Reader Characteristics, Reading Order, and Facial Emotions Expressed in Reading Science Texts

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Abstract: Emotion plays an important role in online reading and self-regulated learning. It could influence reading processing and even the outcomes through motivation functions. Since previous studies mostly adopted questionnaires to access readers' emotions, research that applied facial emotion detection non-intrusively during reading process is still limited. Therefore, the purpose of this study was to investigate how readers' on-going emotions fluctuated under different reading conditions, i.e., with different reader characteristics and reading orders, using a facial emotion analysis system. 21 participants were recruited and presented with four conflicting scientific texts that included positive or negative arguments on genome editing. These participants were divided into the high and low engagements and then were assigned different reading orders of positive-first or negative-first articles. The results showed that participants who read negative-first expressed more sadness and less happiness. Meanwhile, the high engagements showed more anger when reading positive-first, but the low-engagements showed more anger when reading the negative-first. Reading negative-first performed better, but writing performance did not differ according to the group membership or reading order. These findings suggest that (1) the influence of emotions on online reading multiple and conflict science texts and performance is complex; negative activating emotions like sadness and anger could be beneficial to reading performance, while positive activating emotions like happiness could be harmful for reproductive performance. (2) Using facial expression to non-intrusively detect readers' momentary emotions provides meaningful insights into the fluctuation of emotion during reading science texts. With only six basic emotions, it may not be enough to fully show the motivational transitions in reading process. The interpretation of these facial emotions should be considered beyond their surface meaning.

Keywords: Facial expressions, emotions, reader characteristics, reading order, scientific article

1. Introduction

Self-regulated learning (SRL) has been found an important element in distance or online learning situations (You & Kang, 2014). Reading multiple texts online was also one of these situations that required learners' self-regulation to persist and to overcome challenges during learning processes. Emotions, which was relating to learners' goal setting, motivation, and cognitive strategies used, can be vital to self-regulation and persistence in SRL (Muis et al, 2018). Meanwhile, when reading multiple scientific articles with conflicting arguments and controversial topics, emotion also profoundly influence learners' understanding through the allocation of cognition resources during processing (Danielson et al., 2022; Pekrun, 2022; Trevors, 2021). Thus, in this study, we aimed to understand how students' emotional states change during a scientific reading task in an online environment.

Traditionally, emotions could be categorized according to two dimensions: valence (positive or negative) and activation (activating or deactivating). Believed to be a subjective experience, previous studies adopted self-report questionnaires to investigate students' emotions in learning situations. For instance, the Achievement Emotions Questionnaire (AEQ) as well as the Epistemically-Related Emotion Scales (EES) both developed by Pekrun and colleagues (Pekrun et al., 2005; Pekrun et al., 2017b) were two renowned and frequently used questionnaires. Based on self-report data of emotions, previous research found an average positive effect of positive emotions on learning outcomes, and effect of negative emotions were generally negative (Lajoie et al., 2021; Pekrun, 2022).

However, despite the numerous findings, self-report questionnaires have several limitations. On the one hand, although questionnaires are able to measure students' anticipatory and retrospective feelings, their on-going emotion states and the changes of emotions during the tasks were hard to collect. On the other hand, sometimes participants may not be able to tell how they feel or they may conceal their real opinion, so there may be discrepancies between the data we obtained and the real situations (Mason et al., 2018; Wang et al, 2021). While some researchers incorporated multiple time point measurement to capture the changes of emotions through questionnaire (Tulis & Fulmer, 2013), others adopted physiological or behavioral measures like hart rate (HR) and facial expression recognition tools to collect participants' expressive emotional states (Mason et al., 2018; Lajoie et al., 2021; Wang et al, 2021). Through these multi-modal data, different patterns of emotion fluctuations have been observed. For example, in Tulis & Fulmer (2013), they found that a moderate level of anxiety may motivate learners to exert more effort and to persist in a challenge task, which suggested that negative emotions could also be beneficial in learning process. Meanwhile, research also found that positive emotions may be harmful in some situations. Experiencing happy mood may distract students from the contents, but rather focused on irrelevant aspects of the learning task (Mensink, 2021; Trevors et al., 2017). That is to say, to examine how exactly emotions change during students' learning process, as well as to understand its relation with students' motivation and learning outcomes, tools that could capture on-going emotional data were essential. Previous research suggested that facial expressions were significantly correlated to students' real emotion, which could further be use to recognize their comprehension toward the learning content (Sathik & Jonathan, 2013).

