Assessing Python Programming Through Personalised Learning Styles Model

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Abstract Learning styles, cognitive traits, personality, and learning preferences can vary greatly. That is why there is a great variety in how people receive and process information. Personalizing learning materials according to learner's learning styles could enhance learner's learning motivation and lead to better learning performance. This paper examines the relationship between learner's learning styles and learning performance by proposing three different sets of documentation to test the relationship between the two learning styles of Felder-Silverman and learning performance. To test the proposed documentations and hypotheses, 182 participants in Multimedia University, Cyberjaya, Malaysia answered the Index of Learning Styles (ILS) questionnaire by Felder-Silverman and participated in a documentation experiment in Python programming. The data gathered was analysed using statistical Chi-square test. The results showed that learning performance was enhanced when the documentation was provided in a learning style that matched the subject's learning style. The confirmed personalised learning styles model can be beneficial to teachers and

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e-learning recommendation systems when they provide students with materials that are personalised.

Keywords Knowledge management · Knowledge discovery · Web-based computing · Personalisation

1 Introduction

Many methods have been studied and applied in the presentation of knowledge or information to beginners. Learning had previously taken place in a given place and time. Teachers had often been seen as the primary source of new information [1, 2]. Nonetheless, this strategy is facing difficulties because, for example, the world is evolving, increasing the number of applicants, new enrolment from various countries, expanded penetration of research areas and Internet development adds to the challenge. In comparison to these problems, the academic experience varies dramatically from generation to generation.

Students now have faster access and multiple ways to search for information on the Internet with the invention of the Internet and the creation of the World Wide Web (WWW). Therefore, users can exchange information more easily than ever before. To newcomers, improved dissemination of learning around the world means that people can better themselves with schooling as it can boost their living standard and socio-economic position. Technology development and information access raise the number of knowledgeable people, posing a problem for government organizations. They need to ensure that there is enough space to gather information and educate these people to achieve the goal of lifelong learning. Other challenges, such as geographic separation, lack of accessible places, and time constraints, require researchers to consider other knowledge delivery approaches. Current knowledge-based solutions could not address the complexities and limitations.

Different learning strategies were designed to overcome the challenges and limitations faced by learners, instructors and universities. A new approach to learning has been established with a steady increase in Internet speeds, the minimalism introduced with Web 2.0 standards and wider accessibility. This modern learning methodology is also called e-learning. This technique for the distribution of information reduces geographic isolation, time constraints and restrictions on location.

2 Background Study

Different learners have unique characteristics, for instance learning styles, learning preferences and personalities. Every individual acquires and processes information in a different way. Personalizing learning materials according to learner's learning styles could enhance learner's learning motivation and contribute to a better performance.

The process of learning and acquiring knowledge is a complicated and challenging process. A few factors such as acquiring and processing of knowledge by learners in terms of their common knowledge, developmental characteristics, and environmental components has an important part to play in this process. The learning process is influenced by various factors that will present different challenges to learners. There are several results from different research studies show that taking these differences into account while creating learning and teaching settings contributes to the increase of the effectiveness of learning activities, and efficiency in class [3–5].

The learning needs of the students can be addressed when considering their learning interests and demands [5]. The integration of information and communication technology (ICT) into educational settings has also contributed significantly to learning methods [6, 7]. This technology has driven developments in e-learning settings and their personalization according to learner's knowledge-acquisition needs.

An individual's preferred method of learning can be determined by first identifying the individual's learning style as learning styles describe learner's attitudes and actions when it comes to learning. Learning styles are crucial in educational environments as it may support students and teachers to become more self-conscious of their own strengths and weaknesses [8]. Learning styles are also one of the most vital factors to be utilised for taking into account individual differences [9].

Learning styles are the learning patterns and variations of an individual [10–12]. Numerous research studies investigate the efficiency and productivity of learning settings based on different individual learning styles. Such research studies indicate that the learning process in environments appropriate for learning styles has a positive impact on students' memory and application of information to a particular course or subject [6]. In addition, other empirical studies have shown that learning environments based on learning styles have a significant impact on the results or success of students performance [13–15].

3 Methodology

The research objectives of this paper are:

- To investigate the impact of student's learning styles and their performance in an introductory programming course.
- To propose a method in using information of student's learning styles as a guide in personalizing student's learning materials delivery approaches and study habits in the learning of programming.
- To evaluate the proposed method for the design of learning strategies.

