Original Research Paper

Reciprocity Effect between Cognitive Style and Mixed Learning Method on Computer Programming Skill

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Abstract: Many universities undertake mixed learning to meet the required needs. Mixed learning is a blend of F2F classroom education and online learning education. The strength of mixed learning is that it supports student cognitive styles more than non-mixed learning. The right mix of mixed learning provides more constructive and conducive learning. Meanwhile, the programming language is the primary skill that students must master to create computer application programs. The question is: Is there an effect on student cognitive style and learning methods on mixed material 30% F2F and 70% asynchronous online and on the contrary mixture on student programming skills? Therefore, this study aims to determine the effect of reciprocal interaction between cognitive styles and mixed learning methods on programming skill achievement. This research method is experimental research. The study found that: Although there is no difference in the achievement of student learning skills based on tests on mixed learning methods, further test on student cognitive styles found that there are differences in the achievement of student learning skills in mixed learning methods; students with auditory and visual cognitive style who learn with mixed learning-2 have better programming skill achievement than students with auditory cognitive style who learn with mixed learning-2; students with kinesthetic and visual cognitive styles who learn with mixed learning-2 have superior programming skill achievement compared to students with kinesthetic cognitive styles who learn with mixed learning-1. The research novelty is: There has been no previous research on the reciprocal effect of cognitive styles and mixed learning methods with a mixture of 30% F2F and 70% online and vice versa.

Keywords: Cognitive Style, Mixed Learning, Computer Programming, Learning Method

Introduction

The rapid advancement of Information and Communication Technology (ICT) makes it easier to realize multimedia in learning to support student cognitive styles. Besides that, the use of ICT also has a positive impact on the learning process as well as realizing learning efficiency (Aljuboori *et al*., 2020). However, the rapid development of ICT has increased pressure for universities to include greater use of technology and innovation in the curriculum (Tyler-Wood *et al*., 2018). Therefore, it is not surprising, if many tertiary institutions adopted mixed learning approaches as a solution (Nazarenko, 2015). Mixed learning is a perfect blend of F2F classroom education and asynchronous online learning education (Pierce, 2017).

Mixed learning research has long been a concern of researchers and lately, it has become an important research topic because it has a combined advantage of learning in the classroom and outside the classroom. Unfortunately, research on mixed learning skills is still limited (Nazarenko, 2015). The benefits of mixed learning are the best approach to learning strategy by taking the strengths of Face-To-Face (F2F) and online learning (Sleator, 2010). One of the strengths of mixed education is that it provides a conducive learning environment for students and supports a variety of student cognitive styles (Pierce, 2017). That makes sense that prior research indicated, mixed learning is superior to non-mixed learning in learning achievement (Van Niekerk and Webb, 2016). Mixed learning can maximize student learning outcomes by applying appropriate technology learning to fit student cognitive style in transferring skills correctly and at the right time (Lieser and Taff, 2013).

The right combination of mixed learning provides social support and constructive learning for students (Opina *et al*., 2011) and creates conducive interactions in learning activities (Pierce, 2017). However, the question is:

- How is student learning skill achievement based on student cognitive style?
- How is the student' skill achievement from two different mixed learning and is there a reciprocal influence between student cognitive style and mixed learning methods?
- What will the results be if there is a mutual influence between cognitive styles and mixed learning methods?

Therefore, this study aims to determine the effect of reciprocal interaction between cognitive styles and mixed learning methods on learning skill achievement.

The mixed learning method combines education between F2F classroom education and online learning education (Hogarth and Biggam, 2009; Almpanis *et al*., 2010). F2F class education strength is the high intensity of interaction between students and lecturers in facilitating cooperative learning and clarity of lecture materials (Agosto *et al*., 2013). The F2F classroom education offers real and meaningful interactions between students and teachers, while pure online education cannot replace it (Tang and Chaw, 2013). The problem is, the F2F classroom education requires higher tuition fees, especially in well-known tertiary institutions (Norman, 2016). Online learning is a significant part of university education to support conventional F2F learning (Seta *et al*., 2018). Communication that occurs in online learning is synchronous and asynchronous (Clark and Barbour, 2015).

In synchronous online, education is delivered remotely in real-time by the teaching lecturer to students (Alammary, 2019; Anggrawan and Satria, 2020). In contrast, learning material in asynchronous online education is given indirectly to the student (Anggrawan and Satria, 2020). In asynchronous online, students can access material or modules stored on the server computer anytime and anywhere through computers connected via the internet to specific web addresses (Anggrawan and Satria, 2020). Asynchronous online learning constitutes independent learning for students (Anggrawan and Satria, 2020) or collaborative learning (Alammary, 2019) by some students who agree to study. Students and lecturers agree that one of the main weaknesses of online learning is the lack of F2F interaction (Król, 2016). Meanwhile, asynchronous online education strength takes advantage of various multimedia forms: Text, audio, visual still and moving and other forms for learning purposes supporting student cognitive styles (Clark and Barbour, 2015).

Every student has a cognitive style that reflects a way of learning that is preferred and easier for students to understand. Students with high specific cognitive styles have more significant difficulties acquiring knowledge than weaker cognitive styles (Psycharis *et al*., 2014). There are three types of cognitive styles: Visual, auditory and kinesthetic (Rhouma, 2016). Students with visual cognitive styles prefer and easily understand the lessons presented in writing, pictures, graphs and tables (Rhouma, 2016; Anggrawan *et al*., 2019). In other words, students with visual cognitive styles in learning rely on their sense of sight. Auditory students prefer the lesson presentation in voice or lecture form (Anggrawan *et al*., 2019). So, in other words, students with auditory cognitive style rely on the sense of hearing. Kinesthetic students prefer to learn in interactive information media and special situations (Anggrawan *et al*., 2019). In essence, learning should support student cognitive styles to improve performance and success learning (Eudoxie, 2011). So it makes sense and inevitable, if later, more and more universities have created systems and organized innovative mixed education to accommodate student cognitive styles and the learning needs of 21st-century students (Lieser and Taff, 2013).

