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The Exploration of Student Emotion Experience and Learning Experience in E-Learning Platform

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ABSTRACT — Previous studies have shown that emotion is crucial in student learning. However, most studies in the e-learning environment have yet to consider emotion as part of learning that could lead to successful learning. Thus, this study explored the relationship between student emotion state, emotion sequences, and student learning experience. A preliminary data collection was conducted to explore the relationship between emotional experience and student learning experience, which involved 16 students. Students were asked to learn a programming subject in an e-learning environment. E-learning is designed to store the students' emotional experience and activity during learning. The sequential pattern mining technique was used to extract the data, exploratory data analysis was conducted to visualize the emotional trajectory during the learning process, and regression analysis was used to explain the relationship between students' emotional learning experiences. The results showed that emotional experience might affect student experience in learning. In one-sequence emotion, all emotion states contributed to the learning experience with p-values < 0.01 except for neutral and disgust with p-values < 0.05. The one-sequence emotion model shows R-squared = 0.585; Adj. R-squared = 0.734; F-statistic = 6.920; Prob (F-statistic) = 0.00702. Meanwhile, in two-sequence emotion, none of the emotion sequences contributed to the student learning experience. Lastly, three-sequence emotion models also showed that most sequences did not influence student learning experience. The only sequence of emotions that influenced the student learning experience was surprise-neutral-surprise. These results suggest that emotion should be considered in learning design as it can influence student experience.

KEYWORDS — Emotion Analysis, Emotion Trajectory, Emotion Sequences, Learning Experience, Regression Model.

I. INTRODUCTION

Most learning processes emphasize conveying information and facts. This information and facts are bundled as a collection called knowledge [1]. Three domains need to be considered and are strongly related to education: the cognitive domain, the affective domain, and the psychomotor domain [2]. The cognitive domain measures a student's capabilities in learning and applying knowledge. The affective domain measures a student's behavior and desire to learn. In contrast, the psychomotor domain focuses more on the student's interest in learning through the manipulation of objects and physical activities [3], such as tasks and homework.

Learning is a natural process of making mistakes. Making mistakes in learning will result in experiencing negative emotions. Mistakes are part of a learning process that needs to happen to achieve improvements. During learning sessions, students experience mixed emotions and create changes through different perspectives and approaches. In the end, the students will experience positive emotions due to success in solving problems with various approaches or negative emotions due to difficulties in learning, requiring them to think of another approach. This cycle of making, accepting, and solving mistakes creates a constant learning process where the outcome is uncertain, depending on the student's state. As in [4], making mistakes can be considered a positive stimulant that triggers disequilibrium for self-reflection. On the other hand, mistakes can also be treated as a signal for instructors to take preventive actions by finding the root cause so the students can absorb the materials completely without any misunderstandings. A similar concept was proposed by [5], in which they proposed an affective state model during complex learning. During the learning process, the proposed model assumed that students are in one of two possible conditions for achieving a task or goal, namely engagement (positive emotion) when the student is pursuing the main goal of the learning or disengagement (negative emotion) which can also be interpreted as 'boredom' emotion when someone stops or ignores the task or goal to be achieved from the learning carried out. Positive emotions have been empirically shown to enhance student academic performance [6], [7]. Meanwhile, negative emotion was shown not to have a relation with performance [7].

The learning fields of science, math, engineering, and technology naturally involve failure and are associated with emotional responses [8]. As in [9], challenges, confusion, and difficulties are unavoidable and important in learning. These failures and mistakes are not shown in classes because educators show the polished version of the materials. This has caused students to believe that making mistakes equals not being good at it. However, mistakes, failures, and confusion are normal responses in complex learning processes that could be helpful for signals on how to learn better [10]. These responses should be the norm in learning instead of being avoided or hidden. Thus, emotion is an essential factor in the learning process.

Educators in conventional learning settings are adept at recognizing student emotional states. The educators easily understand student affective cues during learning and address them positively according to the student's emotional state, which may impact the learning process. The role of educators has an impact on students' learning process through guided learning. Guided learning is the most efficient way to help students gain information in their long-term memory [11]. Meanwhile, minimal guidance learning only works on students with high learning aptitude since they have proper strategies for integrating new information alone [11]. In addition, emotion is also essential for the student to navigate and process their knowledge [12]. This is why educators must understand students' emotional cues during learning in order to have a positive impact on the learning process [12]–[15]. As in [16], positive emotions that appear during exam preparation have a strong correlation with the student's motivation during the learning phase and impact the learning outcome.

In the e-learning context, however, the teachers have a hard time understanding students' emotional cues. Most e-learnings are only used as a medium to share learning material and tasks [17]. In terms of technology, current e-learning is not equipped with intelligent modules that can recognize student progress to create personalized learning [18]. Thus, the student's emotional state is undetectable in the e-learning platform. Continuous negative emotions that are unmonitored during the learning process might lead the student to feel dissatisfied with the learning material [19]. Therefore, identifying the students' cognitive-emotional states is critical in leading to success in learning [20]–[22]. Current developments in e-learning have not yet fully explored the ability to detect students' emotional state during learning [23].