This study applied an exercise-based experiment. These experiments were conducted with undergraduates from the Faculty of Computing and Informatics as participants. The authors did not inform the experimental participants about

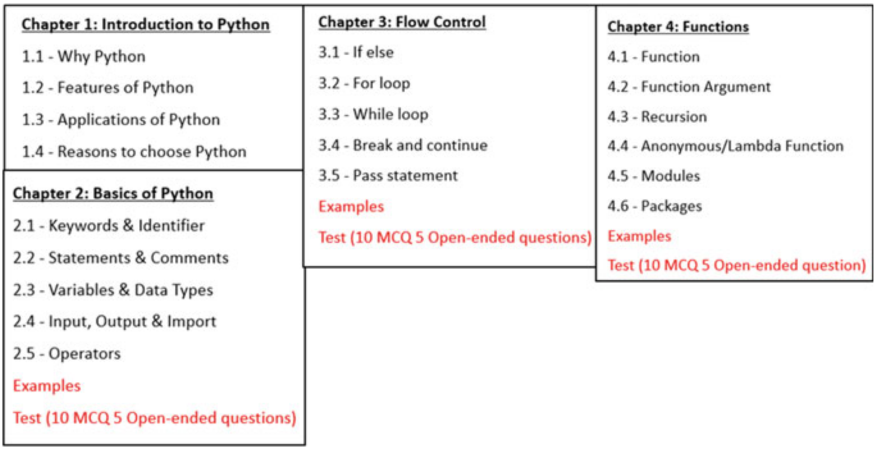

Fig. 1 Python learning syllabus

the research goals. The materials, examples and test questions are adapted from Schneider [16], as shown in Fig. 1.

An e-learning system has been designed and coded using Microsoft VB.NET and ASP.NET to automate the process of assessing students' pre-dominant learning styles using the Felder-Silverman model [12] and the personalization of students' learning materials. After completion, the system was configured and deployed in Microsoft Azure (cloud service) as shown in Fig. 2.

This system is coded to automate the process of assessing students' pre-dominant learning styles using the Felder-Silverman model, personalise of students' learning materials and record students' learning performance. A different experimental setting is developed for this part, which was chosen in order to compare student's learning styles and learning preferences. After the learning styles are assessed, the system will personalise the learning materials according to four different documentation styles, namely Verbal/Sequential, Verbal/Global, Visual/Sequential, and Visual/Global. Figure 3 shows the two sets of learning styles (Visual/Verbal and Sequential/Global) tested in this series of experiments. The participants can attempt to do the examples at the end of each chapter or sub-chapter. After that, they need to attempt a test at the end of each chapter or sub-chapter.

This experiment involves 182 Computer Science undergraduates at Multimedia University (MMU) Cyberjaya, which were categorised into three different documentation groups. The groups comprise of personalised learning style (*pLS*) group, opposite learning style (*oppLS*) group and control group (*ctrlGrp*). For the *pLS* group, learning works best when students are instructed in their preferred learning style. We would like to investigate whether the best for people with one learning style might not work so well with people in the *oppLS* group with different learning style. Finally, the control group (*ctrlGrp*) underwent the traditional method of learning materials given to them without involving any digital usage of e-learning system. Upon using