Thus, in this study by combining multimodal analytic tools that can reveal temporal changes with those that could compare group differences, we aimed for a closer look at the roles of emotions playing in reading conflict scientific articles. Specifically, we utilized an automated facial emotion recognition system, the Facial Emotion Analysis Tool (FEAT, Lin et al., 2019; Wu & Lin, 2018) to record participants' emotions during reading tasks. FEAT detects different facial muscle movements to identify facial expressions based on the Facial Action Coding System (FACS, Ekman and Friesen, 1978) and categorized these expressions into six basic emotions (i.e., happiness, sadness, anger, disgust, fear, and surprise, Ekman, 1992). Readers were grouped according to their characteristics (reading interest and self-efficacy) and were assigned with articles of various orders (negative argument first or positive first) so that group comparisons could be observed.

We proposed the following two research questions to examine the interplay of students' characteristics, their expressed emotions, and text features. The relations between participants' expressed emotion and post reading performance will also be discussed.

RQ1: When reading positive or negative texts in different order, what types and patterns of emotions do readers with different characteristics exhibit?

RQ2: Do readers' expressed emotions differ significantly while reading negative or positive argument articles, according to their personal characteristics and the reading order?

2. Methods

2.1 Participants

Twenty-one undergraduate and graduate students (16 female, 76%, M_{age} = 24, SD = 2.55) in a university in the northern part of Taiwan participated in the study. Participants were instructed to read four articles about genome editing babies. A facial expression analysis tool (FEAT) was used to record participants' emotion during reading task. Two participants' data were excluded from the following analysis since their emotional responses were too low (most of the intensity of emotion were below the 0.1 criteria). The final sample consisted of three male and 16 female participants with an average age of 23.89 (SD = 2.66). The age of the participants followed a normal distribution and there was no significant difference between the ages of the four groups ($F(3,15) = 1.905$, $p = 0.17$).

2.2 Procedures

The entire experiment was consisted of four sessions. In the first session, participants' prior knowledge, interest toward genome editing technologies, self-efficacy in reading multiple documents, and basic demographic information were accessed. Then, the camera was calibrated to ensure that participants' facial expression could be captured before they started reading the articles on a computer. Each article could only be read once. Participants were allowed to read each article according to their speed. While they were reading, their facial expressions were collected automatically. In the next session, participants completed a writing task and a multiple-choice questions test. Finally, an interview has been conducted to explore the cause of participants' emotional changes during the reading task. Line graphs depicting participant's emotional changes during the reading task were presented to participants, and they were asked to recall retrospectively what they were thinking or feeling during the task. Participants also reported the difficulty of each article in the interview.

2.3 Reading Materials

All participants need to read four articles about genome editing technology, including two expository texts, and two stories. In the expository texts, benefits and drawbacks of applying genome editing were discussed; while successful and failed cases of genome editing babies were presented in stories. The words in each text were around 351 words. Participants were randomly assigned to two groups which read these articles with different orders. The PN group read the positive expository or positive story first, and the NP group were first presented with negative expository or negative story.

2.4 Measures

2.4.1 Interest

Participant's interest was measured with self-developed questionnaire. Participants responded to statements from 1 (strongly disagree) to 6 (strongly agree). A higher score indicated a stronger interest/ higher self-efficacy. The interest questionnaire contains six questions (e.g., "I am interested in genome editing related topics", and "learning more about genome editing related topics is meaningful to me"). The reliability coefficients for overall questionnaire was acceptable (Cronbach α = .79).

2.4.2 Self-efficacy

Participant's self-efficacy was measured with self-developed questionnaire. Participants responded to statements from 1 (strongly disagree) to 6 (strongly agree). A higher score indicated a higher self-efficacy. The self-efficacy questionnaire contains eight questions (e.g., "I can understand the hardest part while reading multiple documents", "I am confident that I can understand the contents of article from different sources"). The internal consistency for the self-efficacy questionnaire was good (Cronbach α = .93).