Substantially, mixed learning provides better effectiveness than education that relies only on the conventional F2F education method (Van Niekerk and Webb, 2016). Besides, students respond positively and easily adapt to mixed learning (Anggrawan *et al*., 2019); actually, mixed learning brings excellent opportunities for students to master the subject matter and achieve success in education (Lieser and Taff, 2013). Moreover, mixed learning patterns provide a more conducive learning environment and increase student learning achievement (Bazelais and Doleck, 2018). In fact, despite online learning education or conventional F2F classroom education has disadvantages, but mixed learning can overcome it as long as mixed learning is mixed with the right mix (Opina *et al*., 2011). According to Kanuka and Rourke (2013), some experts argue that the portion of the online learning mix in mixed learning is 25 to 50%; meanwhile, other experts determine the amount of the online learning mix in mixed learning is between 30 and 70% (Kanuka and Rourke, 2013). In short, there is no certainty about the portion of the online learning mix in mixed learning. Thus, the mixed learning main obstacle lies in the accuracy of the mixture; of course, the right mix in one subject does not mean it is suitable for another course (Anggrawan *et al*., 2019). Likewise, although certain courses have produced evidence of satisfactory learning success with mixed learning, this does not mean that the same conditions apply to other courses. So, the mixture accuracy and the suitability of mixed learning in each subject must be scrutinized scientifically. Thus, in essence, scientific research on mixed learning is necessary to determine how well the student learning success due to the mutual influence between cognitive styles and mixed learning methods. In other words, if there is a mutual influence between cognitive styles and mixed learning methods, it is necessary to know what the results are?

In short, in connection with this research, the formulation of the research problem explicitly is:

(a) What learning methods are better than the two kinds of mixed teaching methods; is the mixture of 70% learning in class and 30% online learning outside the classroom or 30% learning in class and 70% online learning outside the classroom?
(b) Is there a reciprocal influence between student cognitive styles and mixed learning methods applied in teaching?
(c) If there is a reciprocal influence, how will it affect the achievement of student programming skills?

Programming language courses are essential for students in mastering programming skills (Yindi, 2016; Anggrawan, 2018). The programming skill is the ability of students to create computer applications with programming languages. The visual programming language is event-based programming (Yindi, 2016; Anggrawan, 2018). In other words, program code is made based on specific events or functions so that the sequence of program execution is also an event. In contrast to structured or procedural programming, it will execute program code from the beginning to the end of the program sequentially (Anggrawan, 2018). The visual programming language that is most popular today is Visual Basic.Net or VB.Net (Anggrawan, 2018). VB.Net is an object-oriented programming language (Yindi, 2016; Othman *et al*., 2018). VB. Net has the advantage of being of the visual programming language and high interest from students who learn it (Zhang *et al*., 2011). VB.NET is useful for applying network interfaces and operate records databases (Othman *et al*., 2018).

Related Work

This subsection provides a brief literature review of some of the most recent scientific articles relating to cognitive styles, programming and mixed learning:

- Theodoropoulos *et al*. (2016) investigated the link between cognitive styles and student capabilities in learning programming using games. This study indicates that the cognitive style is a significant learning characteristic to consider when learning the programming lesson. This study uses a survey method to obtain research results
- Awang *et al*. (2017) conducted a study that essentially examined student cognitive styles on academic achievement. Their research results indicate that the student cognitive styles affect academic achievement and each cognitive style has advantages and disadvantages. Their research only focuses on the influence of cognitive styles on student learning outcomes using the survey method in F2F learning
- Ceylan and Kesici (2017) examined the effect of mixed learning on student academic achievement. This research uses a survey method with the quantitative data type. The results of this study found that mixed learning environment significantly helps student academic learning achievement
- Lazarinis *et al*. (2019) examined mixed learning intending to improve teacher programming skills. This study did not link cognitive styles with teacher responses to learning. This previous research also did not mention the percentage of mixing mixed learning materials between F2F and online learning materials. The research method used was a survey. This last study concluded that teachers responded positively to mixed learning experiences
- Maia *et al*. (2017) investigated cognitive style application and their effects on programming

education in F2F teaching. Their research found that student cognitive styles can affect students learning abilities. Their study used a survey method

- Anggrawan *et al*. (2019) examined the influence between cognitive style and gender on mixed learning in Algorithm and programming lesson. This study has a limitation that only investigates mixed learning by mixing 40% F2F material and 60% online material. This means that this earlier study was not a reciprocity effect study; that is, it did not investigate mixed learning with the opposite mixture of mixing 40% F2F material and 60% online material. This earlier study found differences in learning outcomes between students who had different learning styles. Male gender students were more successful than students with the female gender, using the experimental research method
- Alammary (2019) conducted an assessment of the comparison of programming learning experiences between conventional treatments and mixed care methods. This study concluded that mixed learning is more effective in constructing traditional education to improve student learning experiences. This study also confirms that there is an increasing trend in the application of mixed learning programming lessons. This previous researcher also warned that there was still little research related to programming education and mixed learning methods

Literature review of the relative work as mentioned above: (a). Did not examine the comparison of the learning achievement of two mixed learning with the opposite percentage of teaching material mix between F2F and online learning materials; (b). did not examine mixed learning with a blend of 70% learning in class and 30% learning online outside of the classroom and 30% learning in class and 70% learning online outside the classroom; (c). did not research experimental methods on student learning achievement in two mixed learning associated with student cognitive styles and learning methods.

