useful criteria for the selection of problems and puzzles that do this which provided guidance in the programme (2010, p. 21). A variety of logical puzzles and problems were selected, based on the individual problems and their content and level of difficulty. Every second week a short lecture was also given, introducing students to different ways of understanding brain development (from perspectives such as neuroplasticity (Doidge, 2007), computational thinking (Wing, 2006), myelination (Coyle, 2010), and PBL (Falkner et al., 2010)). The idea behind this was to stimulate students' metacognitive processes and encourage a sense of empowerment about their own skills development.

Focussing on cognitive and metacognitive skills rather than on content, in order to assess whether this could support students' academic success, involves offering new "frames of reference" (Mezirow, 1991, p. 167) through which students can learn, by focusing on processes that transform ways of thinking ("habits of mind" (Mezirow, 2003, p. 58)). Dix (2015, p. 140) argues that the essence of all transformative learning is "cognitive transformation involving metacognitive reconstrual". Neuroscientists refer to this as neuroplasticity; Doidge (2007, p. 39) writes about the ground-breaking work of Michael Merzenich who has shown that "practicing a new skill, under the right conditions, can change hundreds of millions and possibly billions of the connections between the nerve cells in our brain maps". Doidge (2007, pp. 39 - 69) goes on to explain how these new and expanded neural maps can then be applied effectively to other tasks in the same cognitive areas as those of the skill that built them. Transformative learning processes such as "examining, questioning, and revising one's own perspective" (Tharp, 2012, p. 180) were practiced in the research programme through parallel learning processes to build skills in the appropriate learning style areas. The impact of learning styles emphasizes the individual nature of the transformative process, which is very autonomous.

3.2 LSI Results & Discussion

Students were offered the option of signing up for the parallel skills-building programme; those who did so became the research group, while the rest of the first year programming class who has volunteered to do the LSI assessments became the control group. Some participants dropped out during the course of the programme (see the Limitations section); only those students with both pre- and post- LSI assessments are included in this study. The control group was made up of twenty one students who attended the normal computer science course (lectures and practicals) but not the workshop programme. The research group was made up of eighteen students who attended the normal computer science course (lectures and practicals) as well as the workshop programme. An independent-samples t-test was conducted to assess the movement of the control and research groups on the y-axis (as downward movement into the negative y quadrants on the LSI grid would indicate development of skills associated with learning styles previous research correlated with academic success in computer science). There was a significant difference in the scores for the research group (M=3.1, SD=15) t(37)=2.08, p=0.04. The implication is that attending the workshops correlates with a change in self-assessed learning style, using Kolb's LSI 3.1 (Kolb & Kolb 2005a), in the direction initially intended by the workshop programme. In other words, attendance at the workshops correlates with self-assessment of statistically significant skills-building and a shift in learning style as hoped by the research programme.

3.3 Limitations

Limitations of the study include the fact that the sample size is small, and that we cannot rule out the influence of factor outside of the workshops in creating change, especially with students motivated enough to volunteer (it is equally possible that they might be motivated to work on improving their computer science skills in other ways too).

4 Conclusion

Pre and post assessment (Kolb's LSI version 3.1 (Kolb, 2007)) of eighteen students involved in the workshop research group compared to twenty one in the control group gave self-assessment placing on the LSI grid. An independent-samples t-test indicated a significant difference in the scores for the research implying correlation between participation in the workshops and change in learning style towards the Converger/[Southerner]/Assimilator categories, i.e. in the direction initially intended by the workshop programme. Although correlation does not equal causation, and the limitations mentioned for the study must be taken into account, it is hoped that the workshop programme contributed towards building the skills that empowered students in growing their learning styles in the manner noted. Replicating the results in the 2017 academic year would go some way towards suggesting that this was the case.

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Appendix 1: Questionnaire

Please fill in the following. For each row assign a 4 to the option most like you, a 3 to the option that is your second choice, a 3 to the option that is your third choice, and a 1 to the option that is least like you.

1. When I learn	I like to deal with my feelings	I like to think about ideas	I like to be doing things	I like to watch and listen
2. I learn best when	I listen and watch carefully	I rely on logical thinking	I trust my hunches and feelings	I work hard to get things done
3. When I am learning	I tend to reason things out	I am responsible about things	I am quiet and reserved	I have strong feelings and reactions
4. I learn by	feeling	doing	watching	thinking
5. When I learn	I am open to new experiences	I look at all sides of issues	I like to analyze things, break them down into their parts	I like to try things out
6. When I am learning	I am an observing person	I am an active person	I am an intuitive person	I am a logical person
7. I learn best from	observation	personal relationships	rational theories	a chance to try out and practice
8. When I learn	I like to see results from my work	I like ideas and theories	I take my time before acting	I feel personally involved in things
9. I learn best when	I rely on my observations	I rely on my feelings	I can try things out for myself	I rely on my ideas
10. When I am learning	I am a reserved person	I am an accepting person	I am a responsible person	I am a rational person
11. When I learn	I get involved	I like to observe	I evaluate things	I like to be active
12. I learn best when	I analyze ideas	I am receptive and open-minded	I am careful	I am practical