2.4.3 Behavioral Emotion Responses

Participants' facial expression were recorded and analyzed using Facial Emotion Analysis Tool (FEAT) (Lin et al., 2019; Wu & Lin, 2018). FEAT is a non-intrusive tool which can detect participants' facial expressions and automatically classify them into one of the six basic emotions. Since it could learn in batches, this facial recognition tool was appropriate for real-time systems. The average accuracy of FEAT is around 90%. While comparing with other deep learning architectures (i.e., GoogLeNet, AlexNet, and CNN), our recognition model had better performance (Wu & Lin, 2018).

The sampling rate of FEAT was 30 frames per second, which means that emotion data would be generated once every 30 milliseconds. The log data generated by the system that has been used in this study includes (1) timestamp, and (2) intensity of six emotions. The intensity of the six emotions ranged from 0 to 1.

2.4.4 Reading Comprehension Performance

In this study, two post reading assessments, including a multiple-choice test (post-test) and a writing task, were used. The post-test contains six multiple-choice questions, through which participants' memory toward articles were accessed. The writing task ask the participants to summarize what they have read about genome editing babies, whether they support or is against the use of genome editing technics and provide arguments for their position. Three researchers separately rated the written responses considering whether they demonstrated two-sided reasoning, elaborated from personal point of view, integrated points from different articles, and the evidences used. A total score was provided to each participant's writing response. The inter-rater reliability (the Kendall's coefficient of concordance; W) of the ratings was 0.93. The discrepancies in ratings were discussed to reach a consensus.

2.5 Statistical Analysis

Data analysis was performed in R environment (version 4.1.0; R Core Team, 2021) and divided into four phases. Firstly, the hierarchical cluster analysis with Ward method was used to group participants based on their characteristics. The dendrogram and elbow method were employed to determine the number of the groups. In the second phase, participants' emotion data generated by FEAT were examined and cleaned to form main dataset. Next, emotion states from main dataset have been used to draw line graphs according to article types and participants' characteristics. From the line graph, changes of participants' emotion during reading task can been seen. Although FEAT identified six basic emotions (i.e., happiness, sadness, anger, surprise, disgust, and fear), the intensity for surprise, disgust and fear were low in this study, which means participants rarely showed these emotions while reading. Therefore, in the following sessions, the results presented and the discussion would focus on happiness, sadness, and anger. Finally, we used the 'lme4' package (Bates et al., 2015) to analyzed the intensity of emotion because LMM could include the random effects and fixed effects. In this study, the participants were regarded as random effect while the emotion, different groups and reading order were regard as fixed effects (Baayen et al., 2008). All the fixed effects were categorical variables. The 'anova' function was used to get F test result and the 'emmeans' package was used to conduct post-hoc comparison for simple main effect (Lenth, 2021).

3. Results

3.1 Cluster Analysis to Group Readers as the High and Low Engagements

Participants were divided into two clusters through the hierarchical cluster analysis with Ward method according to two variables, i.e., participants' interest and self-efficacy. Based on elbow method and dendrogram (see Figure 1 and Figure 2), the results suggested a solution of two clusters. The first cluster was made up of 11 participants who have lower interest toward the topic of genome editing and lower self-efficacy on reading multiple documents. The second cluster consisted of 8 participants who showed higher interest and self-efficacy. Therefore, the first cluster was named low engagement group while the second cluster was named high engagement group.