In essence, the authors in this study conducted research that no one has examined, namely the effect of back and forth between mixed learning methods and cognitive styles on computer programming education. Besides, the authors conducted this mixed learning research with mixed teaching materials divided into 70% online and 30% F2F mix and vice versa, which so far, no one has researched.

Materials and Methods

This study is experimental research. Two different classes get a mixed learning treatment of VB.Net computer programming lesson materials with a mixture of different portions between F2F learning and asynchronous online learning. The combination tested was 70% versus 30% between classroom learning and asynchronous online learning in the first class and vice versa, 30% mixture versus 70% between classroom learning and asynchronous online learning in the second class.

Learning Treatment

Two classes received learning VB.Net Programming courses. Two treatment classes resulted from the random selection from 5 classes in the Computer Science study program at Bumigora University. The number of students in each treatment class consists of 50 students in the first semester of the academic year of 2019/2020.The first mixed learning class (mixed learning-1) got treatment by combining around 30% F2F learning and about 70% asynchronous online learning. Meanwhile, the second mixed learning class (mixed learning-2) got treatment by combining around 70% F2F learning and about 30% asynchronous online learning.

Students acquire VB.Net programming skills through F2F mixed learning materials in class and online learning materials. Students can learn online lessons independently in teaching material modules (or asynchronous online forms) prepared on a computer server. Besides, students can access them anywhere and anytime via the internet and study according to student needs and speed.

This research is an experimental study with two factors. The first factor is mixed learning with two levels and the second factor is the cognitive style with three levels. Thus, this research is an experimental study with a 2×3 factorial design.

Mixed Learning-1 (ML1) and Mixed Learning-2 (ML2) are two learning class groups prepared to realize this experimental research. Table 1 shows the model construction methodology of a 2×3 factorial design.

Table 1: 2 × 3 Factorial design

Mixed learning\ Cognitive style	Mixed Learning-1 (ML1)	Mixed Learning-2 (ML2)
Visual (A1)	A1, ML1	A1, ML2
Auditory (A2)	A2, ML1	A2, ML2
Kinesthetic (A3)	A3, ML1	A3, ML2

