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An Analysis of Correlation Between Learning Style and Online Learning Performance During COVID-19: A Case Study of a Computer Programming Course

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***Abstract*—Learning styles are crucial for online learning because they help understand how individuals best absorb and process information. By considering these, online educators can tailor their instructional approaches to better align with their diverse needs. This study aims to analyze the correlation between learning style and online learning performance under the assumption that each student has multiple learning styles. Students answered the modified online questionnaire based on the Grasha-Riechmann Learning Styles model. There were 348 first-year undergraduate students at Mae Fah Luang University who enrolled in a computer programming course during the COVID-19 pandemic. Basic descriptive statistics and correlation analysis using the Pearson's or Spearman's correlation coefficient were performed. After an overall analysis, respondents were divided into two groups based on their online learning performance for further analysis. Overall, online learning performance was found to be positively correlated with a participant style and negatively correlated with an avoidant style. The results of this additional investigation revealed that the participant style was common among students from both groups. Even though these correlations appeared weak, this represented that the needs of this common style should be met first when making changes to online course design, such as employing gamification strategies.**

***Keywords*—Learning Styles, Online Learning Performance, Correlation Analysis, Correlation Coefficient, Online Learning**

I. Introduction

During the COVID-19 pandemic, the educational system was disrupted. Education institutes had to transform their teaching-learning process to online learning. In 2020, UNESCO reported that higher education institutions (HEIs) were fully closed in 185 countries [1]. Universities worldwide have suddenly been required to change their teaching methods toward online learning [2]. To adhere to the social distancing regulations recommended by the World Health Organization (WHO), all learning materials, activities, and assessments need to be delivered in an online format. Even though online learning is not a new concept in the educational system, the sudden transition has presented a challenge for HEIs to implement fully online learning systems while delivering high-quality education.

Numerous academic sources discuss the challenging aspects, advantages, and effectiveness of online learning during the pandemic. There are various factors to consider when implementing high-quality online education. Most of the studies mention the importance of the student perspective [3], [4]. From the student's perspective, attending fully online classes did not improve engagement in classrooms. Instead, many students reported a lack of communication with both their peers and instructors [5]. The limited opportunities for students to interact and collaborate with their peers potentially resulted in stressful experiences and disengagement [5], [6]. In addition, students also felt easily distracted and found it difficult to maintain their concentration [7]–[9].

One of the important factors from students' perspectives is learning style. Learning styles have a strong impact on student performance toward learning outcomes. Learning styles relate to learning methods; these refer to the way students acquire, interpret, organize, evaluate, and retain information. These also refer to how students develop their skills by utilizing technologies. So, when learning styles and learning methods are matched properly, this results in improved learning outcomes [10]. There are various studies about learning styles in face-to-face classrooms as well as the hybrid between face-to-face and online learning [11]. Nevertheless, there are a limited number of studies that specifically investigate the relationship between learning style and fully online learning during this disruption.

Despite the fact that social distancing is no longer required, online learning has gained importance and will continue even after the COVID-19 pandemic. To improve the quality of online learning, it is important to consider learner learning styles, as we have mentioned previously. Therefore, the purpose of this study was to analyze the correlation between learning style and online learning performance based on the assumption of multiple learning styles per student. This may help us identify opportunities for improvement and reflect the design requirements of our online course.

The remainder of the paper is structured as follows: Section II summarizes the basic concepts of online learning, learning styles, and related works to this study. Following that, Section III explains the details of this case study, including data gathering, preprocessing, and analysis. Section IV presents the results of this study and its discussion. The paper concludes with suggestions for future work in Section V.

II. Literature Review

A. Online Learning

Online learning refers to the use of technology to deliver education [12]–[14]. The terms that are associated with and can often be used interchangeably with online learning are e-learning, computer-based learning, and blended learning [15]. In addition, online learning encompasses distance learning, which refers to the geographical separation between instructors and learners. Online learning can deliver both asynchronous and synchronous instructions. Numerous benefits of online learning have been addressed, including flexibility and accessibility in terms of time and place for learning. Students have the freedom to learn at any time and from any place. Additionally, online learning promotes interactivity between instructors and students [14], [16].

During the pandemic, education systems have been transformed from lecture-based learning into online learning. Institutes transformed to fully online learning, not only the delivery of contents but also the entire learning process, such as assessment methods, collaboration methods, and interaction and feedback methods [2]. There are many digital tools that are available for online learning for both asynchronous and synchronous instructions. Many learning management systems (LMS) have been deployed to carry out online learning processes, such as Google Classroom, Moodle, and Microsoft Team. Social media is also used for communication and sharing learning resources among students and teachers [4].