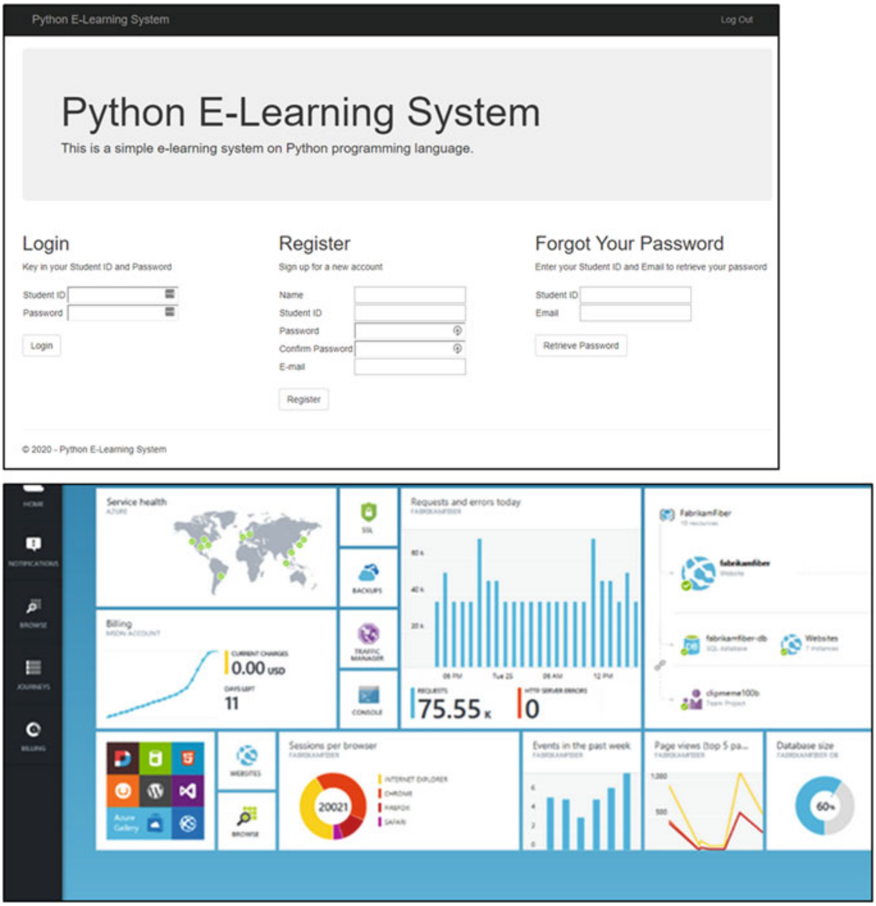

Fig. 2 Snapshots of e-learning system deployed in Microsoft Azure

the manual materials, the control group would attempt the exercise without considering any of their learning styles at all. In summary, our hypothesis is summarised as follows: *H0*—There is no difference among all three documentation groups (*pLS*, *oppLS*, *ctrlGrp*) for the participants in performing the given Python exercise.

4 Results and Discussions

Analysis of data obtained with the student's learning styles to identify some possible patterns and verify if there is some correlation between the participants' learning styles and their performance. In addition, the analysis of data could also help to evaluate whether the method used in this research is feasible in the design of student's