Based on the background, this research proposed empirical evidence on the role of emotional experiences during learning. This research aimed to prove that emotion was essential in learning, even in an e-learning platform. Contributions of this research include: (a) visualizing the emotional trajectory of students during learning sessions; (b) analyzing three types of emotion sequences using statistical methods; (c) showing the relationship between emotion and student's learning experience. This research is divided into four stages. First, the students' emotions during a learning session were logged in the e-learning environment. Second, the students' emotional experiences during the learning process were explored. Third, the emotion was explored, and the emotional trajectory during learning was visualized. Lastly, the relationship between emotion and student learning experience was comprehended.

II. EMOTIONAL EXPERIENCE EXPLORATION

This section explains the exploration of the relationship between emotion and learning experience. The overview of the analysis is shown in Figure 1. The study started with a learning activity design where short instructional learning related to programming was performed. Next, a learning activity was conducted. Data collection was initiated during the activity. Feature extraction and data merging were performed after all the data were obtained. Further, exploratory data analysis (EDA) was conducted, which consisted of exploring the overall student emotion experience and page-specific emotion experience. Lastly, regression analysis was used to understand the relationship between student's emotional and learning experiences.

A. DATA COLLECTION

The data were collected from the students' learning experiences through an e-learning platform that is specifically designed to teach Hyper Text Markup Language (HTML) and cascading style sheets (CSS), as shown in Figure 2. The learning sessions took six weeks. In each session, students were required to study for about 45 to 60 minutes. The platform had several learning resources, including learning materials, practices, and challenges. Furthermore, it was equipped with gamification elements such as badges, a leaderboard, and experience points. The learning platform was designed to be able to log students' experiences during the session. It stores students' profiles, activities on the learning platform, facial expressions during learning, and learning points that consist of experience points and challenge points. The facial expressions were recorded by an e-learning platform through a deep learning module. The deep learning model was based on a previous study [24]. The captured facial expressions were neutral, happy, angry, sad, fearful, disgusted, and surprised. In each session, students were required to finish specific tasks as designed in the learning process.

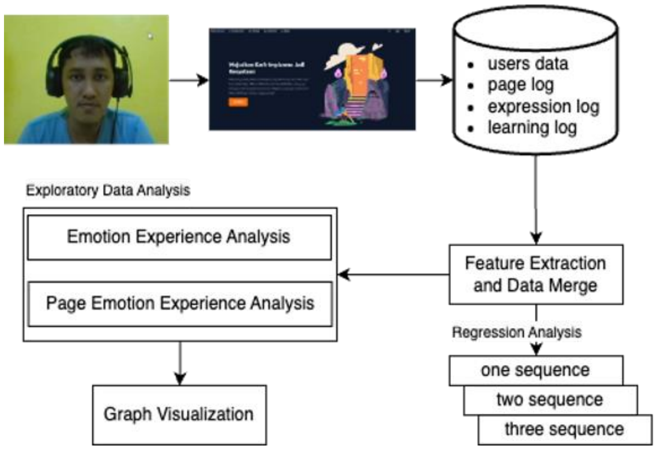

Figure 1. Overview of the emotional experience exploration in an e-learning platform.

B. PARTICIPANT

The current research is a pilot study, so the sampling method used was purposive sampling. The selection of the participants was determined by their fundamental knowledge and experience with established web programming learning platforms called extreme users [25]. In this approach, participants were able to make a direct comparison between their past experiences and the platform used in this research. Therefore, it allowed researchers to identify features that could enhance user engagement during learning.

The participants of this research were 19 students from the Faculty of Computer Science at Universitas Brawijaya. On average, the students were in their fifth semester and had prior knowledge of programming skills. During the experiment, students' ages were ranged from approximately 20–21 years old. In total, there were 5 female students and 14 male students working on the HTML CSS learning experience.

C. DATA PREPROCESSING

The dataset is a combination of multiple tables in the database. User ID and timestamp were used as keys to combine the data tables of the user's data, page log, expression log, and learning log. However, merging page logs and expression logs was a challenge since there was a delay in the expression log when recording the students' facial expressions. The facial expression module required time to identify the users' facial areas. As a result, the timestamp of the facial expression log started seconds after. Thus, there was a timestamp difference between page logs and facial expressions. To overcome this problem, the expression log's timestamp was used as the

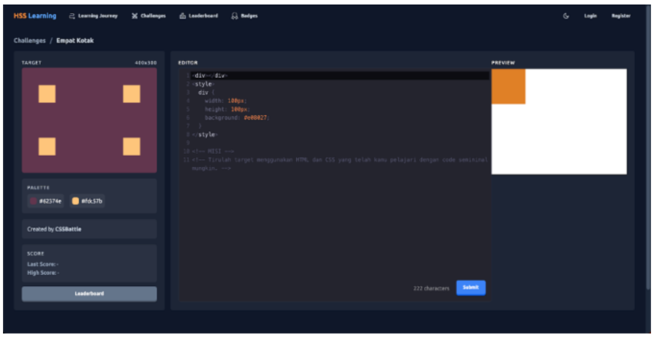

Figure 2. Example of page in HTML and CSS e-learning.

reference for merging two tables. The merged table was then used for further analysis. After careful analysis of data merging and data preprocessing, only 16 data were complete and were used for further analysis.

