2010

The significance of learning style with respect to achievement in first year programming students

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10.1109/ASWEC.2010.33

PROCEEDINGS

21st Australian Software Engineering Conference

— ASWEC 2010 —

PROCEEDINGS

21st Australian Software Engineering Conference

— ASWEC 2010 —

6–9 April 2010
Auckland, New Zealand

Edited by

James Noble, Victoria University of Wellington, New Zealand
Colin Fidge, Queensland University of Technology, Australia

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IEEE Computer Society Order Number P4006
BMS Part Number CFP10134-PRT
ISBN 978-0-7695-4006-1
ISSN 1530-0803

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Editorial production by Randall Bilof
Cover art production by Joe Daigle/Studio Productions
Printed in the United States of America by Applied Digital Imaging

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21st Australian Software Engineering Conference

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***Abstract* - This study investigates the relationship between the Kolb learning style of first-year programming students and their level of achievement. The method of data collection is described and the process of hypothesis testing is explained. The students in this study were predominately converger and accommodator learning styles. Statistical tests indicated no overall difference between the results of students with different learning styles but a difference was found along Kolb's concrete-abstract axis. A number of possible impacts on teaching are discussed and suggestions made for future research.**

Keywords – Software Engineering Education; Learning Style; Programming; Student Behaviour

I. INTRODUCTION

This paper explores the effect of learning style on the achievement of students. There is a significant body of literature in the education field that suggests that activities tailored to a student's learning style will result in a better outcome (learning achievement, as measured by final examination score) for the student. There is also evidence that students who undertake software engineering/computer science degrees tend to fall into particular learning style categories (particularly those associated with abstract thought, viz., Convergers and Assimilators). This may lead to the development of educational activities customised for specific learning styles.

In the next section, we give a brief overview of learning styles, focussing on the model proposed by Kolb [1] . Following this we describe the participants and environment of the study as well as outlining the research method. We then summarise the research results and discuss the implications for teaching first year students. Finally, we conclude the paper by summarising and discussing limitations and future research.

II. LEARNING STYLES

Learning styles, as defined by Kemp et al., are "…traits that refer to how individuals approach learning tasks and process information" (Kemp, Morrison and Ross, [2], p. 40, cited in [3]). Similarly, Keefe and Monk [4] define learning styles as "…the characteristic cognitive, affective, and psychological behaviors [sic] that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment.". Assuming that a learning style exists (or is perceived to exist) and that it is a measurable artifact, then there should be a meaningful way to measure the style of an individual.

There is a vast repository of literature accumulated over the past thirty years that describes many aspects of learning styles; therefore it is not surprising that there are many theories of learning styles. Mitchell [5] claims that there are over one hundred. One of the most used is Kolb's experiential learning model and Learning Style Inventory (LSI).
One of the benefits of choosing Kolb's LSI in research is that it has a standardised questionnaire that is available. It is relatively easy to assess an individual's style by means of a short questionnaire which records an individual's preferences for learning along two continua that measure perception and processing preferences. The questionnaire requires individuals to rank four potential sentence endings to partial sentences such as " I learn best from"; and the answers provide a score (positive or negative) on one of the two continua. The Perception Continuum describes how people think, with Concrete Experience (Feeling) and Abstract Conceptualisation (Thinking) as opposites; whilst the Processing Continuum describes how people do things, with Active Experimentation (Doing) and Reflective Observation (Watching) as opposites. The process concludes by plotting the measures obtained on a graph and individuals are identified as having the preferred learning style from the quadrant in which the measures fall (see Figure 1). The four resulting styles are discussed below [6].

A. The accommodating style: (feel and do) CE/AC

This style is exemplified by "what if" people, those who would rely on intuition rather than logic and are seen as risk takers. They favour an independent discovery approach to learning and enjoy an active involvement.

B. The diverging style (feel and watch) CE/RO

This style emphasises concrete experience and reflective observation. It is imaginative and views concrete situations from many perspectives. Those who exhibit this style tend to be emotional and good at generating ideas.