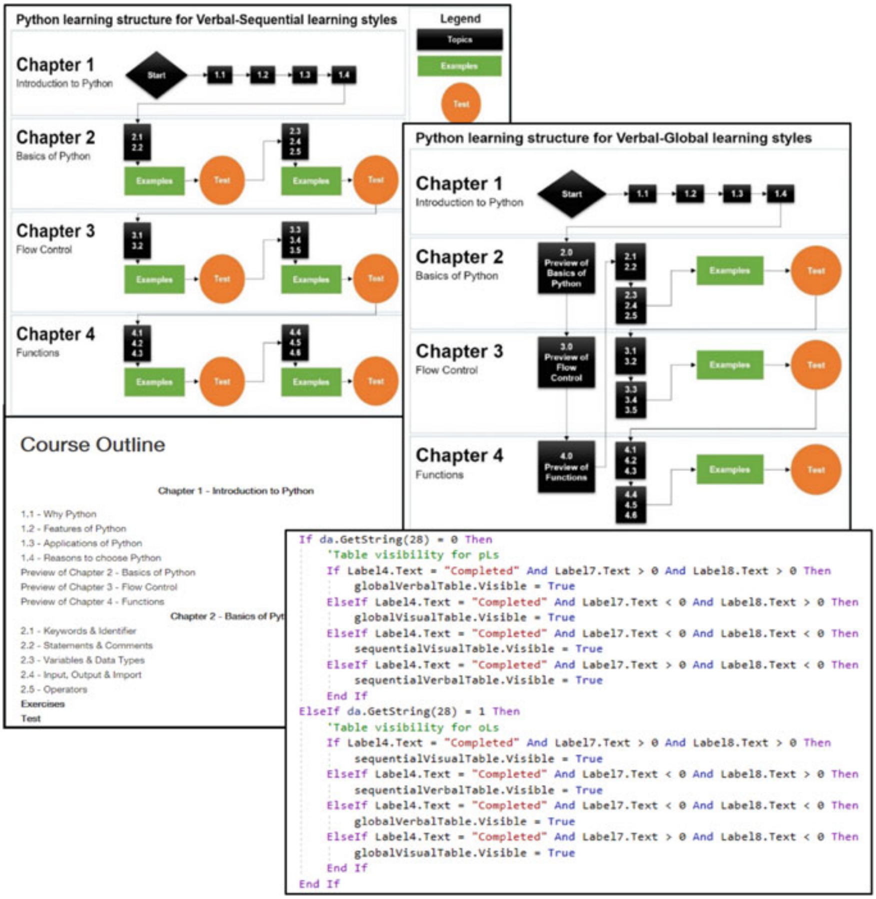

Fig. 3 Snapshots of the e-learning system

learning strategies. To assess student's performance, this research uses indicators of completion time (time taken to complete a test), and comprehension (understanding of a code). We performed a statistical analysis of the 182 responses obtained through the Statistical Package for Social Science (SPSS). The dependent variables of all three Stages (Stage 1 [Chapter 2], Stage 2 [Chapter 3], and Stage 3 [Chapter 4]) are:

(a) Time taken to complete a test (*complTimeStg1*, *complTimeStg2*, *complTimeStg3*).
(b) Comprehension in answering multiple choice questions (*comprMcqStg1*, *comprMcqStg2*, *comprMcqStg3*)
(c) Comprehension in answering structured questions (*comprStrucStg1*, *comprStrucStg2*, *comprStrucStg3*).

Table 1 shows the test results for normality for these dependent variables. Three

Table 1 Results of Kolmogorov–Smirnov normality test

Category	*p*-value	Category	*p*-value	Category	*p*-value
1. *complTimeStg1*	0.123	4. *complTimeStg2*	0.219	7. *complTimeStg3*	0.194
2. *comprMcqStg1*	0.002*	5. *comprMcqStg2*	0.014*	8. *comprMcqStg3*	0.000*
3. *compStrucStg1*	0.008*	6. *compStrucStg2*	0.000*	9. *compStrucStg3*	0.000*

*Statistically significant at 0.050 level (with $p < 0.050$)

dependent variables are normally distributed, (*complTimeStg1*, *complTimeStg2*, *complTimeStg3*), with *p*-values more than 0.050. Therefore, the median is used for other dependent variables instead of the mean.

Table 2 shows the bold-faced cells having dependent variables with higher (mean/median) scores. Three dependent variables (*complTimeStg1*, *complTimeStg2*, *complTimeStg3*) are normally distributed, hence the median is used for the other dependent variables instead of the mean. Each documentation group (*pLS*, *oppLS* and *ctrlGrp*) has different numbers of participants because each group was assigned according to participants' lab classes by the university.

Table 2 The categories descriptive statistics

	Mean			**Std. dev**		
Dependent variable (sample size, *n*)	***pLS* (76)**	***oppLS* (40)**	***ctrlGrp* (66)**	***pLS***	***oppLS***	***ctrGrp***
1. *complTimeStg1* (hh:mm:ss)	**0:14:37**	0:17:37	0:27:51	0:09:21	0:14:42	0:12:15
2. *complTimeStg2* (hh:mm:ss)	**0:32:00**	0:48:41	1:01:34	0:18:20	0:24:25	0:10:00
3. *complTimeStg3* (hh:mm:ss)	**0:20:55**	0:25:08	0:57:19	0:11:27	0:10:11	0:10:11
	Median			**Std. dev**		
	pLS	***oppLS***	***ctrlGrp***	***pLS***	***oppLS***	***ctrlGrp***
4. *comprMcqStg1* (scale: 0–10)	**8.00**	6.00	7.00	1.363	1.207	1.233
5. *comprStrucStg1* (scale: 0–10)	**9.00**	7.50	7.00	1.519	2.444	1.484
6. *comprMcqStg2* (scale: 0–10)	7.00	7.00	6.00	1.467	1.476	1.388
7. *comprStrucStg2* (scale: 0–10)	**10.00**	8.50	8.00	1.285	2.262	1.784
8. *comprMcqStg3* (scale: 0–10)	8.00	8.00	8.00	1.648	1.318	1.115
9. *comprStrucStg3* (scale: 0–10)	9.00	9.00	**10.00**	1.736	1.748	1.686

4.1 Completion Time for Stage 1, Stage 2 and Stage 3

Some items are bold-faced in Table 2 to show that a particular group performs better than the other two groups. For example, the personalised learning group in *complTimeStg1* took 14 min 37 s to complete the exercise in terms of completion time. The opposite learning group, meanwhile, took a longer period of 17 min 37 s and it took 29 min 51 s for the control learning group to perform the same exercise. Furthermore, in *complTimeStg2*, the personalised group completed the fastest. Students in the personalised learning group only took 32 min to complete the given exercise whereas the opposite learning group completed in 48 min 41 s and control learning group finished in 1 h 1 min 34 s. Finally, in terms of completion time for Stage 3, *complTimeStg3*, students in the personalised learning group completed faster in 20 min 55 s as compared to the opposite learning group, 25 min 8 s and the control group, 57 min 19 s.