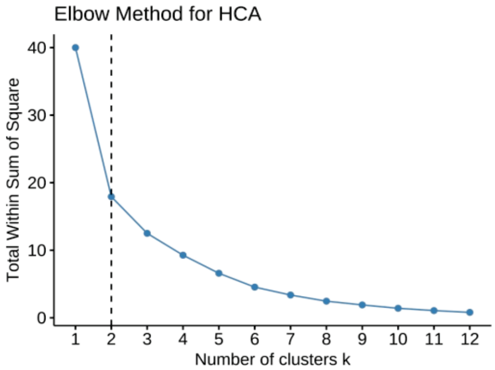

Figure 1. Elbow method for selection of optimal clusters

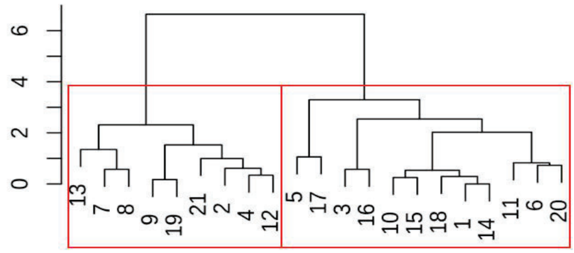

Figure 2. Dendrogram for clusters

Except for interest and self-efficacy ($F_{interest}(1,17) = 19.68$, $p < .01$; $F_{self\text{-}efficacy}(1,17) = 25.04$, $p < .01$), participants' age, prior knowledge, and performance in post-test did not differ between the two groups. Descriptive statistics were presented in Table 1.

Table 1. *Descriptive statistics results by cluster*

	Clusters of Reader Characteristics				ANOVA	
	Cluster 1 (N = 11) Low engagement group		Cluster 2 (N = 8) High engagement group			
Variables	Mean	SD	Mean	SD	*F*	*p*
Age	24.45	2.91	23.12	2.23	1.16	= .30
Interest	16.00	3.13	22.00	2.56	19.68	< .01
Self-efficacy	28.91	4.37	38.25	3.45	25.04	< .01
Prior Knowledge	41.82	14.01	47.50	10.35	0.94	= .35
Writing task	46.36	12.06	46.25	10.61	0.00	= .98
Post-test	7.64	2.16	8.38	2.67	0.45	= .51

Moreover, participants were also compared according to their reading order, participants who read negative article first (i.e., negative expository/story) were labeled NP group (N = 8), while participants who read positive article first (i.e., positive expository/story) were labeled PN group (N = 11). Participants from different reading order groups did not differ in terms of their interest, self-efficacy, prior knowledge and performance on writing task, but they differed significantly on post-test score ($F(1,14) = 10.93$, $p < .01$). Descriptive statistics were presented in Table 2.

Table 2. *Descriptive statistics results by reading order*

	Reading order				ANOVA	
	Negative article first NP (N = 8)		Positive article first PN (N = 11)			
Variables	Mean	SD	Mean	SD	*F*	*p*
Age	24.00	3.30	23.82	2.27	0.08	= .79
Interest	20.25	3.65	17.27	4.20	2.59	= .13

Self-efficacy	34.50	5.15	31.64	6.74	1.01	= .33
Prior Knowledge	43.75	11.88	44.55	13.68	0.02	= .90
Writing task	8.12	2.64	7.82	2.23	0.08	= .79
Post-test	53.75	5.18	40.91	11.36	10.96	< .01