C. The assimilating style (think and watch) AC/RO

Individuals with this style prefer abstract conceptualisation and reflective observation. They have the opposite style to those with the accommodating style. Those who exhibit this style are logical and concise, dealing well with ideas and concepts. This learning style is likely to be helpful in science and IT.

D. The converging style (think and do) AC/AE

Individuals classified as having this style prefer abstract conceptualisation and active experimentation. This is the typical style of an engineer; i.e. good at solving practical problems and like to use simulations. This style is opposite to the diverging style,

However, the inventory does have flaws. Hunsaker [7] suggests that while Kolb's theory of cyclic learning has some validity, there are significant issues with the administration and content of the LSI itself. Further, Veres et al. [8] point out that the instability of the LSI is at odds with the nature of the experiential learning model, which relies on learning style being a somewhat stable learner trait. Veres et al. concede that the LSI (the revised version of 1985) does classify learners better than a random assignment, but remain concerned about the stability of the LSI. There is support for this claim in Coffield et al., [9] , who indicate that the Kolb model meets their criteria for test-retest reliability but not for construct validity or predictive validity. In contrast, Kayes [10] reports that the LSI-3 (1999 version) has internally reliable scales. Despite the counter-claims regarding validity, the Kolb model remains popular nonetheless; possibly because it was the first model to be widely disseminated.

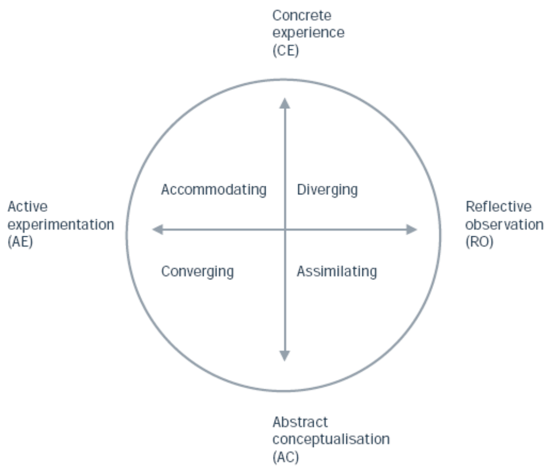

Figure 1: The Dimensions of the Kolb Model (from [9]).

More germane to this study, Byrne and Lyons [11] evaluated student success in a first year programming course across a range of factors including (Kolb) learning style. They concluded that whilst learning style was not significant, it was noticeable that there was a preponderance of Convergers who had selected the programming course, an area which warrants further study. Similarly, Gomes and Mendes [12] found little or no correlation between the achievement and learning style of first year programming students, however Allert [13] reported a difference. Goold and Rimmer [14] maintain that students with a high relative abstraction score tend to do well in computing, a position that is supported by the results of this study. Pillay and Jugoo [15] found that assimilators (abstract thinkers) did better than other LSI types in one study, but not in another. They suggest that assimilators may do better because the lecturer is an assimilator, but have no direct evidence to support this claim.

Although Chamillard and Karolick [16] did not investigate whether students whose learning style corresponded with that of the instructor, they did consider whether the teaching of 24 different instructors tended to favour particular learning styles. Detail on this idea is scant but they did report that one instructor's teaching appeared to favour active learners over reflective learners for Felder's Active/Reflective dimension [17]. They suggested that the instructor should allocate more class time to "reflection". Thus they did not acknowledge significantly different results in a number of learning styles as 'natural' but saw it as requiring remedial action on the part of the instructor, to provide more inclusive teaching. This appears to be justified, since the results for the instructor contrasted with the course-wide results.

Other course-wide results in the same study found that students with a preference for Abstract Conceptualisation, along with those with a dislike for Concrete experience performed better. On the surface these results appear to replicate the results from this study, however looking more closely at the reported results, it is not clear why they chose Kolb's AC, CE, RO and AE scores independently rather than the transformation that Kolb recommends onto the Perception (AC-CE) and Processing (AE-RO) continua, especially since this may have strengthened their results.