D. EXPLORATORY DATA ANALYSIS

Basic EDA was performed to explore the students' learning experiences. Further, an analysis of the students' emotions was conducted to understand their emotional state during learning. The analysis captured all of the emotions during learning. Students' learning experiences are affected by the section where they view or work on a certain task in the learning platform. Therefore, emotion analysis on certain pages was explored to understand the shift of emotions during learning across multiple materials. A simple directed graph was proposed to visualize the emotion trajectory during learning. The proposed visualization graph can be seen in Figure 3, where A and B are denoted as student experienced emotion, the arrow indicates a shift from emotion A to emotion B, n denotes the frequency of emotion shift, and C is the web page where the emotions were shown.

Further, regression analysis was conducted to understand the relationship between emotion and learning experience. The independent variable used in this study was students' emotions. Three sets of emotion sequences were generated to explore the influence of the emotion sequences on the learning experience. In this step, the analysis is different from the previous emotional experience, where the main objective is to visualize the students' learning experiences during learning. In addition, previous analysis captures all the emotions during learning and page-related emotions expressed by students. Meanwhile, this analysis focuses on understanding the relationship between emotion and learning experience. Three sets of emotion sequences were generated. The first set consisted of single emotion states. The second set consisted of sequences of two consecutive emotion states. The third and final set consisted of sequences of three consecutive emotion states. The number of occurrences for each state or sequence within each set was calculated across all students regardless of condition. Since the emotion sequences of two and three were sparse, 8 frequency sequences of emotion and 7 frequent sequences of emotion for two sequences and three sequences were selected, respectively.

III. RESULTS AND DISCUSSION

The experiment results are divided into two main discussions. The first discussion is related to the exploratory data analysis on the emotion experience. The second discussion describes the relationship between the sequence of emotion to student learning experience.

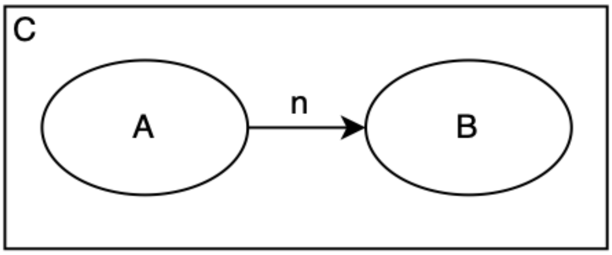

Figure 3. Emotional trajectory visualization.

A. EMOTION TRAJECTORY VISUALIZATION

Emotion trajectory visualization was sampled from 2 students: 1 male and 1 female student. Two visualizations of emotion trajectory consist of overall emotion during the learning process and page-specific emotion. The visualization of overall emotion and visualization of page-related emotion can be seen in Figure 4 until Figure 7.

Figure 4 is the visualization of the overall emotional trajectory for male students during the learning session. Overall, the emotions experienced during learning were happy, surprised, sad, and angry. Regarding the emotion shifts, frequent emotion changes occurred: surprised → sad as much as four times, sad → surprise as much as three times. Meanwhile, others were not as apparent and only occurred once: happy → surprised, surprised → angry, and angry → surprised.

Figure 5 is the visualization of the female student's overall emotional trajectory during the learning session. Overall, the emotions experienced during learning were surprised, happy, neutral, and sad. During the learning process, the students experienced frequent emotion shifts: surprised → happy as much as 3 times, happy → surprised as much as 3 times. Meanwhile, others were not as apparent and only occurred once; they were surprised ↔ neutral and surprised ↔ sad.

Further, the visualization of page-related emotion was explored. The sample was the same students as in the previous visualization. The male students' page-related emotion is illustrated in Figure 6. As shown in Figure 6, the Material page induced happy, surprised, sad, and angry emotions. The Challenge page induced surprised, sad, angry, and happy emotions. The Exercise page stimulated surprised, sad, and angry emotions. On the other hand, the Home page induced surprised and angry emotions. In summary, a mix of positive (surprised) and negative emotions (sad and angry) occurred in the pages. The most prevalent emotion that occurred across pages was surprised ↔ angry shift, with the highest intensity emotion shift across pages.

On the other hand, female students were not actively exploring e-learning. As seen in Figure 7, only three pages with low intensity were explored during the learning. Based on the pages, the Material page stimulated surprised emotion. The exercise page induced surprised, happy, neutral, and sad emotions. Lastly, the Challenge page stimulated surprised and happy emotions. In summary, the student experienced a mix of positive emotions (happy, surprised) and negative emotions (sad), having more than two shifts on the Exercise page. Based on Figure 7, the most frequent emotion shifts occurred across pages, and the page-related emotions were surprised and happy.