B. Learning Styles

Over the last few decades, various learning styles have emerged, including the Kolb Learning Style Inventory (LSI) [17], Dunn and Dunn [18], Felder-Silverman [19], and Grasha-Riechmann Learning Styles model [20]. These approaches aim to comprehend individuals' preferred learning methods. They center around recognizing the unique ways people learn and process information, which subsequently shape their preferred study methods. Therefore, these learning styles are often employed to design instructional strategies tailored to diverse learner types, enhancing the overall learning experience.

In this study, we adopt the learning style from the Grasha-Riechmann Learning Styles model [20], which is a framework designed to understand and classify students' learning styles in higher education settings. It also provides a wide range of learning styles by acknowledging that students have different ways of processing and understanding information. The six types of learning styles proposed by the Grasha-Riechmann Learning Styles model are as follows:

- Competition: Competitive learners are driven by their desire to outperform others. They tend to be the center of attention and to receive recognition for their achievements in class.
- Collaboration: Collaborative learners enjoy group work and cooperation. They enjoy sharing ideas and contributing to collective tasks. They value teamwork, enjoy brainstorming sessions, and often excel in activities that involve joint problem-solving.
- Avoidant: Avoidant learners prefer to stay in the background and observe rather than actively engage. They might feel uncomfortable with extensive interactions or group activities. They often prefer to work alone and might need encouragement to participate more actively.
- Participation: Participant learners actively engage in class activities and seek opportunities to work on both optional activities and course requirements.
- Dependent: Dependent learners seek guidance and support from instructors and peers. They learn only what is required in the course.
- Independent: Independent learners prefer to work on their own as they believe in their learning abilities. They tend to be self-reliant, motivated, and focused on their personal goals. They are comfortable with tasks that require individual effort and responsibility, but they are also willing to consider the ideas of others.

C. Related Works

There are many studies that have explored the challenges and strategies of the paradigm shift in the education system during the pandemic. The challenge of fully online learning can arise from various factors, such as students, instructors, and institutions. In this research, we only focus on the student perspective, particularly on learning styles, which have an imperative impact on the success of learning performances. However, there are few that emphasize learning styles toward disrupted online learning education.

In the research of Barrot et al. [4], the researchers have studied the challenges in online learning. They found that each individual student had varied strategies to cope with the problems they encountered during the online learning process. This means that personal characteristics impact the learning process.

In another work by Adnan and Anwar [3], they have focused on student perspectives, including motivation, peer collaboration on group projects, and communication among peers. The studies found that the majority thought that face-to-face learning was better in terms of motivation, collaboration, and communication. Still, there were some students who had different opinions toward online learning and suggested that online learning was more effective.

In terms of the work related to the Grasha-Riechmann Learning Styles model, but in the face-to-face classroom before this disruption, [21] have studied the relationship between learning style and academic performance. Academic performance was positively correlated with a participant score and negatively correlated with an avoidant score, according to their findings. In comparison to other learning styles, the academic performance of students with the participant style was markedly higher.

III. Case Study

This section represents the case study of our online course, computer programming, at Mae Fah Luang University (MFU). In the past, all classes were held in face-to-face or hybrid classroom settings. However, due to the unprecedented circumstances of the COVID-19 pandemic, a significant shift occurred in the teaching methodology, requiring a complete transition to online classes as a response to this situation.

The details of this case study are separated into three parts. Firstly, the teaching objective and course design for our online class are described. Then, the next subsection explains how we collect the data and process it. Lastly, how to analyze that data is discussed.

A. Teaching Objective and Course Design

The computer programming course is the required subject for first-year students at the School of Information Technology (IT), MFU. The objective of this class is to introduce basic programming concepts such as variables, control flow, and programming syntax.

This course is designed for two hours of learning theory and two hours of practicing by completing computer lab assignments per week. This course evaluation consists of 5% participation, 10% lab assignments, 10% lab tests, 25% group projects, 25% midterm examinations, and 25% final examinations. The main online learning management system (LMS) is the MFU LMS system. Moreover, Facebook is used as a social media platform for communication and discussion. Videos, as one of the teaching materials, are separated into three types: live recording videos, instructional videos before joining class, and supplementary external videos. In order to gain more engagement in online learning, the weekly activities are (i) online pre-test via the MFU LMS system; (ii) live online lecture by Google Meet or Microsoft Team; (iii) in-class online activities such as Kahoot or Padlet; (iv) online post-test after finishing class via the MFU LMS system; and (v) live online class for lab demonstrations and consultation sessions via Google Meet or Microsoft Team or Discord. The online pre-tests and online post-tests are for evaluating student understanding of each chapter but not for grading.