The permanence with which people are attached to their learning style is an idea that is considered either completely correct or completely incorrect depending on the particular model that is considered. This factor, which at first may appear trivial, is quite pivotal to the manner in which educators should treat learning styles. If learning styles are considered fixed, then it is contingent upon educators to provide learning experiences to suit various styles or possibly even at an extreme to counsel individuals that they do not have the learning style necessary to succeed in an area. McKeachie [18] warned of a self fulfilling prophecy arising from the notion of intransigent learning styles that, "some students who have been labeled as having a particular style feel that they can only learn from a certain kind of teaching". He urged that learning styles be merely considered a preference and that students be taught strategies to cope with learning situations that they did not find themselves naturally well-suited.

This paper describes an investigation into potential relationships between learning style and achievement. The subjects were tertiary students enrolled in a first course of programming.

III. THE PARTICIPANTS AND THE RESEARCH ENVIRONMENT

A. *The students*

The 74 students in this study came to university with a range of academic backgrounds. These included traditional young university entrants who completed their school exams the previous year, mature age students (over 20 years old) who were admitted after passing a mature age entry test and also some who entered by alternative entry pathways (e.g. through a summer school enabling programme). The course that was the basis for this study was an introduction to programming that was a part of a student's first semester of tertiary study. This unit provided an introduction to algorithms and problem solving using an object-oriented model and the Java programming language. The class contact, over a 16 week semester, included two one-hour lectures and a three-hour computer laboratory session, where a tutor was available to mark-off completed exercises and also provide feedback or assistance when sought.

The unit was assessed by the completion of online tests (15%), exercises (15%), a project (20%) and an end of semester exam (50%). The online tests largely evaluated programming knowledge whilst the exercises combined that knowledge with process. The project provided the students an opportunity to hone their problem solving skills on a more substantial program, whilst applying the acquired process knowledge. Finally the exam had several sections that attempted to cover a range of domain skills and knowledge.

The first section of the exam involved finding and correcting errors in small code segments; the second required students to interpret pseudo-code segments and define methods by writing signatures for them. In the third section, students were directed to write methods in Java. These did have significant similarities to the programming exercises, although they were not identical in that they required only small segments. The exam's final section involved an assortment of problems, such as explaining and amending UML diagrams and related code segments.

The average score on the various types of assessments varied considerably with generally higher marks in the projects than the tests and both of these considerably higher than exercises and exams. In the exam, the section requiring students to write program segments resulted in an average lower mark than the other three sections that were approximately equivalent. This result is consistent with previous research (cf. [19]) that indicated students find writing code a difficult task to master.

The exam score was selected as the most reasonable measure of a student's skills and knowledge (achievement), since it is conducted at the end of semester and it was the only score available that could be considered a summation of the semester's work.

B. Learning styles of the students

Notwithstanding earlier discussion regarding the pitfalls of the Kolb LSI, the selection of this instrument in this research was largely serendipitous. It was chosen because at the university used in the research (Murdoch), the concept of learning styles was introduced to students in a foundation unit and the university had arranged to use the Kolb LSI as a means to assist students to understand styles of learning. This meant that the preferred learning style of students was immediately available.

Given some further background research into other learning style instruments, it appears that Kolb's LSI was a reasonable choice; at least because this instrument has also been used in a number of other studies that provide for useful comparison. Loo [20] suggested that this instrument remained effective despite some problems. Perhaps, not surprisingly, Mainemelis, Boyatzis and Kolb [21] showed that the majority of studies supported the use of LSI but its use as a guide, to allow matching of the most effective teaching methods with certain students, has been shown to be very limited [22]. Kolb himself suggests that students should be exposed to a variety of learning modes and not simply those that they might prefer.

IV. RESEARCH METHOD

The data for this research were collected at Murdoch University, about students who were enrolled in an introductory programming course. The data sets collected were:

- Achievement: the exam score that a student was awarded as a result of his/her enrolment in the introductory programming course was recorded and used as a measure of academic achievement.
- Learning Style: through enrolment in a Foundation unit and participation in completing a questionnaire, the learning style of each student was assessed using Kolb's LSI.

The research question to be investigated is 'Does the learning style of first-year programming students affect the achievement of those students'? This question can be explored quantitatively by using a form of within-subjects field experiment amenable to analysis by statistical method.