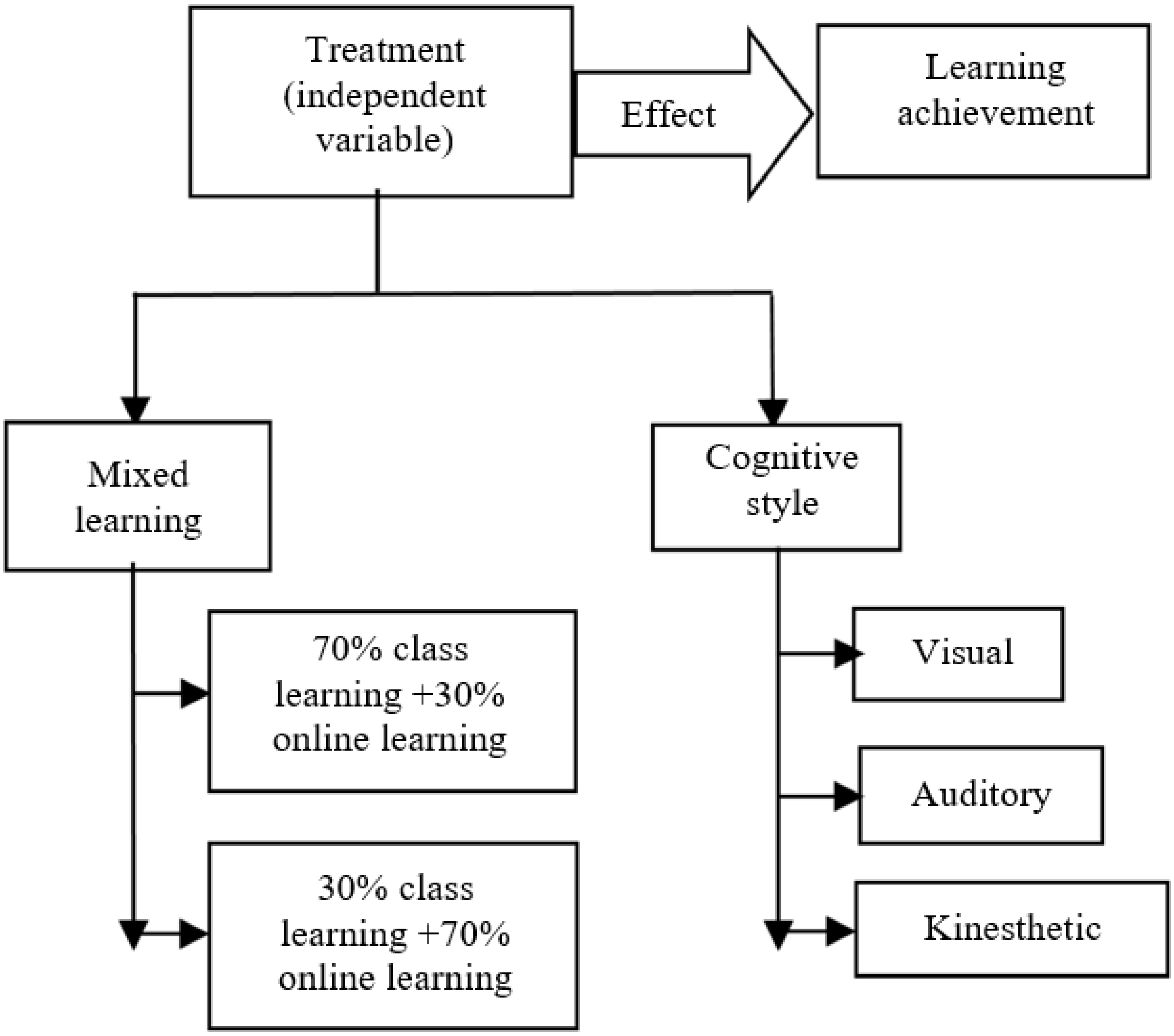

Fig. 1: 2 × 3 Factorial design diagram

So, the reciprocal effect examined in this study is the combined effect of two independent variables (two factors) on mixed learning and cognitive styles in influencing the dependent variable on learning achievement. Figure 1 shows the diagram of the 2 × 3 factorial design model.

The number of classroom learning meetings of the mixed learning-1 and mixed learning-2 takes 7-time meetings (does not include the Exam). F2F mixed learning-1 activities occurred at different times, days, classes and buildings to prevent the threat of spreading external validity. Mixed learning-1 and mixed learning-2 learning activities are as follows: Lecturers provide F2F class lessons, which are structured modules of F2F learning materials that have been classified materials and materials according to F2F learning schedules. Likewise, online learning with structured material has been prepared on a computer server that can be accessed by students (anytime and anywhere) with the asynchronous (or shared) independent learning method via the website.

Data Collecting

The data collected in this study are data on the learning achievement and cognitive style of each student. The instrument in assessing student skill attainment at the end of the lesson is in essay questions. The test instrument used to evaluate student learning achievement has passed the reliability and validity test before being used in the experimental class in this study. Student cognitive style data were collected using a questionnaire conducted in a mixed learning class. The student cognitive style questionnaire instrument uses standard Visual, Auditory, Reading/Writing, Kinesthetic (VARK) instruments that have been tested for reliability and validity.

Research Methods

Learning skill achievement data in this study is ratio data. Due to in this study two classes are treated, then this research method is experimental research, but based on the type and analytical data, this research method is inferential quantitative parametric research,

Testing for normality and homogeneity of data and the instrument validity and reliability was carried out using Shapiro-Wilk, Levene, Pearson Correlation and Cronbach's Alpha. A two-way Anova test was conducted to ascertain a reciprocal influence between student cognitive styles and learning methods; differences in learning achievement due to differences in student cognitive styles and differences in learning achievement between mixed learning methods with 70% learning in class and 30% via online compared to mixed learning methods with 30% learning in class and 70% via online. The Tukey post-hoc test is conducted to analyze the reciprocal effects that occur between cognitive style and learning methods.

Threats to internal validity in this study were overcome by means of students with the same background, namely fresh graduates from high school, meaning that students in this study have equal initial cognitive competence in computer programming, thus can overcome the threat of internal validity in the form of death/friction. Control group in the form of classroom lessons as part of mixed learning prevents this research from threatening history internal validity. The instrument used was a standard instrument or tested instrument of validity and reliability to free from instrument internal validity threat. In overcoming external validity threats in this study, other lecturers (not researchers) carried out the teaching process, thus preventing bias or the deliberate or carelessness of researchers in influencing student achievement. Mixed learning in new students was a new method for students; besides that, students were not aware of the research, thereby preventing the threat of external validity of reactive influence and treatment diffusion. In this study, students only got one experimental treatment so that interplay did not occur before and after treatment, thereby avoiding the threat of multiple treatment disorders.

Results and Discussion

The survey results using the VARK instrument show that students who have visual cognitive styles are 35 students, auditory cognitive styles are 37 students and kinesthetic cognitive styles are 28 students, as shown in Table 2.

Table 2 also shows that in the mixed learning-1 class, the number of students is 50. As many as 20 students have a visual cognitive style, 17 students have an auditory cognitive style and 13 students have a kinesthetic cognitive style. In the mixed learning-2 class, the total number of students is 50 students. Fifteen students have a visual cognitive style, 20 students have an auditory cognitive style and 15 students have a kinesthetic cognitive style.

A research instrument becomes a useful measuring tool if the instrument measures appropriately (or validity) and can be trusted (or reliable). Therefore, the instrument used in this study must meet the validity and reliability requirements of the test.

The Pearson correlation coefficients of the learning achievement instrument (Question-1, Question-2) using Product Moment were 0.799 and 0.917 (Table 3).

Meanwhile, according to Sugiyono (2004), the minimum requirement to be a correct (valid) instrument using Pearson Moment correlation (or Product Moment correlation) is if the correlation between items with a total score is greater than or equal to 0.3. It means that the instrument to measure learning achievement in this research has high validity.

The instrument reliability test to measure learning achievement using Cronbach's Alpha in this research was 0.677 (Table 4). It is indicating that the internal consistency of the instrument was good. The research instrument has reliable internal consistency if the reliability coefficient is equal to or greater than 0.6 (Siregar, 2014).