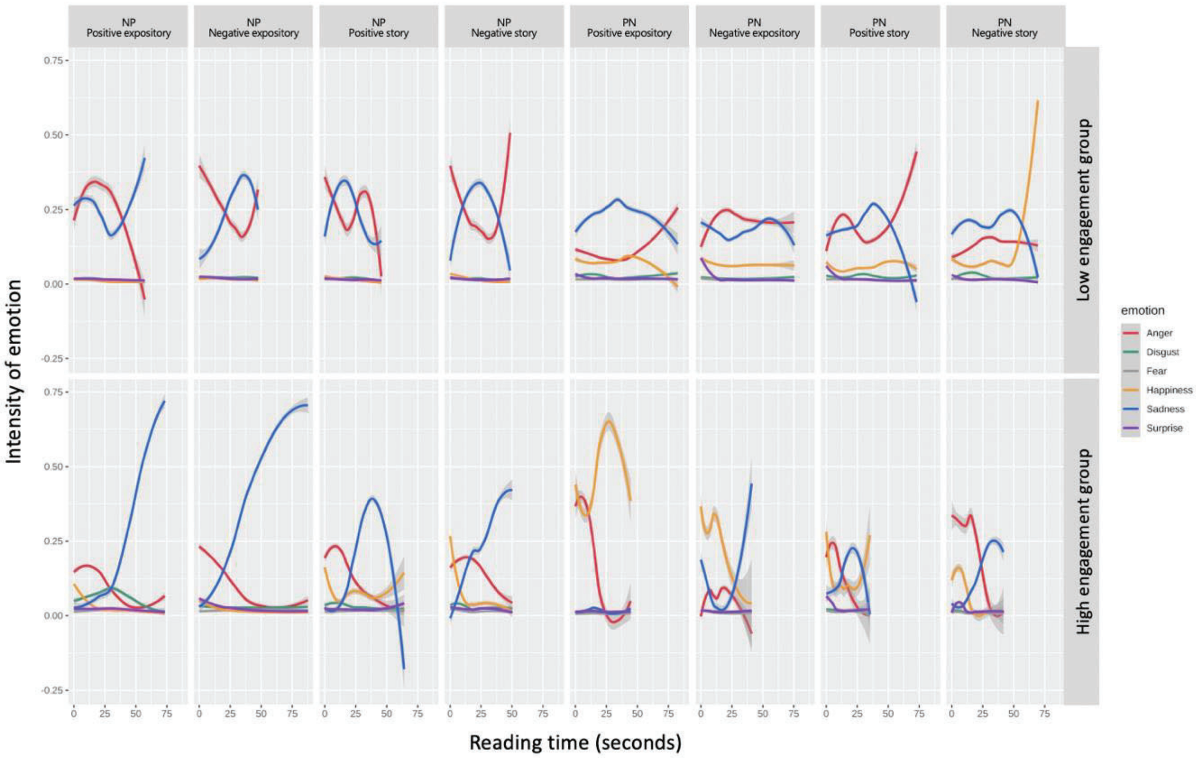

Figure 3. Over Time Changes of Six Basic Emotions (in Various Colors) for the Low and High Engagements in the Reading Order of NP (Negative Argument Article First) versus PN (Positive Argument Article First).

3.2 Emotion Transitions Shown During Reading

In order to explore what kinds of emotions do reader expressed during reading task, and the fluctuation of these emotions, participants' emotion states were aggregated by groups and presented with time and intensity. Different patterns of emotion changes shown by different groups were shown in Figure 1. Reading order were labeled NP and PN, presented on the left vs. right side. The low engagement group (low interest/self-efficacy) was presented at the upper part while the high engagement group (high interest/self-efficacy) was presented at the lower part in Figure 3.

If we compare the differences between reading order (i.e., NP or PN), participants who read negative articles first exhibited greater fluctuation in their emotions. To be more specific, readers from NP group showed emotions with intensity greater than 0.25, while PN group readers' emotion states were within the level of 0.25. In addition, readers from NP group expressed obviously more sadness and less happiness while reading.

On the other hand, if readers with different characteristics were compared, low engagement group showed more anger and less happiness. Specifically, these readers continued to show anger throughout the experiment, and the intensity of their anger was above 0.1 thresholds at most of the time; on the contrary, they rarely showed happiness, and the intensity was mostly within the level of 0.1.

3.3 Group Differences on Expressed Anger, Happiness, and Sadness

To further investigate whether participants' expressed emotion significantly differed with each other, a linear mixed model was conducted with reader characteristics (2: high vs.

low engagement), reading order (2: Negative first, NP vs. Positive first, PN), and emotions (6: happiness, sadness, anger, surprise, disgust, and fear) as independent variables. The three-way interaction effect was significant ($F = 1414.87$, $p < .01$). Table 3~5 shows the simple main effect for each emotion.

As indicated in Table 3, when fixing the level of reading order, low engagement group reading the order of NP expressed more anger than high engagement group ($b = -0.127$, $z = -10.48$, $p < .01$). However, if reading positive article first (PN), the result shows the opposite: high engagement group showed more anger than low engagement group ($b = 0.024$, $z = 2.15$, $p < .05$). On the other hand, when fixing the level of reader characteristics, high engagement group showed more anger in reading the positive article first compared to reading the negative article first ($b = -0.070$, $z = -5.75$, $p < .01$); while low engagement group expressed more anger when the reading order was NP ($b = 0.081$, $z = 7.22$, $p < .01$).