The data were analysed by constructing and testing hypotheses about the research question. Given that there were four LSI groups and that the exam score represented a continuous dependent variable, it would appear that the data may be analysed with single-factor analysis-of-variance (ANOVA). Prior to the analysis, the data were tested for normality and the other usual assumptions associated with the use of ANOVA.

V. RESULTS

The learning styles of the first year programming students were concentrated in the lower hemisphere of KLSI, the Assimilator and Converger groups (Table I). This group can be contrasted with General Arts and Commerce students that had a much lower percentage of Convergers and a higher percentage of Accommodators.

TABLE I. THE KLSI GROUPS OF ENROLLED STUDENTS (FROM[23]).

Course	No. of Students	Accomm odator	Diverg er	Assimi lator	Converg er
Arts & Commerce	198	13%	13%	47%	27%
Programm-ing	48	4%	8%	42%	46%

In order to find out whether it is appropriate to apply ANOVA, it is necessary to confirm whether the data appears to be from a normal distribution. The Anderson-Darling statistic tests whether the data are from a normal distribution and probabilities of $A^2 < 0.05$ would mean that this did not appear to be true. The Shapiro-Wilk statistic considers whether there is evidence of non-normality and again p values of < 0.05 would suggest that such evidence was found. The result of applying these tests to the KLSI groups is shown in Table II. In this data the lowest p values are on the Assimilator group and are above this level. It can be assumed that no evidence can be found to indicate that the data is not from a normal distribution. The normality requirement for ANOVA has therefore been met.

TABLE II. RESULTS OF ANDERSON-DARLING AND SHAPIRO-WILK TESTS ON THE FOUR KOLB LSI GROUPS.

	Accomm-odators	Assimila-tors	Converg-ers	Divergers
Anderson-Darling A^2	0.44	0.52	0.29	0.23
p of A^2	0.18	0.15	0.57	0.47
Shapiro-Wilk W	0.86	0.89	0.95	0.96
p of W	0.19	0.13	0.33	0.62

Stating the primary hypothesis derived from the research question:

> H_o : Students of each KLSI group achieve the same results.
> H_1: Students of each KLSI group achieve different results.

The result of the ANOVA test on the four groups is F=2.73, p = .059, therefore the null hypothesis cannot be rejected and the conclusion is that there is no evidence that the groups are different. Figure 2 shows the mean and a 95% confidence interval for the means.

In this study it was only feasible to include students who completed the unit and those who did not complete the unit have been excluded (as they did not have an exam score). There were a very small number of students with a diverging learning style which explains the wide range for the 95% confidence interval for the mean.

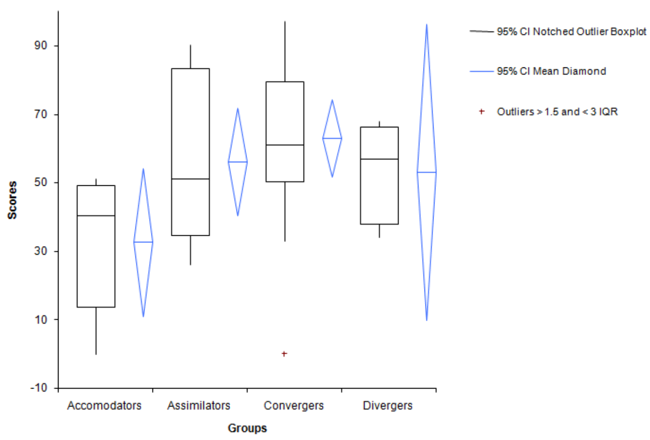

Figure 2: Achievement of the KLSI groups.

In this sample there are small numbers in two of the KLSI groups. To ameliorate any small-sample deviations (as seen in Figure 2), one possible course of action is to combine adjoining groups and to test these two groups along each of the KLSI axes. This was done by combining the groups vertically (see figure 1) and horizontally. A test dividing students into two groups on the (normally vertical) Active/Reflective axis found no difference in the results of the two groups but if the Abstract Conceptualisation/Concrete Experience axes (normally horizontal) is used to divide into two groups there does appear to be a difference in results.

