ECONTECHMOD. AN INTERNATIONAL QUARTERLY JOURNAL – 2019. Vol. 8. No. 2. 17–20

Identification and Analysis of Learning Styles of MOOC Students

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Received June 11, 2019: accepted June 20, 2019

Abstract. The paper presents the results of analyzing the impact of learning styles on the success of the MOOC course. The study was based on the Kolb's learning style questionnaire. The survey was shared among the students of software engineering MOOC course. The results of the survey were statistically analyzed. Compared the influence of different learning styles and their strength to successful completion of the course. Analyzed the strength of different learning styles among the students of different ages and different education. The results of the research show that the learning style has an impact to the course finishing success and should be considered for the effective educational program creation.

Key words: MOOC, learning styles, software engineering.

INTRODUCTION

One of the vital missions of any educational institution is to provide low cost and inexpensive education. The growth of information technologies especially web technologies triggered the appearance of various educational content and free educational resources as well as technology enhanced learning environments. Appearance of massive open online courses (MOOCs) changes the role of teacher within the educational process and switched the students' learning behavior into a new direction aimed to adapt to a new learning culture. MOOCs allow to scale educational environment where all the learners may gain required knowledge without strict scheduling of lessons. And one of the characteristics of such approach is a minimum influence of teacher during the educational process. This factor as well as variety of educational material types and structure allow to construct highly adaptive and agile curriculum suitable for everyone. MOOCs may be applied in different contexts such as schools, universities, corporate education, social projects, etc. But despite the opened opportunities for all the interested student there are certain risks that are caused by such a wide popularity of such courses. The most highlighted problems are low retention and high dropout rates. This may be affected by low motivation since most of the courses are free of charge. The average dropout rates of MOOCs offered by Stanford, MIT and UC Berkley are 80–95 %. [1] The majority of courses reported a completion rate of less than 10 % [3]. That's why a lot of studies concentrated on research regarding the factors affecting students' dropout [4, 5] and predicting attrition [6, 7].

There are related papers aimed to research social profile of participants of MOOCs courses [2]. The design of such MOOC courses suggests different than a classical approach to learning, and a change in the relationship between the instructor, the student and the provided content. Attendees should be able to gain knowledge from a different type of media content and through the interaction with other participants. Therefore, those individuals' learning styles that were not dominant during the classical class are coming to the foreground. Influence of learning styles on the learners' attrition and motivation during participation in MOOCs is widely analyzed [8, 9, 10]. One of the best models of learning styles was developed by David Kolb.

The purpose of this research is to investigate the impact of learning styles on the final result of the MOOC course in software engineering field and analyse the learning styles among the students of different age and different education.

MATERIALS AND METHODS

David Kolb's model selected in order to investigate relations among course success and learning style. According to the model four different learning styles exists: Accommodator, Converger, Diverger, Assimilator. In order for learning to be effective, Kolb postulated, all four of these approaches must be incorporated. During this research the adapted learning model is used. According to this adapted model there is an association between the learning cycle and learning styles. Figure 1 shows the four learning styles: Activist, Reflector, Theorist, Pragmatist and appropriate learning phase.

These four learning styles are assumed to be adaptable, rather than being fixed personality characteristics.

Fig. 1. The association between the learning cycle and learning styles

In order to define the style of each student of MOOC course the Kolb's Learning Style Questionnaire has been used [10–14]. This Questionnaire consists of 80 questions. All questions are optional. At the end all ticked questions should be counted and total count of ticked questions is divided into four categories in accordance to the learning styles: Activist, Reflector, Theorist, and Pragmatist. The total scores for each learning style determine the strength of preference. There are 5 strengths for each of four learning styles: very strong preference (VS), strong preference (S), moderate preference (M), low preference (L), very low preference (VL).

This questionnaire has been shared among the attendees of MOOC course in software engineering field. In addition, attendees were asked to specify theirs age and education. The education question consists only 3 values: Education in IT, Education in other areas, Other.

RESULTS AND DISCUSSION

The 61 responses have been received after sharing the questionnaire. All the responses were divided into 2 categories: attendees who successfully finished MOOC and attendees who were not able to finish due to the drop out or bad results of final test. In the Table 1 represented the main statistical information after analyzing all the answers. The students' age is divided into 2 categories: <24 years and >=24 years. The goal is to separate these students who are learning at the moment and those who already finished any higher institution.