Table 2: Total mixed learning students based on cognitive style

Mixed learning\Cognitive style	Mixed Learning-1 (ML1)	Mixed Learning-2 (ML2)	Frequency
Visual	20	15	35
Auditory	17	20	37
Kinesthetic	13	15	28
Total	50	50	100

Table 3: Validity test of the learning achievement instrument with Pearson correlation

		Exam score	Question-1	Question-2
Exam score	Pearson correlation.	1	0.799**	0.917**
	Sig. (2-tailed)		0.000	0.000
	N.	100	100	100
Question-1	Pearson Correlation.	0.799*	1	0.563**
	Sig. (2-tailed)	0.000		0.000
	N.	100	100	100
Question-2	Pearson Correlation.	0.917**	0.563**	1
	Sig. (2-tailed)	0.000	0.000	
	N.	100	100	100

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)

Table 4: Reliability test of the study achievement with cronbach's alpha

Cronbach's alpha	N of Items
0.677	2

Table 5: Homogeneity test result

	Levene statistic	Df1	Df2	Sig.
Exam score	3.634	1	98	0.060

Table 6: Normality test result

		Kolmogorov-Smirnov			Shapiro-Wilk		
ML1 ML2		Statistic	Df	Sig.	Statistic	Df	Sig.
Score Total	ML1	0.172	50	0.001	0.957	50	0.065
	ML2	0.125	50	0.049	0.957	50	0.068

Table 7: Two-way anova test

Source	Type III sum of squares	Df	Mean square	F	Sig.
Corrected model	2391.060[a]	5	478.212	17.907	0.000
Intercept	483277.397	1	483277.397	18096.459	0.000
VAK	352.599	2	176.299	6.602	0.002
ML1 ML2	70.389	1	70.389	2.636	0.108
VAK*ML1 ML2	2090.029	2	1045.014	39.131	0.000
Error	2510.330	94	26.706		
Total	497565.000	100			
Corrected Total	4901.390	99			

R Squared = 0.488 (Adjusted R Squared = 0.461)

Table 8: Tukey post-hoc test of learning achievement of hybrid learning-1 and hybrid learning-2 based on student cognitive styles

					95% Confidence interval	
(I) Interaction	(J) Interaction	Mean difference (I-J)	Std. error	Sig.	Lower bound	Upper bound
AML 1	AML 2	10.90*	1.768	0.000	5.76	16.04
	KML 1	9.92*	2.013	0.000	4.06	15.77
	KML 2	2.5	1.864	0.761	-2.92	7.92
	VML 1	5.46*	1.749	0.028	0.37	10.55
	VML 2	-2.38	1.895	0.807	-7.90	3.13
AML 2	AML 1	-10.90*	1.768	0.000	-16.04	-5.76
	KML 1	-0.98	1.925	0.996	-6.58	4.62
	KML 2	-8.40*	1.768	0.000	-13.54	-3.26
	VML 1	-5.44*	1.647	0.017	-10.23	-0.64

Table 8: Continue

	VML 2	-13.28	1.801	0.000	-18.52	-8.04
KML 1	AML 1	-9.92*	2.012	0.000	-15.77	-4.06
	AML 2	0.98	1.925	0.996	-4.62	6.58
	KML 2	-7.42*	2.013	0.005	-13.27	-1.56
	VML 1	-4.45	1.908	0.191	-10.00	1.10
	VML 2	-12.30*	2.042	0.000	-18.24	-6.36
KML 2	AML 1	-2.5	1.864	0.761	-7.92	2.92
	AML 2	8.40*	1.768	0.000	3.36	13.54
	KML 1	7.42*	2.013	0.005	1.56	13.27
	VML 1	2.96	1.749	0.539	-2.13	8.05
	VML 2	-4.88	1.895	0.113	-10.40	0.63
VML 1	AML 1	-5.46*	1.749	0.028	-10.55	-0.37
	AML 2	5.44*	1.647	0.017	0.64	10.23
	KML 1	4.45	1.908	0.191	-1.10	10.00
	KML 2	-2.96	1.749	0.539	-8.05	2.13
	VML 2	-7.85*	1.782	0.000	-13.03	-2.66
VML 2	AML 1	2.38	1.895	0.807	-3.13	7.90
	AML 2	13.28*	1.801	0.000	8.04	18.52
	KML 1	12.30*	2.042	0.000	6.36	18.24
	KML 2	4.88	1.895	0.113	-0.63	10.40
	VML 1	7.85*	1.782	0.000	2.65	13.03

The requirement for conducting a two-way Anova parametric statistical test is that the data used must have the same or homogeneous variants (Siregar, 2014). Therefore, this study uses the Levene test to determine whether the learning outcome data is homogeneous or not. Likewise, the data is must normal distribution as a condition to perform a two-way Anova parametric statistical test (Siregar, 2014). Therefore, this study uses Shapiro-Wilk to test the normality of the data.

The Levene test significance value on the test result score (0.060) is higher than the alpha value of 0.05 (Table 5); this indicates that the data variance is homogeneous.

The normality test of learning outcomes data with Shapiro-Wilk shows the significant value of Mixed Learning-1 (ML 1) is 0.65 and Mixed Learning-2 (ML 2) is 0.68 (Table 6). The significance value for the two mixed learning test scores is greater than the alpha value (0.05), so the learning achievement for both mixed learning is normally distributed.

Using a two-way Anova is to determine how the combination of two independent variables affects the dependent variable (Montgomery, 2012).

Based on the two-way Anova test, there is an interaction between cognitive styles and teaching methods (the significant value of VAK*ML1ML2 is 0.00), which is smaller than the alpha value (0.05) shown in Table 7. Thus, the cognitive style and teaching methods influence each other in programming learning.