TABLE III. NORMALITY TESTS ON ABSTRACT AND CONCRETE LEARNING STYLE GROUPS.

	Abstract	Concrete
Anderson-Darling A^2	0.28	0.27
p of A^2	0.62	0.57
Shapiro-Wilk W	0.97	0.95
p of W	0.44	0.69

As before, the combined datasets were tested for normality (see Table III) before using a t-test to detect any difference in the means of the two groups.

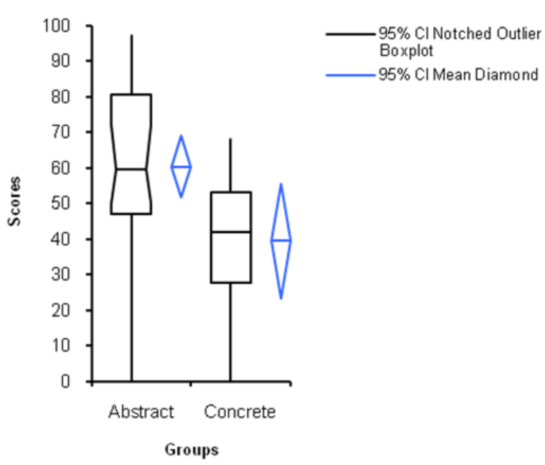

Figure 3: Kolb's Abstract and Concrete Groups vs. Achievement.

The revised hypothesis is:

- H_0: There is no difference in achievement of the two KLSI groups identified as Abstract Conceptualisation or Concrete Experience.

- H_1: There is a difference in achievement of the two KLSI groups identified as Abstract Conceptualisation or Concrete Experience.

The t-test result was a t value of 2.43 which has a 2-tailed probability of .02. This is significant at the 0.05 level and hence it can be concluded that there is a significant difference between the groups. In the sample there are approximately three times as many students in the Abstract group as the Concrete Group.

Whilst it is acknowledged that "achievement" is a complex artefact and no doubt has many contributing variables, a further analysis of the data was undertaken in order to attempt to acertain the direct contribution of learning style to achievement. In this analysis, the raw LSI score was deemed the independent continous variable and the exam score the dependent variable. Considering the LSI score to be a continuous variable is reasonable in this case as the scores are represented by a continous scale. Linear regressions, split by LSI group, were performed in order to measure the correlation between LSI score and exam score.

An investigation into the contribution of the active-reflective and concrete-abstract axes to exam score for each of the KLSI groups resulted in extremely low correlation coefficients for the Convergers and Assimilators (0.15 and -0.36 respectively). The Diverger and Accomodator groups were the smallest in the sample but the correlation coefficient between the exam score and the transformed active-reflective scores (AE-RO) were -1.0 for the Accomodators and +0.80 for the Divergers. The former result means that all of the variance in the exam score for an Accommodator is explained by the LSI score-a somewhat implausible result. Considering the latter result, this means that 64% of the variance in the exam score for a Diverger can be explained by the LSI score. If the LSI were a major contributor to the achievement, then this is a significant result, however the the question remains as to why this result was not replicated across all four groups. It is likely that these results are anomalies due to the small sample sizes of these groups.

It appears from these results that extreme learning styles in either direction on this axis may not be conducive to achievement. At the very least this warrants further investigation. In Figure 4 the scores on the active reflective axis have been transformed so that they appear on the x-axis on this graph in the normal location for KLSI (although clearly the values differ).

To recap, the results are that achievement is independent of learning style across the four Kolb groups and it appears that evidence for a direct correlation between learning style and achievement is tenous at best. However, there is a significant difference between the two Kolb "hemispheres", represented as Abstract Conceptualisation and Concrete Experience respectively.