4.2 Comprehension

As for comprehension in answering multiple choice questions and structured questions in the given exercise to students in all three stages, *comprMcqStg1*, the personalised learning group has the highest median. Next, let us consider the comprehension in answering multiple choice questions and structured questions in the specified exercise to students in all three stages. For *comprMcqStg1*, the personalised learning group has the highest median of 8.00 correct answers (out of 10), as compared to the opposite learning group, which has a median of 6.00 correct answers, and the control learning group, which has a median of 7 correct answers. In comparison, for *comprStrucStg1*, the personalised learning group has a median of 9.00 correct answers, while the opposite learning group has a median of 7.50 correct answers, and the control learning group has a median of 7.00 correct answers. The rubric used for the scale 0–10 were based on the exercises extracted from the Python practices evaluation scheme [16]. For each variable assessed, ten coding questions are formulated. Each correct Python answer contributes to one unit of score into the scale of 0–10.

For Stage 2, *comprMcqStg2*, both the personalised learning group and the control learning group have an average of 7.00 correct answers, while the opposite learning group has an average of 6.00 correct answers. Regarding *comprStrucStg2*, the personalised learning group has the highest median value of 10.00 correct answers as compared to the opposite learning group, which has a median of 8.50 and the control learning group, which has a median of 8.00 correct answers.

All three learning groups, personalised learning group, opposite learning group and control learning group has the same median value of 8.00 correct answers for *comprMcqStg3*. Lastly, as for *comprStrucStg3*, the control learning group has the

Table 3 Multivariate effects on dependent variables

Category	F	p-value
1. *complTimeStg1*	12.730	**0.000***
2. *complTimeStg2*	25.512	**0.000***
3. *complTimeStg3*	140.222	**0.000***

*Statistically significant at 0.050 level with $p < 0.050$ (2-tailed)

highest median of 10.00 correct answers whereas the personalised learning group and opposite learning group only has a median of 9.00 correct answers.

4.3 Significance Among the Three Documentation Groups

Table 3 shows the results of the separate multivariate tests. These F-tests are performed to indicate the specific dependent variables that are important across the three different learning groups. The p-values are derived by MANOVA (Multi-variate Analysis of Variance) testing of results between subjects. These results imply high significance differences in mean scores through Wilks' Lambda = 0.651, $F(6,394) = 15.708$ ($p < 0.0001$).

With respect to *complTimeStg1*, *complTimeStg2*, and *complTimeStg3* in Table 2, participants from the personalised learning (*pLS*) group complete their entire task faster than the opposite learning (*oppLS*) group and the control learning group. When the standard significance level of 0.050 (95 percent probability) is found in Table 3, the personalised learning group provides evidence that *complTimeStg1*, *complTimeStg2*, and *complTimeStg3* are much quicker. The personalised learning group participants are significantly faster than the opposite and the control learning groups.

The non-parametric Mann–Whitney test is used because the six dependent variables (*comprMcqStg1, comprStrucStg1, comprMcqStg2, comprStrucStg2, comprMcqStg3*, *comprStrucStg3*) are not normally distributed over the comparison of the three learning groups. Table 4 shows that *complTimeStg1*, *complTimeStg2*,

Table 4 Mann–Whitney test results on the learning groups

	Mean rank				
Categories	*pLS*	*oppLS*	*ctrlGrp*	χ^2	p-value
1. *comprMcqStg1*	76.16	41.95	63.39	20.852	**0.000***
2. *comprStrucStg1*	76.34	49.11	56.05	13.629	**0.001***
3. *comprMcqStg2*	68.43	64.66	48.41	7.799	**0.020***
4. *comprStrucStg2*	77.59	56.08	47.84	16.718	**0.000***
5. *comprMcqStg3*	70.23	55.10	54.54	5.631	0.060
6. *comprStrucStg3*	54.24	58.20	69.06	4.330	0.115

*Statistically significant at 0.050 level with $p < 0.050$ (2-tailed) *complTimeStg3*, *comprStrucStg2* with *p*-values < 0.050 have significant differences among the three learning groups. However, *comprMcqStg3* and *comprStrucStg3* with *p*-values greater than 0.05, have no significant difference among the three learning groups. For the advanced Stage 3, the participants performed well to complete the given task, irrespective of which type of documentation was given to them.