B. Data Gathering and Data Preprocessing

The online questionnaire based on the General Class Form of the Grasha-Riechmann Learning Styles Scales, or GRSLSS, was generated with some modifications for this online course. The original questionnaire consisted of 60 items, 10 items for each learning style, with a five-point Likert scale for responses ranging from strongly disagree to strongly agree. We revised the items because some questions refer to face-to-face classrooms; consequently, three items were removed. Moreover, [22] stated that questionnaire length resulted in less attention to the questions and responses (the longer its length, the less attention it gets). Because of this boredom, respondents could give inaccurate responses, resulting in less accurate data collection. Due to the length of the original questionnaire, it was divided into two online questionnaires that were distributed twice, and some similar questions were combined.

This online questionnaire was distributed to MFU first-year undergraduate students who enrolled in the computer programming course in order to gather data. There were 397 students from different majors, which are computer engineering, software engineering, and multimedia technology and animation. Next, the incomplete questionnaires, including those of dropout respondents, were omitted. Therefore, 348 students remained for analysis, which represented 87.66% of the total population.

The students were evaluated using a T-score [23], which was determined by aggregating their scores for the whole semester. This score was used as a measure of online learning performance.

The next step was to calculate the mean score of each learning style for each student. The calculation steps were the same as stated in [20], except for identifying an individual learning style for each student. The sum of each learning style's items divided by its number determines this mean score.

C. Data Analysis

Table I depicts the summary of basic descriptive statistics, which is divided into two cases: (i) Case 1, the basic descriptive statistics for all students; and (ii) Case 2, the basic descriptive statistics for each group of students. This table presents the means of learning style variables for each case, as well as their mean T-scores. The values in the brackets next to the mean values are the standard deviation (SD).

In terms of Case 2, a total of 348 students ($N = 348$) were separated into two groups using the T-score. If the T-score was greater than or equal to 50 (the mean of this T-score variable), the student was assigned to Group 1, with 216 students in total ($N = 216$). The remaining students were placed in Group 2, with 132 students in total ($N = 132$). This separation by online learning performance helps to examine the common and unique correlations found between the two groups, and Group 1 represents better online learning performance.

As highlighted in Table I, the top three mean learning style variables for both cases (Case 1 and Case 2) were collaborative, dependent, and participant. In Case 2, the scores of independent, collaborative, and participant variables in Group 2 were lower than those in Group 1, with a larger data distribution. For example, the mean collaborative score of Group 1 was 3.97 with a SD of 0.69, while that of Group 2 was 3.77 with a SD of 0.81.

TABLE I
BASIC DESCRIPTIVE STATISTICS

Variable	Mean (SD)		
	Case 1: No group separation	Case 2: Group separation	
	All students $N = 348$	Group 1 $N = 216$	Group 2 $N = 132$
Independent	3.35 (0.61)	3.42 (0.6)	3.25 (0.6)
Avoidant	2.68 (0.63)	2.58 (0.6)	2.85 (0.65)
Collaborative	**3.89 (0.74)**	**3.97 (0.69)**	**3.77 (0.81)**
Dependent	**3.93 (0.49)**	**3.93 (0.46)**	**3.93 (0.52)**
Competitive	2.91 (0.72)	2.89 (0.74)	2.94 (0.69)
Participant	**3.84 (0.66)**	**3.95 (0.61)**	**3.64 (0.68)**
T-score	50 (10)	56.35 (3.45)	39.65 (8.95)

To calculate the correlation coefficients and their significance, either Pearson's product moment correlation coefficient (r) or Spearman's rank correlation coefficient (r_s) will be used based on the types of variables being studied. Pearson's product moment correlation coefficient, henceforth referred to as the Pearson test, is used when both variables have a normal distribution, whereas Spearman's rank correlation coefficient, henceforth referred to as the Spearman test, is used when the distribution of one or both variables is skewed [24]. These variables were investigated to determine whether each of them was normally distributed. This investigation used kurtosis and skewness values derived from descriptive statistics, including histograms. This found that the T-score variables of Case 1 and Group 2 from Case 2 were skewed. Thus, the Pearson test was used with the variables of Group 1 from Case 2, whereas the Spearman test was performed with those of Case 1 and those of Group 2 from Case 2. The p-value (p) of these tests was then calculated to represent the probability of obtaining this correlation. This was used to determine whether the calculated correlation between two variables was statistically meaningful or coincidental. Given a defined significance level α, where $\alpha = 0.05$, a p-value less than this significance level was statistically significant.