Table 3. *Model of 3-factor interactions on Anger*

Fixed level	Comparison	Anger			
		b	*SE*	*z*	*p*
NP (Negative article first)	High-Low	-0.127	0.012	-10.48	< .01
PN (Positive article first)	High-Low	0.024	0.011	2.15	< .05
High engagement group	NP-PN	-0.070	0.012	-5.75	< .01
Low engagement group	NP-PN	0.081	0.011	7.22	< .01

Statistic results of participants' expressed happiness were presented in Table 4. When fixing the reading order as NP, high engagement group showed more happiness than low engagement group ($b = 0.026$, $z = 2.16$, $p = .03$). Similarly, high engagement group also showed more happiness when the reading order was PN ($b = 0.202$, $z = 17.86$, $p < .01$). In addition, for both high and low engagement readers showed more expression of happiness when reading positive article first ($b_{high} = -0.235$, $z = -19.21$, $p < .01$; $b_{low} = -0.059$, $z = -5.34$, $p < .01$).

Table 4. *Model of 3-factor interactions on Happiness*

Fixed level	Comparison	Happiness			
		b	*SE*	*z*	*p*
NP (Negative article first)	High-Low	0.026	0.012	2.16	< .05
PN (Positive article first)	High-Low	0.202	0.011	17.86	< .01
High engagement group	NP-PN	-0.235	0.012	-19.21	< .01
Low engagement group	NP-PN	-0.059	0.011	-5.34	< .01

Finally, Table 5 shows the results of participants' expressed sadness. When reading negative article first, low engagement group showed more sadness ($b = -0.025$, $z = -2.02$, $p = .04$). Likewise, they also showed more sadness than the high engagement group when the reading order was PN ($b = -0.132$, $z = -11.76$, $p < .01$). Meanwhile, both student groups showed more sadness when they read negative article first ($b_{high} = 0.149$, $z = 12.23$, $p < .01$; $b_{low} = 0.041$, $z = 3.68$, $p < .01$).

Table 5. *Model of 3-factor interactions on Sadness*

Fixed level	Comparison	Sadness			
		b	*SE*	*z*	*p*
NP (Negative article first)	High-Low	-0.025	0.012	-2.02	< .05
PN (Positive article first)	High-Low	-0.132	0.011	-11.76	< .01
High engagement group	NP-PN	0.149	0.012	12.23	< .01
Low engagement group	NP-PN	0.041	0.011	3.68	< .01

4. Discussion and Conclusion

4.1 The Interplay of Reader Characteristics, Reading Order, and Emotions

In this study, we aimed to investigate how students' emotional states changed during self-regulated reading process. Self-directed learning in an online situation has become more and more common for today's learners. Thus, understanding how students' emotion fluctuated during learning task is important since emotion was critical to students' persistence and self-regulation in online learning environments. Moreover, in an online situation, students usually found controversial information with conflicting arguments. Learners' emotion toward these different articles, especially the scientific ones, largely influence how they construct meaning.

In our first research question, we examined the types and patterns of emotion changes caused by the interplay between reader characteristics and reading order, while the text topic was "genome editing." The text encompassed two subtexts: some descriptions and arguments to positively support the genome editing and others, negatively. An interesting result regarding reading order has been found. Readers who read negative articles first tended to exhibit a larger fluctuation in their emotions, especially in sadness. As reported in the interview session, when readers were suddenly exposed to the overwhelming negative impact of genome editing techniques, they felt "worried" about the applications to new generation. Some also reported that they felt an incongruence between their previous knowledge and the new information presented in the text, which made them "confused." Thus, the fluctuation may be due to the negative descriptions and arguments from the article. Previous studies (Mason, 2018; Mensink, 2021; Pekrun, 2022) suggested that the types of emotions, levels of arousal (intensity of these emotions), as well as the number of emotions experienced, all influence students' reading process and reading performance. Participants' performance in this study was partially confirmed with the previous results. On the one hand, the PN group, which experienced a higher number of emotions, performed lower than the participants in the NP group. On the other hand, the NP group, which experienced more intense negative emotions, outperformed the PN group. Our results confirmed the results of previous epistemic emotion studies. For example, Pekrun et al. (2017b) found that negative activating epistemic emotions such as anxiety, confusion, and frustration were positively correlated with learning strategies (e.g., critical thinking, metacognitive self-regulation, etc.). In addition, Tulis & Fulmer (2013) found that both positive and negative emotions could be beneficial for learning outcomes. That is, experiencing a low to moderate level of negative activating emotions may contribute to continuous engagement during difficult tasks. In contrast, Dever and colleagues (2022) found that experiencing more emotions during reading and assessment was associated with lower performance in reproductive tests due to the limited resources that have been spent to manage emotions. Thus, although the NP group experienced intense negative emotions, it could be that they adopted more analytical strategies, and since they spent less cognitive resources on emotion management, they performed better in the post test.