B. STATISTICS OF EMOTIONAL SEQUENCES

This section describes the statistical analysis of the emotional sequences experienced by the students. There are

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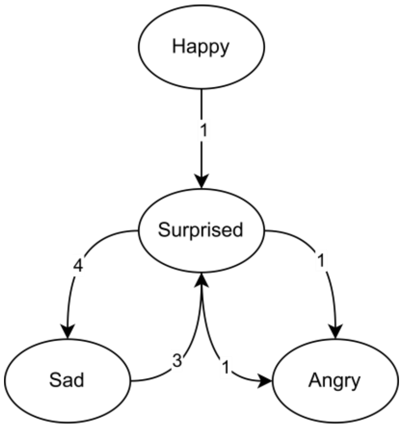

Figure 4. Student A overall emotional trajectory.

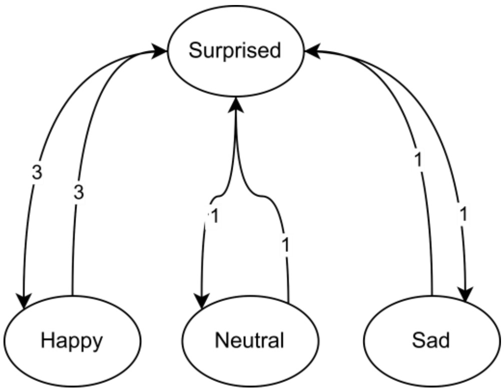

Figure 5. Student B's overall emotional trajectory.

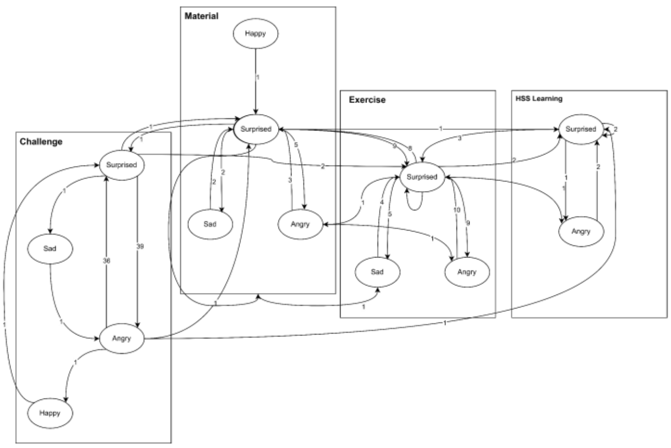

Figure 6. Student A's page-related emotion trajectory.

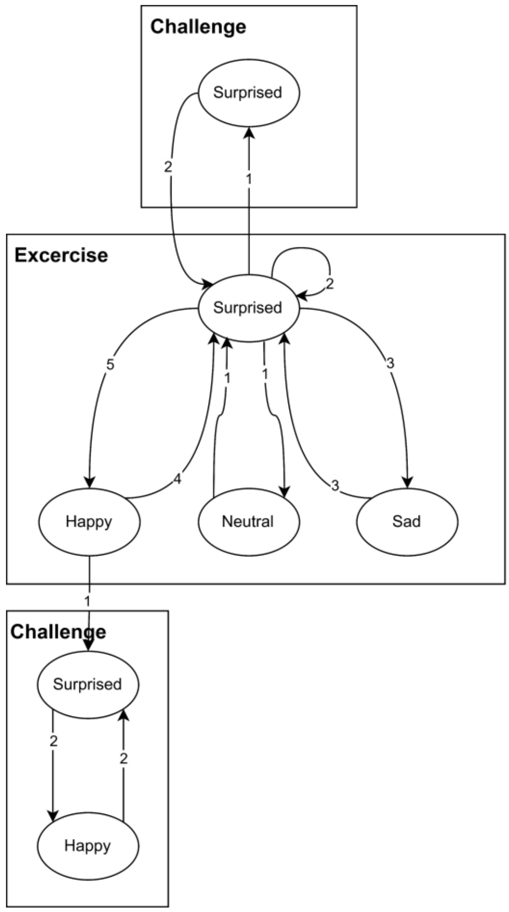

Figure 7. Student B's page-related emotional trajectory.

three types of emotional sequences: one-sequence emotion, two-sequence emotion, and three-sequence emotion. The explanation of each sequence is as follows.

Table I shows statistics on one-sequence emotion. The statistics include mean, standard deviation, minimum, and maximum. Based on Table I, the most frequent emotions in every student were surprised emotions, followed by angry and happy emotions; these emotions, at minimum, appear 4 times, 0 times, and 0 times, respectively. This result showed that some students did not experience certain emotions during learning. In addition, even though the surprised emotion appeared to be the most frequent emotion during learning, it also had a high standard deviation. This result showed that the surprised emotion was the most frequent emotion with a high distribution, but not all students experienced it. Another fact is that this emotion appeared in every student with a minimum of four appearances during learning. Meanwhile, disgusted emotion had the lowest appearance during learning, with only two appearances.