IV. RESULTS AND DISCUSSION

The correlation matrix among variables and their significance are presented in Table II. The statistically significant correlation values, including their p-values, are shown in bold. From a perspective of overall correlation without group separation, the results of the Spearman test represented a weak positive correlation between the T-score and the participant score ($r_s = 0.2953, p < 0.01$). A weak negative correlation was also found between the T-score and the avoidant score ($r_s = -0.2244, p < 0.01$). The scatter plots of these two pairs above are shown in Fig. 1 and Fig. 2 respectively, in order to graphically illustrate the relationship. A straight line in both scatter plots is a trend line that represents a positive or negative trend. Fig. 1 illustrates a weak positive correlation; as the participant score increased, so did the T-score. Conversely, Fig. 2 shows a weak negative correlation; as the avoidant score increased, the T-score decreased. Note that points in both scatter plots were in scattered form, and the trend could be noticeable even though it was not clear. Besides, a very weak positive correlation was found between two pairs: (i) the T-score and the independent score ($r_s = 0.1794, p < 0.05$) and (ii) the T-score and the collaborative score ($r_s = 0.1669, p < 0.05$).

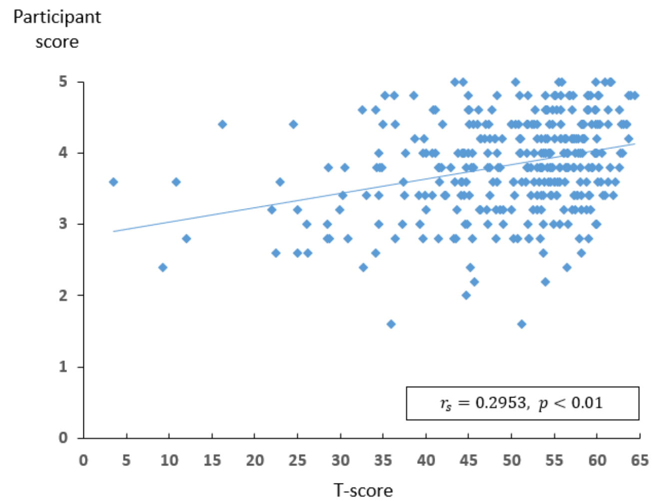

Fig. 1. Scatter plot of T-score and Participant score

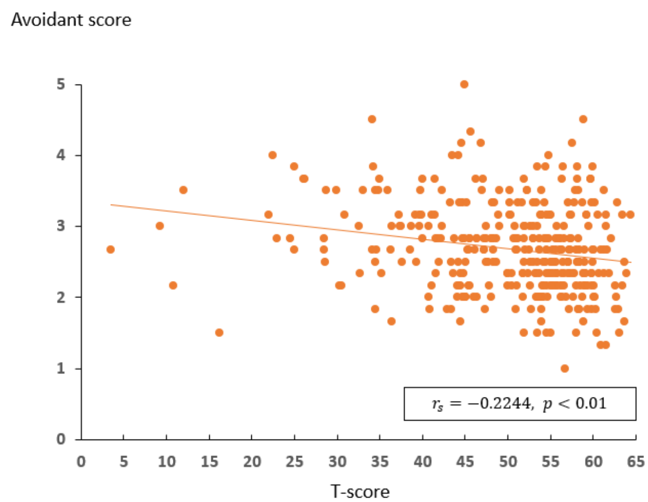

Fig. 2. Scatter plot of T-score and Avoidant score

With Group 1, the results of the Pearson test showed that three pairs of weak positive correlations were found: (i) the T-score and the independent score ($r = 0.2581, p < 0.001$); (ii) the T-score and the participant score ($r = 0.2334, p < 0.001$); and (iii) the T-score and the collaborative score ($r = 0.2030, p < 0.01$). Furthermore, a very weak positive correlation was found between the T-score and the competitive score ($r = 0.1870, p < 0.01$). On the other hand, the results of the Spearman test for Group 2 showed that there was only a weak positive correlation between the T-score and the participant score ($r_s = 0.2157, p < 0.05$). No other significant correlations were found.