The two-way Anova test showed that the significant value of the difference in learning achievement between students who received mixed learning-1 and mixed learning-2 was greater than the alpha value (ML1 ML 2 significant value 0.108). Thus, the conclusion is that there is no difference in learning achievement between teaching done with mixed learning-1 and mixed learning-2. There are differences in learning achievement between students with different cognitive styles in mixed learning-1 and mixed learning-2. In this case, the significance level of student cognitive style (VAK) on the two-way Anova test (0.002) is smaller than the alpha value (0.05), which means that there are differences in learning achievement between students who have different cognitive style. So, the conclusion is, even though the two teaching methods show no different student learning achievement, this does not mean that there is no difference in learning achievement based on student cognitive styles.

This finding is the novelty found in this study, that although the accomplishment of learning skills for both teaching methods is equally good, it does not mean that the learning method is suitable for all students. However, it turns out that students with specific cognitive styles may not be ideal for that teaching method. The implication is that students can achieve maximum learning success; the way is, learning methods facilitate learning media that support student cognitive styles.

Tukey post-hoc test is a follow-up test when an interaction occurs in the two-way Anova test (Montgomery, 2012). Tukey post-hoc test can tell

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precisely where the differences between the two independent variables affect the dependent variable. Therefore, this study conducted Tukey post-hoc test.

Based on the results of Tukey post-hoc test (Table 8), in mixed learning-1, the results of the Tukey post-hoc test show: (a). The learning achievement of students who have auditory cognitive styles is better than students who have kinesthetic and visual cognitive styles; (b). The learning achievement of students who have kinesthetic cognitive styles is not different from students who have visual cognitive styles.

Based on the results of Tukey post-hoc test (as shown in Table 8), in mixed learning-2, the results of the Tukey post-hoc test show: (a). The learning achievement of students who have auditory cognitive styles is worse than students who have kinesthetic and visual cognitive styles; (b). The learning achievement of students who have kinesthetic cognitive styles is not different from students who have visual cognitive styles.

Meanwhile, the comparison of learning achievement on the Tukey post-hoc test between students taught with mixed learning-1 and mixed learning-2 shows:

(a) Mixed learning-1 students who have auditory cognitive styles have better skill achievement than mixed learning-2 students who have auditory cognitive styles
(b) Mixed learning-1 students who have auditory cognitive styles have no different skill achievement compared to mixed learning-2 students who have kinesthetic and visual cognitive styles
(c) Mixed learning-1 students who have kinesthetic cognitive styles have worse skill achievement than mixed learning-2 students who have visual and kinesthetic cognitive styles
(d) Mixed learning-1 students with kinesthetic cognitive styles have no different skill achievement than mixed learning-2 students with auditory cognitive styles
(e) Mixed learning-1 students who have visual cognitive styles have better skill achievement than mixed learning-2 students who have auditory cognitive styles
(f) Mixed learning-1 students with visual cognitive styles have no different skill achievement than mixed learning-2 students who have kinesthetic cognitive styles
(g) Mixed learning-1 students with visual cognitive styles have worse skill achievement than mixed learning-2 students with visual cognitive styles

The results of this study have also revealed which learning styles are superior in the achievement of student computer programming learning in mixed learning-1 and mixed learning-2. This finding is the strength of the contribution of this study when compared to previous related works.

Conclusion

The two-way Anova test concluded that:

(a) There was no difference in the programming skills achieved between students who learn with mixed learning with a mixture of around 30% F2F learning and about 70% asynchronous online learning and students who learn with mixed learning with a blend of approximately 70% F2F learning and about 30% asynchronous online learning
(b) There are differences in programming skills acquired between students who have different cognitive styles both in mixed learning with a mixture of about 30% F2F learning and about 70% asynchronous online learning and also in mixed learning with a combination of about 70% F2F learning and about 30% asynchronous online learning

The results with Tukey post-hoc test concluded that:

(a) Students with auditory and visual cognitive styles who learn with mixed learning with a mixture of around 30% F2F learning and about 70% asynchronous online learning have better programming skills achievement than students with auditory cognitive styles who study with mixed learning with a blend of approximately 70% F2F learning and about 30% asynchronous online learning
(b) Students with kinesthetic and visual cognitive styles who learn with mixed learning with a blend of approximately 70% F2F learning and about 30% asynchronous online learning have programming skills that are superior to students with kinesthetic cognitive styles who learn with mixed learning with a mixture of around 30% F2F learning and about 70% asynchronous online learning

This means although the student programming skill achievement of the two mixed learning methods when assessed based on the learning method is equally good, it happens that student programming skill achievement of two mixed learning methods differs when evaluated based on the student cognitive styles.

Besides, this study also found that: In mixed learning with a mixture of around 30% F2F learning and about 70% asynchronous online learning, students who have an auditory cognitive style have superior programming skill achievement than students who have a kinesthetic and visual cognitive style. Meanwhile, students who have kinesthetic and visual cognitive styles do not differ in their programming skill achievement in mixed learning with a mixture of around 30% F2F learning and about 70% asynchronous online learning. In mixed learning with a blend of around 70% F2F learning and about 30% asynchronous online learning, students with an auditory cognitive style have worse programming skill achievement than students with a visual and kinesthetic cognitive style. Meanwhile, students who have kinesthetic and visual cognitive styles do not differ in their programming skill achievement in mixed learning with a blend of around 70% F2F learning and about 30% asynchronous online learning.

This research novelty is to study the reciprocal effects of student cognitive styles and hybrid learning with a mixture of 30% F2F subject matter combined with 70% asynchronous online subject matter and vice versa that no one had researched before.