TABLE I
ONE-SEQUENCE EMOTION STATISTICS

Emotions	Mean	Std. Dev.	Min	Max
Angry	34.94	94.51	0.00	382.00
Disgusted	0.38	0.72	0.00	2.00
Fearful	2.06	3.60	0.00	12.00
Happy	26.38	55.60	0.00	231.00
Neutral	6.81	10.69	0.00	41.00
Sad	9.88	14.49	0.00	58.00
Surprised	74.06	118.01	4.00	410.00

Table II shows statistics on two-sequence emotions. Based on Table II, the combination of angry-surprised emotion, surprised-angry emotion, surprised-happy emotion, and happy-surprised emotion had high appearances in every student. It showed that students tended to be surprised before and after they were angry or happy during learning or vice versa. All two-sequence emotions did not appear to be present in the students during learning. Similar to one-sequence emotion, in two-sequence emotion, the frequent emotions tended to have high standard deviation. It showed that the frequent two-sequence emotions were sparsely experienced in some students during learning. Meanwhile, the surprised-neutral emotion was the least common emotion among the two-sequence emotions during learning.

Table III shows statistics on three-sequence emotions. Unlike one-sequence and two-sequence emotions, the three-sequence emotions occurred the least due to them being less experienced by the students during learning. Based on Table III,

TABLE II
TWO-SEQUENCE EMOTION STATISTICS

Emotions	Mean	Std. Dev.	Min	Max
Angry-surprised	32.69	90.51	0.00	365.00
Happy-surprised	23.81	51.55	0.00	214.00
Neutral-surprised	6.19	9.87	0.00	38.00
Sad-surprised	8.06	12.18	0.00	48.00
Surprised-angry	32.94	90.23	0.00	364.00
Surprised-happy	23.94	51.62	0.00	214.00
Surprised-neutral	5.94	9.38	0.00	37.00
Surprised-sad	8.25	11.20	0.00	43.00

TABLE III
THREE-SEQUENCE EMOTION STATISTICS

Emotions	Mean	Std. Dev.	Min	Max
Surprised-sad-surprised	6.88	9.49	0.00	35.00
Surprised-happy-surprised	21.88	48.56	0.00	201.00
Surprised-neutral-surprised	5.50	9.11	0.00	36.00
Happy-surprised-sad	2.62	5.95	0.00	24.00
Happy-surprised-happy	14.75	37.74	0.00	154.00
Surprise-angry-surprised	30.88	86.45	0.00	348.00
Angry-surprised-angry	26.00	81.58	0.00	325.00

the combination of happy and surprised emotions and angry and surprised emotions continue to have a high frequency. The combination of angry and surprised emotions had a higher appearance overall. This information showed that students tended to feel angry and surprised sequentially. Another result was that students were not likely to have changes in emotion, especially from being happy to sad after being surprised. They were more likely to return to the previous emotion instead of shifting to a different emotion.

C. RELATIONSHIP OF EMOTIONAL AND LEARNING EXPERIENCES

Regression analysis was used to understand the relationship between emotional sequences and learning experiences. Three sets of emotion sequences were generated to understand the relation of a single emotion and a series of emotions to the students' learning experiences.

The first model is a one-sequence model, as shown in Table IV. This model used a single emotion as the independent variable, and the learning experience points as the dependent variable. The independent variables were angry, disgusted, fearful, happy, neutral, sad, and surprised emotions. The model shows that fear and surprise had a negative impact on how students gained their learning experience, with surprise being the highest. Fear and surprise appeared to have a negative impact on students' learning since most of the learning materials were new learning resources to the students. The current learning platform provides a new and unique aspect to the learning flow for the students. The well-known learning platform, such as w3schools, displays material in the categorization of syntax components [26]. However, the categorization of syntax components makes it difficult for students if they do not have prior knowledge of related theory. Students tend to be confused about how to start learning and are overwhelmed with memorizing HTML and CSS components. This problem can be handled by simplifying the concepts through the implementation of a learning journey that

TABLE IV
ONE-SEQUENCE EMOTION MODEL

Emotions	Coef.	Std. Err.	t	$P > \|t\|$
Const.	356.98	34.04	10.48	0.000
Angry	82.52	19.40	4.25	0.003^{**}
Disgusted	152.08	57.06	2.66	0.029^{*}
Fearful	-120.70	22.82	-5.28	0.001^{**}
Happy	89.24	20.41	4.37	0.002^{**}
Neutral	39.62	15.44	2.56	0.033^{*}
Sad	89.54	21.92	4.08	0.004^{**}
Surprised	-84.36	20.02	-4.21	0.003^{**}
$^{**}p < 0.01$; $^{*}p < 0.05$				

classifies the subjects as basic, intermediate, and advanced levels. As a result, students can easily digest the concepts.