In our second research question, we compared whether the emotions expressed by participants differed by student group. As the result suggested, readers who read negative text first expressed more sadness and less happiness. It's probable that, after being exposed to the terrible outcomes caused by genome technology, readers would read the subsequent paragraphs with more worries, which would be portrayed as sadness. In the meantime, readers' happiness can decrease because of concerns about the application of this technique. On the contrary, readers who read positive texts first may maintain a neutral or even positive attitude toward the reading task and the genome editing technique; thus, they may be relaxed while reading, and their emotional states would also fluctuate with the ups and downs in the texts. As for anger, participants in the low engagement group expressed more anger if they read negative text first, while readers in the high engagement group expressed more anger when they read positive text first. According to participants' reflections in the interview, most of them reported that they did not feel angry but were concentrated on the reading task. Based on this interpretation, it's reasonable to see that readers from the low engagement group showed more anger if the reading order is NP, since they were prompted to be more serious. However, readers with high interest and self-efficacy showed more anger when the reading order was PN. This result was contrary to our expectations. A possible explanation could be that high engagement readers in the PN group were relatively conservative when talking about the application of genome editing to humans. When reading articles on the benefits of this technique, they may feel more serious since the content is against their beliefs.

According to the results of this study, one thing could be inferred is that maybe the interpretation of facial expression should be done with more caution. As suggested above, participants' anger and sadness should not be explained literally. Most of the time, participants did not feel anger or sadness, although the facial expression has been identified as that. According to the reports in the interviews with participants, anger was more like a focused state or feeling serious about the reading task, while sadness could be interpreted as participants' reflection on the content of the reading. A distinctive difference between facial expression and participants' feelings showed in anger. Anger was usually categorized as a negative activating emotion, but seriousness was a relatively positive deactivating emotion. The function of these emotions in learning was also absolutely different. Thus, when using facial emotion detection tools, multi-modal data is highly recommended. By combining self-report questionnaires with physiological mechanisms (e.g., pupil dilation, skin response, heart rate, etc.) or behavioral responses (facial expressions, body position, etc.), a clearer and more accurate understanding of the emotions expressed by the participants could be gained.

4.2 Conclusion and Limitations

Overall, this study addressed students' momentary emotions during reading conflicting scientific articles. Line graphs were used to depict the fluctuations of emotions in temporal dynamics. We discovered that reader characteristics (interest and self-efficacy) would interact with text features (positive-negative argument order), causing different patterns of emotional responses. By combining the multimodal analytic tools that can reveal temporal changes with those that could compare group differences, we can have a closer look at the roles of emotions playing in reading conflict science articles. Despite the findings of this study, there are several limitations to be considered.

On the one hand, the sample size of this study is small, and most of them were graduate students. This may be the main reason why we did not find a significant difference in readers' writing performance, since graduate students were familiar with the process of integrating new information with prior knowledge and creating arguments to support their position. Future research can expand the participants to a more diverse sample and, with a larger sample size, reexamine whether the results still hold true. On the other hand, according to readers' reports in the interview session, the articles used in this study were not very difficult. Most of the participants only gave 1~2 points on a 6-point scale. Future research should adopt material with different levels of difficulty to see if students' emotion patterns are more apparent or if there is a different pattern when it comes to challenging tasks.

Finally, in this study, we found that techniques that can automatically capture students' facial expressions and record their emotion changes can provide unique insights into students' learning processes. The Facial Emotion Analysis Tool (FEAT) is one of these tools. However, the limitation of FEAT is that it currently only identifies the six basic emotions. The recognition of emotions should at least be expanded to include concentration and confusion. By doing so, we can get a clear picture of students' learning processes.

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