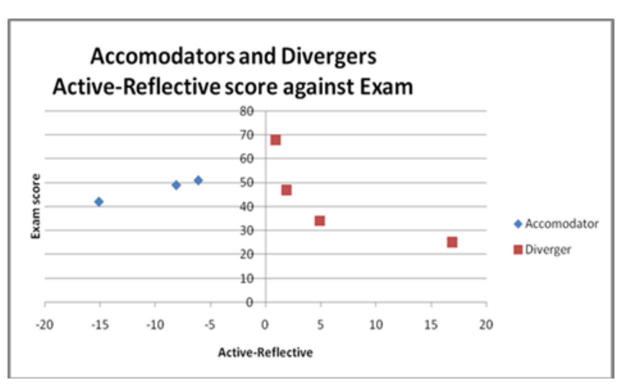

Figure 4: Diverger and Accomodator groups active-reflective axes against exam score.

VI. CONCLUSION-IMPACT ON TEACHING

In some respects this study heralds no startling message about learning styles and first year students taking programming units. It confirms earlier results such as those from Byrne and Lyons [11], viz, that achievement appears to be independent of learning style. What is useful about this research is that it shows a significant difference between abstract and concrete thinkers (as measured by Kolb's LSI). This result shows that abstract thinkers perform better in the exam than concrete thinkers.

It appears that students with a preferred learning style that favours concrete experience over abstract conceptualisation are less likely to perform well in a traditional introductory programming course. There are several inferences that could be drawn from this result:

- It could be assumed that these students do not have what it takes to be programmers and so should be encouraged to take a different course.
- If a more abstract learning style is required for success then it might be considered appropriate to assist students to convert to a learning style of this kind.
- Perhaps the curriculum is not appropriate and its design improperly favours abstract thinkers.
- Perhaps the pedagogy is at fault and is not catering for students with a variety of learning styles.
- Perhaps the nature of the course and especially the assessment requires changing to be more inclusive.

If the first inference is taken seriously then a valid conclusion would be to conduct a learning style pre-test of students in order to screen out those with an inappropriate learning style; only those with a strong Abstract Conceptualisation element would be accepted as it is likely that they will succeed in this course. It does appear, because of the relatively high numbers of abstract thinkers, that students already to some degree self-select i.e. those who choose to do programming may do so because it offers them the types of intellectual challenge that fits their particular learning style.

However given the current situation where universities are needing to attract students to the SE/CS discipline, it may be more appropriate to work harder to retain those whose learning styles are currently unfavourable to achievement. This may be especially important for the future of the discipline since the learning styles that are concerned may be related to students who are risk takers and generators of ideas. Perhaps the discipline would be enriched and enhanced by being more inclusive?

A limitation of the work was the number of students in the sample (74). This meant that if there were to be an equal distribution of students across learning styles, then each sub-group would contain approx. 18 students. What actually happened was that there were more students in the Converger and Assimilator groups, which makes the results obtained for the remaining groups questionable.

Another limitation was that the study evaluated only first year students. Given that learning style can change over time, it may be that students who do not perform well in first year, achieve more by, say, third year, as their learning style evolves. There is some evidence for this effect in other disciplines, so a re-test of the same students after two years at university might provide a valuable insight.

Further work will include repeating the study at another university with a larger-sized group and multiple instructors to check the validity of the instrument. Also, it would be instructive to use another learning style inventory either in addition to Kolb's LSI or as a replacement, especially given the concerns raised by other researchers about construct validity and test-retest reliability in the Kolb model. Finally, it may also be useful to collect data about other variables that may affect achievement and to assess their contribution to acheivement against that of learning style.

VII. REFERENCES

[1] D. A. Kolb, "Management and the learning process," in *Organizational Psychology: A Book of Readings*, D. A. Kolb, I. M. Rubin, and J. M. McIntyre, Eds. Englewood Cliffs, NJ: Prentice-Hall, 1974, pp. 27-42.

[2] J. Kemp, G. Morrison, and S. Ross, *Designing effective instruction*. New York: Macmillan College Publishing Company, 1998.

[3] B. Akkoyunlu and M. Y. Soylu, "A Study of Student's Perceptions in a Blended Learning Environment Based on Different Learning Styles," *Educational Technology & Society,* vol. 11, pp. 183-193, 2008.

[4] J. W. Keefe and J. S. Monk, *Learning style profile examiners' manual*. Reston, VA: National Associationg of Secondary School Principals, 1986.