Previous studies have simplified the Periodic Table of HTML, making it easier for students to prioritize concepts that need to be understood first [27]. Participants showed an expression of surprise in a positive sense because there were interactive features (code exploration with closed options); playgrounds (free code exploration), exercises with hints; and challenges. These features gave students the freedom to fail while still getting proper feedback for the next stage. Meanwhile, fear might affect student learning due to the learning exercise that students had to do, and the exercise was in the form of exploration, where students had to integrate their knowledge to solve the problem. On the other hand, other emotions showed positive results in helping the student, especially happiness, disgust, and sadness. These negative emotions might be able to improve a students' learning experience. The p-value < 0.01 of each emotion in Table IV shows that all emotions influenced the experience points gained by students except for neutral and disgusted emotion. The summary shows R-squared = 0.585; Adj. R-squared = 0.734; F-statistic = 6.920; Prob (F-statistic) = 0.00702. The model suggested that 73.4% of the variance in the dependent variable was explained by the independent variable.

The second model is a two-sequence model as shown in Table V. In this model, two-sequence emotions were used as the independent variable, and learning experience points were used as the dependent variable. The independent variables are angry-surprised emotion, happy-surprised emotion, neutral-surprised emotion, sad-surprised emotion, surprised-angry emotion, surprised-happy emotion, surprised-neutral emotion, and surprised-sad emotion. The two-sequence model results can be seen in Table V. The sequences consisted of combinations of surprised emotion and four other emotions (angry, happy, neutral, and sad). The result showed that sequences ending with surprised emotion had a negative impact on experience points, otherwise, the impact was positive. However, in this model, none of the p-values < 0.05 showing that the variables might not influence learning experience points. One possible hypothesis is that even if the combination emotions end with surprised emotion had a negative impact, it did not affect the students' learning experiences. This was due to most of them had prior knowledge in programming. However, the learning flow that they experienced might negatively influence the learning in a positive sense. The model summary shows R-squared = 0.463; Adj. R-squared = -0.151; F-statistic = 0.7544; Prob (F-statistic) = 0.652. The model in two-sequence emotions could not predict the outcome variable

TABLE V
TWO-SEQUENCE EMOTION MODEL

Emotions	Coef.	Std. Err.	*t*	*P* > | *t* |
Const.	219.59	75.38	2.91	0.02
Angry-surprised	-36.64	50.95	-0.71	0.49
Happy-surprised	-47.28	77.53	-0.61	0.56
Neutral-surprised	-41.52	115.20	-0.36	0.72
Sad-surprised	-89.87	76.91	-1.16	0.28
Surprised-angry	36.80	51.23	0.71	0.49
Surprised-happy	49.29	79.46	0.62	0.55
Surprised-neutral	48.22	115.68	0.41	0.68
$^{**}p < 0.01$; $^{*}p < 0.05$				

TABLE VI
THREE-SEQUENCE EMOTION MODEL

Emotions	Coef.	Std. Err.	*t*	*P* > | *t* |
Const.	323.22	77.061	4.194	0.003
Surprised-sad-surprised	-2.22	11.56	-0.19	0.85
Surprised-happy-surprised	-38.29	47.50	-0.80	0.44
Surprise-neutral-surprised	118.53	43.23	2.74	0.025*
Happy-surprised-sad	-53.30	62.27	-0.85	0.41
Happy-surprised-happy	33.14	52.67	0,62	0.54
Surprise-angry-surprised	-36.23	42.26	-0.85	0.41
Angry-surprised-angry	36.77	43.54	0.84	0.42
$^{**}p < 0.01$; $^{*}p < 0.05$				

well, as shown by the negative value of the adjusted R-squared, which is -0.151.

The third model is a three-sequence model, as shown in Table VI. This model used three-sequence emotions as the independent variable, and learning experience points were the dependent variable. The independent variables were surprised-sad-surprised emotions, surprised-happy-surprised emotions, surprised-neutral-surprised emotions, happy-surprised-sad emotions, happy-surprised-happy emotions, surprised-angry-surprised emotions, and angry-surprised-angry emotion. The three-sequence model's results can be seen in Table VI. The model showed a different result compared to the previous model's result. Not all sequences ending with surprise had a negative impact on the experience points. However, only the combination between angry-surprised emotions, happy-surprised emotions, and neutral-surprised emotions showed a positive impact on the learning outcome. Similar to the previous result, none of the p-values were ≤ 0.05. The model summary showed R-squared = 0.611; Adj. R-squared = 0.271; F-statistic = 1.797; Prob (F-statistic) = 0.214. The model in three-sequence emotion could explain a very small portion of the model by 27% variance of the dependent variable by the independent variable.

Based on the research findings in Table IV until Table VI, the model in Table IV has the most significance when compared to the other models. In the one-sequence model, surprised and fearful emotions indicated that the learning platform implemented in this research had value in the learning journey, feedback, and simplification of HTML and CSS concepts. The simplification of this notion is critical because the elements of HTML and CSS material are complex and require computational concepts to comprehend [28]. As for two-sequence and three-sequence emotion models, neither influenced student learning experiences because the combination of emotion sequences became less and less as the sequences increased. Based on the value mentioned previously, this platform has the potential for future research into student engagement and elements that elicit emotional responses from participants while creating a learning experience. Emotional experience may be added for further analysis and consideration in designing personalized and tailored learning.