TABLE 1. THE SUMMARY INFORMATION ABOUT THE RESULTS OF THE SURVEY

Category	Count of responses
Total count of responses	61
Successfully finished course	26
Not finished course	35
Education in IT	16
Education in other areas	38
Other education	7
< 24 years	20
>= 24 years	41

Each question is related to corresponding learning style. Table 2 represented the most popular learning styles after analyzing each response and summarizing the ticked answers for each response. According to the analyzed results the Reflector learning style has the most ticked answers in 46 responses.

Table 3 represented the relation between most popular learning style and the success of passing the MOOC course.

Additionally, 5 strengths for each of four learning styles have been analyzed for each response.

TABLE 2. MOST POPULAR LEARNING STYLES

Learning style	Count of responses
Activist	2
Pragmatist	9
Reflector	46
Theorist	4

TABLE 3. RELATION BETWEEN THE LEARNING STYLE AND COURSE SUCCESS

	activist	pragmatist	reflector	theorist	total
Passed the course	1	5	28	1	35
Not passed the course	1	4	18	3	26
Grand Total	**2**	**9**	**46**	**4**	**61**

The Figure 2 and Figure 3 show the relation among learning styles strengths and the success of passing the MOOC course.

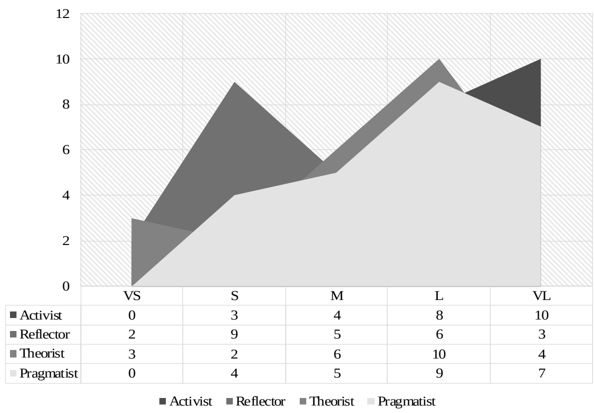
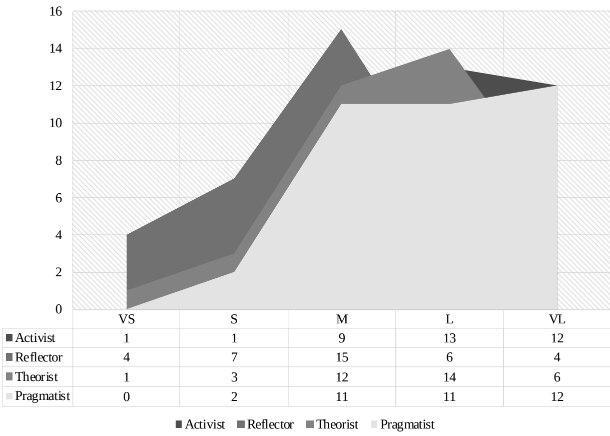


Fig. 2. The total amount of different learning strength for those who passed the course

According to the results the students who passed the online course have the strong and very strong preferences for more than one learning style. Also, there are 3 students with the very strong Theorist learning style.

Among the students who have not completed the course, there are far fewer those who have strong learning styles. In this group of students there is a large number of students with no clear dominant learning styles. In general, it can be determined that those students who have completed the course have more diverse learning styles that simultaneously have more dominant properties. In the group of students who haven't passed the course the learning styles have the less strength. As a consequence, it can be argued that that the delivery of the training or teaching materials should be done according to the students' learning styles and strength of each style.



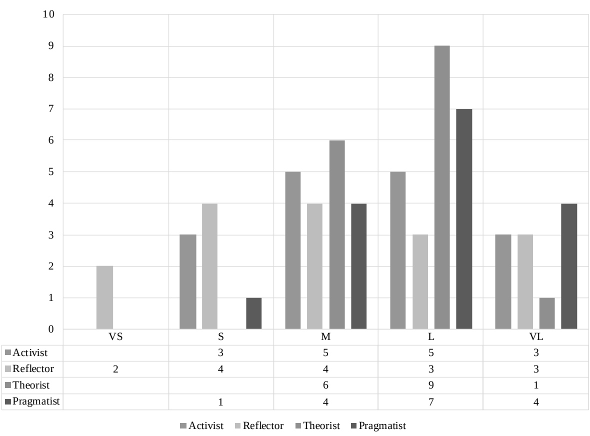
	VS	S	M	L	VL
Activist	1	1	9	13	12
Reflector	4	7	15	6	4
Theorist	1	3	12	14	6
Pragmatist	0	2	11	11	12

Fig. 3. The total amount of different learning strength for those who not passed the course

The Figure 4 and Figure 5 show the relation among education and consolidated statistics about the strength of learning styles.