In Table 4, with respect to *comprMcqStg1*, *comprStrucStg1*, *comprMcqStg2* and *comprStrucStg2*, participants from the personalised learning group show significantly better results than those from the opposite and the control learning groups in the early stages. This therefore follows the rejection of the H0 hypothesis in Sect. 3 for these variables. Such rejection means that in facilitating learning to the learners, the personalised and control learning group was distinct. As noticed by Ho and Tan [17], most undergraduates also come from the sequential learning style. As such, the sequential documentation style suits most intermediate students, who usually have a sequential learning style. These results support the personalization of learning styles that can be beneficial to teachers and e-learning in consistent with the previously published works [18–23]. The personalized materials according to students' learning styles establish significant improved comprehension in both the multiple choices and structured responses as shown in Table 4.

5 Conclusion

In conclusion, this paper provides the following three major contributions.

- A Python introduction technique was proposed to cater to four different learning style groups namely Verbal/Sequential, Verbal/Global, Visual/Sequential and Visual/Global. Results from the two series of experiments conducted in this research demonstrated that students participating in personalised learning environments are more motivated and tend to complete faster than those in a traditional learning environment. Lecturers can benefit from this Python introduction technique especially in educating students in an introductory programming course.
- Next, an assessment methodology was designed for the recognition of learning styles that will help lecturers to identify suitable methods in teaching. This assessment methodology presents frameworks for lecturers or teachers to prepare students' learning materials for different learning groups, for example, the personalised learning group (*pLS*), the opposite learning group (*oppLS*) and the control learning group (*ctrlGrp*).
- The results from this series of experiment provide ways or options for lecturers or teachers to develop their learning strategies. Knowing the learning styles of each learner can help lecturers or teachers to identify students' learning preferences and strengths, which can be utilised in instructional designs as to improve the students' learning performance.

To date, limited research has been conducted to improve learning experience and academic achievement by integrating students' learning styles in their learning process. It provides some key ideas to the existing literature in improving performance of learning programming. The results of this paper have also contributed to the knowledge and literature in educational research. To reiterate, this research aims to use the assessment of learning styles to improve learning in programming by developing a method for learning programming, particularly in Python. The following presents conclusions on the findings to the research objectives and research questions.

Firstly, different people have different learning styles, which can change the way they learn [18] and performance in different situations. For this reason, how we present new materials to students can change how well people learn. We have shown that, in the field of learning programming, the students' learning style can influence how they perceive the materials given to them. Therefore, it motivates us to figure out the students' learning styles, and present the information to them in a manner that is more suitable to them, so that they can learn more efficiently. These findings examined how multiple learning styles affect how well people learn programming in order to propose ways for teachers to develop their materials.

Secondly, e-learning services are not new anymore, but tailoring them in such a way as to help different types of learners is still a challenge. For this reason, we have proposed a way to personalise learning materials on an e-learning system according to students' learning styles. This is well supported from the concept of personalised learning styles model literature [19–23]. The purpose of the e-learning is to help learners to accomplish their learning objectives. Because learning styles theory suggests that how difficult it is for someone to learn something new could be greatly influenced by whether the materials they are presented with matches their learning style or not, the idea of personalisation is very attractive. This is why it makes sense to assess students and trainees' learning styles and choosing to present materials in a way that matches that. For this reason, it has become more common for lesson plans include a plan for how to address students with different learning styles. That is why our findings are relevant to educational theory and practice.

Thirdly, the proposed method for the design of learning strategies is assessed. Pertaining the results shown in the series of experiments in this paper, the participants from the personalised learning group (*pLS*) completed their entire task faster than the other learning groups, namely the opposite learning group (*oppLS*) and the control learning group (*ctrlGrp*). It is hypothesised that providing instruction based on individuals' preferred learning styles improves learning and this can be incorporated into the design of learning strategies by lecturers or teachers.

In the future, we may try a course on advanced topics and analyse it with Structural Equation Modelling (SEM). SEM is a multivariate statistical technique, which can simultaneously analyse a series of dependent relationships [24]. SEM allows the evaluations of a single model containing all relationships in a hypothesis. This could be more accurate than trying to analyse each way of learning programming individually.

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