IV. CONCLUSION

The current study is an initial work of emotional experience exploration during learning. Understanding students' emotions will lead to better and more efficient learning by tailoring it to suit the students' needs. Students experience different emotions during learning, which are shown in the emotional trajectory visualization. Surprise was the most prevalent emotion experienced by students. Based on the visualization, several pages could stimulate students' negative emotions during learning. Further, three regression models were built to understand the relationship between students' emotions and learning experiences. In terms of the emotion regression model, using a single emotion sequence was shown to be able to explain the relationship between emotion and learning experience. Meanwhile, two-sequence and three-sequence emotions were not shown to have a relationship to the learning experience. In this empirical study, emotion has been shown to influence students' learning. The findings suggest that emotion should be considered in learning design as it can influence students' experience.

Future work may consider using more data as this experiment only used 16 students' data due to incomplete data from 19 participants. The current learning experience still needs to be improved in generating a summary of most students' learning experiences since students may access the learning platform differently. Further study can group students with a similar emotional learning experience. Further study may also explore other students' traits in learning, such as the cognitive domain, psychomotor domain, or other features in learning.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest in the research and preparation of this paper.

AUTHORS' CONTRIBUTIONS

Conceptualization, Fitra Abdurrachman Bachtiar; data collection, Fitra Abdurrachman Bachtiar; methodology, Fitra Abdurrachman Bachtiar; data extraction, Riza Setiawan Soetedjo; visualization, Riza Setiawan Soetedjo; software, Fitra Abdurrachman Bachtiar; formal analysis and results interpretation, Fitra Abdurrachman Bachtiar, Joseph Ananda Sugihdharma, Retno Indah Rokhmawati, Lailil Muflikhah; writing—original draft preparation, Fitra Abdurrachman Bachtiar, Riza Setiawan Soetedjo, Joseph Ananda Sugihdharma, Retno Indah Rokhmawati, Lailil Muflikhah; writing—final draft preparation, Fitra Abdurrachman Bachtiar, Riza Setiawan Soetedjo, Joseph Ananda Sugihdharma, Retno Indah Rokhmawati, Lailil Muflikhah; funding acquisition, Fitra Abdurrachman Bachtiar.

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REFERENCES

[1] E. Calcagni and L. Lago, “The three domains for dialogue: A framework for analysing dialogic approaches to teaching and learning,” *Learn. Cult. Soc. Interact.*, vol. 18, pp. 1–12, Sep. 2018, doi: 10.1016/j.lcsi.2018.03.001.

[2] A. Chanaa and N. El Faddouli, “An analysis of learners’ affective and cognitive traits in context-aware recommender systems (CARS) using feature interactions and factorization machines (FMs),” *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 8, pp. 4796–4809, Sep. 2022, doi: 10.1016/j.jksuci.2021.06.008.

[3] K.R. Salim, M. Puteh, and S.M. Daud, “Assessing students’ practical skills in basic electronic laboratory based on psychomotor domain model,” in *Procedia - Soc. Behav. Sci.*, 2012, pp. 546–555, doi: 10.1016/j.sbspro.2012.09.687.

[4] W.S. Lee, “An experimental investigation into the application of a learning-from-mistakes approach among freshmen students,” *Sage Open*, vol. 10, no. 2, pp. 1–10, Apr. 2020, doi: 10.1177/2158244020931938.

[5] S. D’Mello and A. Graesser, “Dynamics of affective states during complex learning,” *Learn. Instr.*, vol. 22, no. 2, pp. 145–157, Apr. 2012, doi: 10.1016/j.learninstruc.2011.10.001.

[6] M. Carmona-Halty, M. Salanova, S. Llorens, and W.B. Schaufeli, “Linking positive emotions and academic performance: The mediated role of academic psychological capital and academic engagement,” *Curr. Psychol.*, vol. 40, no. 6, pp. 2938–2947, Jun. 2021, doi: 10.1007/s12144-019-00227-8.

[7] J. Camacho-Morles *et al.*, “Activity achievement emotions and academic performance: A meta-analysis,” *Educ. Psychol. Rev.*, vol. 33, no. 3, pp. 1051–1095, Sep. 2021, doi: 10.1007/s10648-020-09585-3.

[8] B. Kort, R. Reilly, and R.W. Picard, “An affective model of interplay between emotions and learning: Reengineering educational pedagogy-building a learning companion,” in *Proc. IEEE Int. Conf. Adv. Learn. Technol.*, 2001, pp 43–46, doi: 10.1109/icalt.2001.943850.

[9] J.M. Lodge *et al.*, “Understanding difficulties and resulting confusion in learning: An integrative review,” *Front. Educ.*, vol. 3, pp. 1–10, Jun. 2018, doi: 10.3389/feduc.2018.00049.