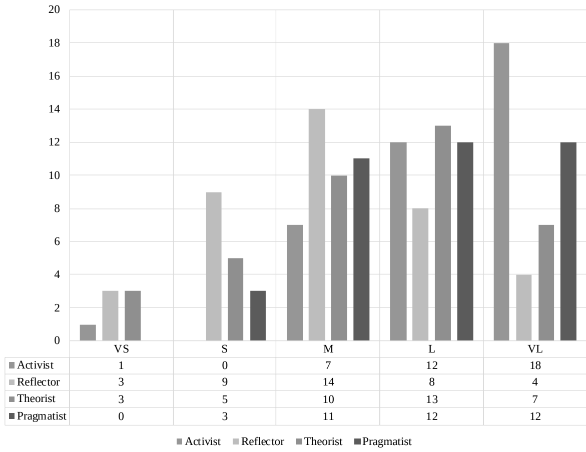
Among the students who have selected education in other areas there are more those who have Activist learning style, even if this style is not expressed with a high strength. Except the Reflector the Theorist learning style is also most popular among the students of this educational category regardless of strength.

The Figure 6 and Figure 7 show the relation among age and consolidated statistics about the strength of learning styles. All the responses are divided into 2 categories: students of age less 24 years old and students with more than 25 years old.



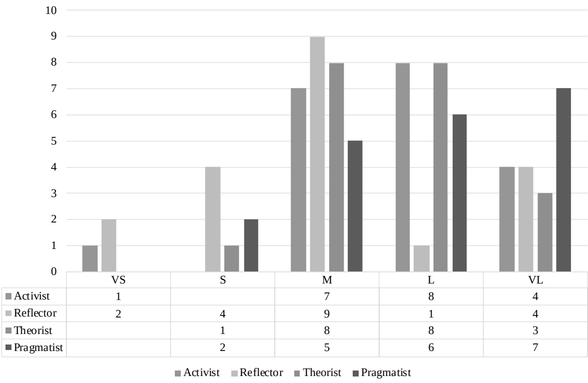
	VS	S	M	L	VL
Activist		3	5	5	3
Reflector	2	4	4	3	3
Theorist			6	9	1
Pragmatist		1	4	7	4

Fig. 4. The relation between the strength of learning styles and IT Education



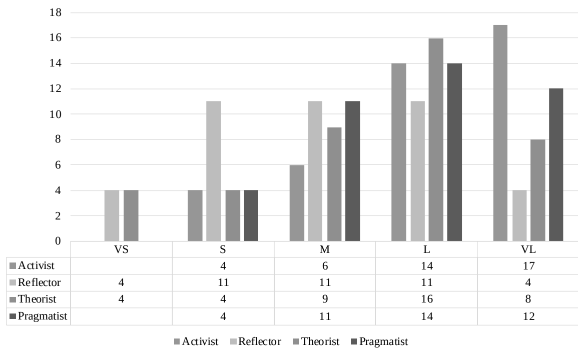
	VS	S	M	L	VL
Activist	1	0	7	12	18
Reflector	3	9	14	8	4
Theorist	3	5	10	13	7
Pragmatist	0	3	11	12	12

Fig. 5. The relation between the strength of learning styles and Education in other areas



	VS	S	M	L	VL
Activist	1		7	8	4
Reflector	2	4	9	1	4
Theorist		1	8	8	3
Pragmatist		2	5	6	7

Fig. 6. The relation between the strength of learning styles and students less than 24 years old.



	VS	S	M	L	VL
Activist		4	6	14	17
Reflector	4	11	11	11	4
Theorist	4	4	9	16	8
Pragmatist		4	11	14	12

Fig. 7. The relation between the strength of learning styles and students over 25 years old

The Theorist learning style with various strength more often present among the students over 25 years old.

CONCLUSIONS

The popularity of online massive courses through its accessibility, openness and agility is increasing every year. But there is still a problem of motivation and a high level of attendees' attrition. One of the ways to improve the quality of the course is to adapt and deliver the educational materials to a specific learning styles. The research analyzed the Kolb's learning styles theory through survey conducted among 61 students who finished the MOOC course in the Software Engineering field. According to the results it was established that students who passed the online course have the strong and very strong preferences for more than one learning style. The most popular learning style is Reflector. Activist learning style is more popular among students who do not have IT education then students who have IT education. The Theorist style more often present at participants over 25 years old. All the results of the research are presented in graphical format.

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