[5] D. P. Mitchell, "Learning style: a critical analysis of the concept and its assessment," in *Design for learning: aspects of educational technology*, R. Hoey, Ed. London: Kogan Page, 1994.

[6] D. H. Jonassen and B. L. Grabowski, *Handbook of Individual Differences Learning and Instruction*. London: Lawrence Erlbaum Associates, 1993.

[7] J. Hunsaker, "The Experiential Learning Model and the Learning Style Inventory: An Assessment of Current Findings," *Journal of Experiential Learning and Simulation,* vol. 2, pp. 145-152, 1981.

[8] J. G. Veres, R. R. Sims, and T. S. Locklear, "Improving the reliability of Kolb's revised learning style inventory.," *Educational and Psychological Measurement,* vol. 51, pp. 143-150, 1991.

[9] F. Coffield, D. Moseley, E. Hall, and K. Ecclestone, "Learning styles and pedagogy in post-16 learning: A systematic and critical review," Learning and Skills Research Centre, Trowbridge, Wiltshire 2004.

[10] D. C. Kayes, "Internal validity and reliability of Kolb's learning style inventory.," *Journal of Business and Psychology,* vol. 20, pp. 239-257, 2005.

[11] P. Byrne and G. Lyons, "The effect of student attributes on success in programming," in *Proceedings of the 6th annual conference on Innovation and technology in computer science education* Canterbury, United Kingdom: ACM Press, 2001, pp. 49-52.

[12] A. Gomes and A. J. Mendes, "A study on student's characteristics and programming learning.," in *World Conference on*

Educational Multimedia, Hypermedia and Telecommunications, Chesapeake, VA, 2008, pp. 2895-2904.

[13] J. Allert, "Learning Style and factors contributing to success in an introductory Computer Science course," in *IEEE International Conference on Advanced Learning Technologies*, 2004, pp. 385-389.

[14] A. Goold and R. Rimmer, "Indicators of Performance in First-year Computing," *ACM SIGCSE Bulletin,* vol. 32, pp. 39-43, 2000.

[15] N. Pillay and V. Jugoo, "An Investigation into Student Characteristics affecting novice programming performance," *SIGCSE Bull.,* vol. 37, pp. 107-110, 2005.

[16] A. Chamillard and D. Karolick, "Using Learning Style Data in an Introductory Computer Science Course," in *SIGCSE ' 99* New Orleans, LA, USA: ACM, 1999, pp. 291-295.

[17] R. Felder and R. L. Silverman, "Learning and teaching styles in engineering education," *Engineering Education,* vol. 78, pp. 674-681, 1988.

[18] W. J. McKeachie, "Learning Styles can become Learning Strategies," *The National Teaching and Learning Forum,* vol. 4, pp. 1-3, 1995.

[19] M. McCracken, T. Wilusz, V. Alstrum, D. Diaz, M. Guzdial, D. Hagan, Y. B.-D. Kolikant, C. Laxer, L. Thomas, and I. Utting, "A multi-national, multi-institutional study of assessment of programming skills of first-year CS students," *ACM SIGCSE Bulletin,* vol. 33, pp. 125-180, 2001 2001.

[20] R. Loo, "Confirmatory factor analysis of Kolb's Learning Style Inventory (LSI-1985)," *British Journal of Educational Psychology,* vol. 69, pp. 213-219, 1999.

[21] C. Mainemelis, R. E. Boyatzis, and D. A. Kolb, "Learning Syles and adaptive flexibility: testing experiential learning theory.," *Management Learning,* vol. 33, pp. 5-33, 2002.

[22] W. Smith, S. S, and K. Townsend, "The impact of surface and relective teaching and learning on student academic success," in *7th Annual European Learning Styles Information Network Conference*, Ghent, 2002.

[23] L. Fowler, V. Campbell, D. McGill, and G. G. Roy, "An Innovative Approach to teaching First Year Programming Supported by Learning Style Investigation," in *14th Annual Conference for Australasian Association for Engineering Education*, Melbourne, Australia, 2003.

ACKNOWLEDGEMENTS

The authors are indebted to Prof. G. G. Roy, who provided the software tool used in the teaching for this research.

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