[10] S. D’Mello, B. Lehman, R. Pekrun, and A. Graesser, “Confusion can be beneficial for learning,” *Learn. Instr.*, vol. 29, pp. 153–170, Feb. 2014, doi: 10.1016/j.learninstruc.2012.05.003.

[11] A.Y. Kolb, D.A. Kolb, A. Passarelli, and G. Sharma, “On becoming an experiential educator: The educator role profile,” *Simul. Gaming*, vol. 45, no. 2, pp. 204–234, Apr. 2014, doi: 10.1177/1046878114534383.

[12] J.C. Richards, “Exploring emotions in language teaching”, *RELC J.*, vol. 53, no. 1, pp. 225–239, Apr. 2022, doi: 10.1177/0033688220927531.

[13] A. Gupta, A. D’Cunha, K. Awasthi, and V. Balasubramanian, “DAiSEE: Towards user engagement recognition in the wild,” 2022, *arXiv:1609.01885*.

[14] S. Lane, J.G. Hoang, J.P. Leighton, and A. Rissanen, “Engagement and satisfaction: Mixed-method analysis of blended learning in the sciences,” *Can. J. Sci. Math. Technol. Educ.*, vol. 21, no. 1, pp. 100–122, Mar. 2021, doi: 10.1007/s42330-021-00139-5.

[15] J. Hilliard, K. Kear, H. Donelan, and C. Heaney, “Students’ experiences of anxiety in an assessed, online, collaborative project,” *Comput. Educ.*, vol. 143, pp. 1–15, Jan. 2020, doi: 10.1016/j.compedu.2019.103675.

[16] M. Stephan, S. Markus, and M. Gläser-Zikuda, “Students’ achievement emotions and online learning in teacher education,” *Front. Educ.*, vol. 4, pp. 1–12, Oct. 2019, doi: 10.3389/feduc.2019.00109.

[17] S.B. Gupta and M. Gupta, “Technology and e-learning in higher education,” *Int. J. Adv. Sci. Technol.*, vol. 29, no. 4, pp. 1320–1325, Feb. 2020.

[18] F. Gjermeni and B. Percinkova, “Combining intelligent algorithms and e-learning styles to create an improved intelligent system in evaluating an e-learning student's profile,” *Anglisticum: Int. J. Lit. Linguist. Interdiscip. Stud.*, vol. 7, no. 2, pp. 11–21, Feb. 2018, doi: 10.5281/zenodo.1186399.

[19] R. Wu and Z. Yu, “Exploring the effects of achievement emotions on online learning outcomes: A systematic review,” *Front. Psychol.*, vol. 13, pp. 1–15, Sep. 2022, doi: 10.3389/fpsyg.2022.977931.

[20] J.L. Plass and S. Kalyuga, “Four ways of considering emotion in cognitive load theory,” *Educ. Psychol. Rev.*, vol. 31, no. 2, pp. 339–359, Jun. 2019, doi: 10.1007/s10648-019-09473-5.

[21] M. Jiang and K. Koo, “Emotional presence in building an online learning community among non-traditional graduate students,” *Online Learn. J.*, vol. 24, no. 4, pp. 93–111, Dec. 2020, doi: 10.24059/olj.v24i4.2307.

[22] J. Hill, R.L. Healey, H. West, and C. Déry, “Pedagogic partnership in higher education: Encountering emotion in learning and enhancing student wellbeing,” *J. Geogr. High. Educ.*, vol. 45, no. 2, pp. 167–185, May 2021, doi: 10.1080/03098265.2019.1661366.

[23] O. Tapalova and N. Zhiyenbayeva, “Artificial intelligence in education: AIED for personalised learning pathways,” *Electron. J. e-Learn.*, vol. 20, no. 5, pp. 639–653, Dec. 2022, doi: 10.34190/ejel.20.5.2597.

[24] K. Zhang *et al.*, “Detecting faces using inside cascaded contextual CNN,” in *2017 IEEE Int. Conf. Comput. Vis. (ICCV)*, 2017, pp. 3190–3198, doi: 10.1109/ICCV.2017.344.

[25] B.A. Heiman and M. Beringer, “Mobile device-based offers: Determinants of consumer response in sophisticated (extreme) users,” *Int. J. Comput. Appl.*, pp. 129–140, 2010.

[26] A.P.M.D. Rosa, L.M.M. Villanueva, J.M.R.S. Miguel, and J.E.B. Quinto, “Web-based database courses e-learning application,” *Int. J. Comput. Sci. Res.*, vol. 7, pp. 1531–1543, Jan. 2023, doi: 10.25147/ijcsr.2017.001.1.115.

[27] B. Frost. “Atomic design methodology.” Access date: 31 May 2024. [Online]. Available: http://atomicdesign.bradfrost.com

[28] T.H. Park, B. Dorn, and A. Forte, “An analysis of HTML and CSS syntax errors in a web development course,” *ACM Trans. Comput. Educ.*, vol. 15, no. 1, pp. 1–21, Mar. 2015, doi: 10.1145/2700514.