Other new things obtained from this research are:

(a) The comparative test to determine which learning method is superior for the achievement of learning skills is not sufficient only with a comparative test based on the learning method but also based on the student cognitive style
(b) This study finding can be the beginning of a breakthrough in teaching with certain learning methods based on groups of students with the same cognitive style to achieve better skills. Or in other words, maybe the division of teaching classes no longer contains various cognitive styles with specific teaching methods for better learning achievement

This research result implies that each learning method must significantly facilitate learning media that support student cognitive styles. Another implication is the need to test various learning methods to determine which learning method is most suitable for each cognitive style for superior learning outcomes.

Further research will investigate what percentage of cognitive styles affect learning outcomes and compare student achievement between students with strong and weak cognitive styles by grouping or not grouping classes based on student cognitive styles. Thus, further research complements or refines existing research to make it more realistic about how much influence each one has cognitive style towards learning outcomes in mixed learning methods, including strong and weak cognitive styles.

Besides, this study has limitations in the learning factors studied, which only involve cognitive styles and mixed learning method with a combination of mixing 30% versus 70% between F2F subject matter and online subject matter and mixing vice versa, with a mixing variety of 70% versus 30% between F2F subject matter and online subject matter. So, further research needs to involve other internal student factors such as student interest in learning subjects and learning motivation. Likewise, it is necessary to do further research by applying external factors of mixed learning methods with various other variations (other than 30 and 70% or other than 70 and 30%) between F2F and online learning materials and also with other learning methods such as flipped learning and collaborative learning.

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Author’s Contributions

Anthony Anggrawan: Is responsible for preparing the weight distribution of teaching materials in the two teaching methods of mixed learning-1 and mixed learning-2 and for carrying out the creation of a computer programming application module, including examples of implementing all programming problems into the flow chart as well as the programming language of VB.Net. He is also responsible for writing the article contents, including analyzing data on student programming skills in mixed learning-1 and mixed learning-2 teaching methods.

Christofer Satria: Designs and develops asynchronous online learning modules on a server computer to equip the learning modules with animated images and sounds.

Mayadi: Assisted in implementing the VARK survey to determine student cognitive styles in both teaching methods. He also implements lesson modules on computer servers and monitors computer systems for all student asynchronous online learning activities.

Ni Gusti Ayu Dasriani: Is responsible for completing the relevant references needed in the article, including double-checking the manuscript format correctness and writing the text.

Ethics

The authors confirm that this manuscript has not been published in other journals and does not have ethical concerns.

References

Agosto, D. E., Copeland, A. J., & Zach, L. (2013). Testing the benefits of blended education: Using social technology to foster collaboration and knowledge sharing in face-to-face LIS courses. Journal of Education for Library and Information Science, 54(2), 94-107. https://www.jstor.org/stable/43686938

Alammary, A. (2019). Blended learning models for introductory programming courses: A systematic review. PloS One, 14(9), e0221765. doi.org/10.1371/journal.pone.0221765

Aljuboori, A. F., Fashakh, A. M., & Bayat, O. (2020). The impacts of social media on university students in Iraq. Egyptian Informatics Journal, 21(3), 139-144. doi.org/10.1016/j.eij.2019.12.003

Almpanis, T., Patrick, S., McLellan, R., Dinsmore, C., Faustino, A., & Basuki, W. (2010). Proposing a framework for blended and flexible course design. Proceedings of the IADIS International Conference on Cognition and Exploratory Learning in Digital Age, (pp. 263-268), IADIS Press. https://ssudl.solent.ac.uk/id/eprint/1429/

Anggrawan, A. (2018) Algoritma dan Pemgrograman: Implementasi pada VB.Net dan Java. Penerbit ANDI, ISBN-10: 979296326X.

Anggrawan, A., Ibrahim, N., Muslim, S., & Satria, C. (2019). Interaction between learning style and gender in mixed learning with 40% face-to-face learning and 60% online learning. International Journal of Advanced Computer Science and Applications (IJACSA), 10(5), 407–413. doi.org/10.14569/IJACSA.2019.0100550

Anggrawan, A., & Satria, C. (2020). Development and assessment of the English grammar asynchronous online learning module before being applied in real lesson. Journal of Computer Science, 16, 1516-1525. doi.org/10.3844/jcssp.2020.1516.1525

Awang, H., Abd Samad, N., Faiz, N. M., Roddin, R., & Kankia, J. D. (2017, August). Relationship between the learning styles preferences and academic achievement. In IOP Conference Series: Materials Science and Engineering (Vol. 226, No. 1, p. 012193). IOP Publishing. doi.org/10.1088/1757-899X/226/1/012193

Bazelais, P., & Doleck, T. (2018). Investigating the impact of blended learning on academic performance in a first semester college physics course. Journal of Computers in Education, 5(1), 67-94. doi.org/10.1007/s40692-018-0099-8

Ceylan, V. K., & Kesici, A. E. (2017). Effect of blended learning to academic achievement. Journal of Human Sciences, 14(1), 308-320. doi.org/10.14687/jhs.v14i1.4141

Clark, T., & Barbour, M. K. (2015). Online, blended and distance education in schools: Building successful programs. Virginia: Stylus Publishing. ISBN: 1620361647

Eudoxie, G. D. (2011). Learning styles among students in an advanced soil management class: Impact on students' performance. Journal of Natural Resources and Life Sciences Education, 40(1), 137-143. doi.org/10.4195/jnrlse.2010.0006u

Hogarth, D. A., & Biggam, D. J. (2009). Adapting the Blended Approach to Enhance the Student Elearning Experience: An Original Framework. In IADIS International Conference (pp. 3-8).