Without group separation for this online course, the learning performance was positively correlated with the participant

TABLE II
CORRELATION MATRIX AMONG VARIABLES

	Case 1: No group separation		Case 2: Group separation			
	All students using Spearman test $N = 348$		Group 1 using Pearson test $N = 216$		Group 2 using Spearman test $N = 132$	
	r_s - T score	p-value	r - T score	p-value	r_s - T score	p-value
Independent	0.1794	0.0194	**0.2581**	**0.0001**	-0.0448	0.6098
Avoidant	**-0.2244**	**0.0078**	-0.0968	0.1564	-0.1258	0.1507
Collaborative	0.1669	0.0254	**0.2030**	**0.0027**	0.0874	0.3192
Dependent	0.0224	0.6942	0.0459	0.5021	0.0094	0.9152
Competitive	0.0451	0.4393	0.1870	0.0058	0.0185	0.8330
Participant	**0.2953**	**0.0022**	**0.2334**	**0.0005**	**0.2157**	**0.0130**

score and negatively correlated with the avoidant score. This finding is consistent with the results of [21] for the face-to-face classroom and also student interactions in our online class. For our online class, some students always participated in our activities, such as in-class activities, pre-tests, and post-tests, which represents a characteristic of the participant learning style. In contrast, some usually did not participate in activities or complete assigned tasks.

With group separation, the results revealed that the participant learning style was common between these two groups. This also found that the learning performance of students from Group 1 who obtained a better score was positively correlated with three learning styles: (i) independent, (ii) participant, and (iii) collaborative, while that of Group 2 was positively correlated with only the participant learning style. These results are also in accordance with how students engaged in our online course. For students with the collaborative learning style, this could be seen from working on a group project, for which students requested additional time for group consultation. Also, they were more cooperative during online lab hour when separating as a small group to help each other with assignments or a group project. Students with the independent learning style believe they can learn on their own. This could be evident in the design and implementation of their own project, as well as in their questioning that was not covered in the learning curriculum. Furthermore, because there are many distractions, the need for inspiration, and self-discipline in online learning, this style could be very helpful.

When Pearson's and Spearman's correlation coefficients result in a weak correlation, it means that there is a low degree of linear or monotonic association between the two variables being compared. It is important to note that weak does not necessarily mean unimportant; it simply means that there is not a strong, easily discernible connection between the two variables based on the correlation coefficient alone. Other factors and analyses may be needed to understand the relationship more fully. As a result of these complexities, research on the correlation between learning style and learning performance has yielded mixed findings, with many studies reporting weak or inconclusive correlations [25], [26].

Even though these correlations appeared to be weak, this still reflects room for improvement in the online course design. According to the findings, the enjoyment of class participation, activities, and discussion is a characteristic of students with the participant learning style; introducing more in-class activities on several game-based learning platforms and discussions may draw more attention and encourage them to improve their learning performance. Note that these platforms are used for gamification activities. Apart from game-based learning platforms, this may include using appropriate gamification elements such as points, levels, and rewards. This refers to employing gamification, as this is a strategic way to enhance engagement in learning and improve important capabilities like decision-making and cooperation [27]. Similarly, [28] reported that using gamification as an attractive motivator among group members boosted group cohesion and achievement. Therefore, employing this strategy may facilitate both participant and collaborative learning styles.

V. CONCLUSION

This paper presents an analysis of the correlation between learning style and online learning performance during COVID-19 with a case study of an online computer programming course. The students took a questionnaire based on the Grasha-Riechmann Learning Styles model, with the assumption that each student has multiple learning styles. Thus, this is an analysis without identifying the individual learning style of each respondent. An overall analysis of all respondents was performed at first, and then these respondents were separated into two groups based on their online learning performance for further analysis. In terms of overall analysis, online learning performance was positively correlated with the participant learning style and negatively correlated with the avoidant learning style. The findings of this further analysis showed that the participant learning style was common among students from both groups. This study also revealed that the learning performance of students in the first group with better performance was positively correlated with three learning styles: (i) independent, (ii) participant, and (iii) collaborative, whereas the latter group was positively correlated with only the participant learning style. Although these correlations appeared weak from an overall and further analysis, this showed that the needs of more facilitating this common learning style should come first in the case of changing the design of this online course, such as adding more in-class activities through different applications and employing gamification. This could be an extension of this study. Furthermore, another interesting research topic is employing machine learning algorithms to cluster student learning styles because of the possible correlation between the styles themselves.

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