Kanuka, H., & Rourke, L. (2013). Using Blended Learning Strategies to Address Teaching Development Needs: How Does Canada Compare?. Canadian Journal of Higher Education, 43(3), 19-35. doi.org/10.47678/cjhe.v43i3.184741

Król, S. (2016). E–learning as an innovative method of education. World Scientific News, 48, 178-182. http://yadda.icm.edu.pl/yadda/element/bwmeta1.element.psjd-753853c5-5dfe-4f18-a1b4-7258b5416dbf

Lazarinis, F., Karachristos, C. V., Stavropoulos, E. C., & Verykios, V. S. (2019). A blended learning course for playfully teaching programming concepts to school teachers. Education and Information Technologies, 24(2), 1237-1249. doi.org/10.1007/s10639-018-9823-2

Lieser, P., & Taff, S. D. (2013). Empowering students in blended learning. Journal of Applied Learning Technology, 3(3), 6-12. https://www.academia.edu/5028527/Empowering_Students_in_Blended_Learning

Maia, M. C. O., Serey, D., & Figueiredo, J. (2017, October). Learning styles in programming education: A systematic mapping study. In 2017 IEEE Frontiers in Education Conference (FIE) (pp. 1-7). IEEE. doi.org/10.1109/FIE.2017.8190465

Montgomery, D. C. (2012) Design and Analysis of Experiments. United States: John Wiley & Sons, Inc. ISBN-10: 1118146921.

Nazarenko, A. L. (2015). Blended learning vs traditional learning: What works? (a case study research). Procedia-Social and Behavioral Sciences, 200, 77-82. doi.org/10.1016/j.sbspro.2015.08.018

Van Niekerk, J., & Webb, P. (2016). The effectiveness of brain-compatible blended learning material in the teaching of programming logic. Computers & Education, 103, 16-27. doi.org/10.1016/j.compedu.2016.09.008

Norman, S. (2016). Traditional Education and Advantages of Online Learning. Diambil Dari Internet Pada Tanggal.

Opina, A. S., Velarde, J. D., & Sicat, A. S. (2011). Blended instruction at centro escolar university, Philippines. International Journal of Arts & Sciences, 4(8), 93-99. https://www.proquest.com/openview/4bcd5938775b449004ac5d5c6e1b441f/1?pq-origsite=gscholar&cbl=626342

Othman, K. A., Isa, M. A. M., Baharuddin, M. A., Ghazali, M. A., Khan, Z. I., & Zakaria, N. A. (2018, September). Forest monitoring system implementation using visual basic and android application. In 2018 18th International Symposium on Communications and Information Technologies (ISCIT) (pp. 447-451). IEEE. doi.org/10.1109/ISCIT.2018.8587963

Pierce, D. (2017). What effective blended learning looks like. THE Journal (Technological Horizons In Education), 44(1), 18-21. https://thejournal.com/articles/2017/01/11/what-effective-blended-learning-looks-like.aspx

Psycharis, S., Botsari, E., & Chatzarakis, G. (2014). Examining the effects of learning styles, epistemic beliefs and the computational experiment methodology on learners' performance using the easy java simulator tool in stem disciplines. Journal of Educational Computing Research, 51(1), 91-118. doi.org/10.2190/EC.51.1.e

Seta, H. B., Wati, T., Muliawati, A., & Hidayanto, A. N. (2018). E-Learning Success Model: An Extention of DeLone & McLean IS'Success Model. Indonesian Journal of Electrical Engineering and Informatics (IJEEI), 6(3), 281-291. doi.org/10.11591/ijeei.v6i3.505

Siregar, S. (2014) Statistik Parametrik Untuk Penelitian Kuantitatif. Jakarta: Bumi Aksara, ISBN: 9786020000000.

Sleator, R. D. (2010). The evolution of eLearning Background, blends and blackboard…. Science progress, 93(3), 319-334. doi.org/10.3184/003685010X12710124862922

Sugiyono. (2004). Metode Penelitian Bisnis. Bandung: Alfabeta. https://www.tokopedia.com/senen25/metode-penelitian-bisnis-by-prof-dr-sugiyono-tahun-2004

Tang, C., & Chaw, L. (2013). Readiness for blended learning: Understanding attitude of university students. International Journal of Cyber Society and Education, 6(2), 79-100. doi.org/10.7903/ijcse.1086

Theodoropoulos, A., Antoniou, A., & Lepouras, G. (2016). How do different cognitive styles affect learning programming? Insights from a game-based approach in Greek schools. ACM Transactions on Computing Education (TOCE), 17(1), 1-25. doi.org/10.1145/2940330

Tyler-Wood, T. L., Cockerham, D., & Johnson, K. R. (2018). Implementing new technologies in a middle school curriculum: a rural perspective. Smart Learning Environments, 5(1), 1-16. doi.org/10.1186/s40561-018-0073-y

Rhouma, W. B. (2016). Perceptual learning styles preferences and academic achievement. International Journal of Arts & Sciences, 9(2), 479. https://www.researchgate.net/publication/326113022_Perceptual_Learning_Styles_Preferences_and_Academic_Achievement

Yindi, D. (2016, May). Visual basic program designing based on computational thinking capabilities training. In The 2nd Information Technology and Mechatronics Engineering Conference (ITOEC 2016) (pp. 175-178). Atlantis Press. doi.org/10.2991/itoec-16.2016.31

Zhang, C., Chen, X., & Li, J. (2011, August). Research of VB programming teaching mode based on the core of computational thinking ability training. In 2011 6th International Conference on Computer Science & Education (ICCSE) (pp. 1260-1263). IEEE. doi.org/10.1109/ICCSE.2011.6028861