Emotion and the Ability to Understand the Video

A/B Testing

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Executive Abstract

This project aims to explore the relationship and causal effects between emotions and the ability to understand the video by analyzing and building statistical models from the designed survey, including the A/B testing video and capturing emotional data from all teams. The emotions consist of happiness, sadness, neutrality, anger, contempt, disgust, surprise, and fear, and the controlled variables are age, gender, and a constant value.

During the experiment, we built the ordinary least squares(OLS) models for emotions and quiz accuracy. To determine the actual emotions of a participant, we used 2 methods, the first one was to use machine recognition of facial expressions in each frame, while another one was to just ask participants to report their emotions by themselves. After the A/B testing, the outcomes like p-values are used to find if there is a causal effect and then analyze to what extent it affects participants' understanding of the video.

The results of the OLS model show that nearly every emotion except fear would not have a significant statistical effect on quiz accuracy, no matter if the emotion is collected automatically by the machine or self-reported. Moreover, the results show that when participants' emotions are fluctuated but not extremely violated, the understandability of the video can be enhanced positively, like contempt, anger, and surprise. However, since the machine may miss recognizing the emotions or the participants may fake their facial expressions, the results may be different from the common intuition.

1. Introduction

Learning and emotions are inextricably linked. Depending on whatever emotions are influencing or coloring the event, emotions can either help or hinder learning. People's cognitive abilities are inherently influenced by emotions, in which numerous studies have shown that human cognitive abilities are contributed to by their emotions, for instance, Tyng, Chai M., et al. (2017) introduced the effects of emotions on memory, as well as roles played by different brain regions on memory. Vuilleumier (2005) mentioned the effects of emotions on human attention. Jung, Nadine, et al. (2014) present experiments on how emotions affect human logical reasoning. Isen, Alice M., et al. (1987) studied the relationship between emotions and problem-solving capabilities. It is not difficult to find relevant scholars who attach importance to the role of emotions on human cognitive capabilities. The function of cognitive capabilities is known as the skills for people to acquire and process new knowledge. Robinson (2012) presents one area of research in differential psychology that focuses on correlations between academic learning and lifetime achievement, which is measured by one's cognitive abilities. Hence, to promote learning and long-term retention of learning materials and maximize student engagement, emotional impacts should be carefully investigated and taken into account in learning design in education.

A vast amount of literature has shown how positive and negative emotions can play a role in facilitating or impeding people's learning and academic achievement. Um et al. (2012) argued positive emotions created through mood induction would decrease the perceived difficulty of learning materials. In addition, motivation, satisfaction, and perception of the learning contents would all be boosted by positive emotions and enacted as the energy behind one's learning. Kremer, Telma, et al. (2019) conducted an experimental study on how negative emotions will influence one's learning outcomes. The result of this study showed negative emotions likely to reduce a person's time spent on learning since they automatically activate avoidance attitudes which will cause hindering the processing of the learning.

The report aims to analyze and study if there are causal effects of different emotions, for instance: anger, contempt, disgust, fear, happiness, neutrality, sadness, and surprise, on an individual's learning outcomes. In this experimental study, we will measure learning outcomes based on individuals' pre and post-video quiz scores.

The rest of the report will be organized as follows: Section 2: Empirical Experimental Settings; Section 3: Result Obtained; Section 4: Conclusions.

2. Empirical Experimental Settings

We collect and analyze data from the real world to test hypotheses and draw conclusions about the relationships between other variables. In the experiment, firstly, we designed the survey that includes an A/B testing educational video and collected data from all teams, requiring each team member to complete and distribute the survey to others around them. Specifically, the experiment begins by asking participants to consent to start the study and then includes a pre-quiz question about the definition of A/B testing. The pre-quiz section helps us to get the number of correct answers and the correct rate before watching the video. While the participants watch the video of an A/B testing presentation, we automatically collect different frames to read their micro-expressions and calculate their emotions (Emot). To control the data collection environment, we ensure the participants cannot fast-forward, go backward, or pause the video. In addition, after watching the video, they need to answer a few questions in the post-quiz and select the emotions they are feeling. These actions help us to figure out the correct rate in post-quiz and the self-awareness of emotions. Finally, the survey includes a section for collecting other demographic information, such as age, gender, race, ethnicity, and employment status. The demographic data can be used to help understand how different factors may potentially impact participants' emotions and understanding of the video content.

After successfully collecting data, our team decided to analyze the data by using OLS (Ordinary Least Squares) in R Project for Statistical Computing. OLS is a statistical method for estimating the unknown parameters in a linear regression model, and it can be used to fit a linear model to a set of data and determine the relationship between the predictor variables and the response variable. Since time dummies are not available in the data, it's hard to estimate the effect of time on the outcome of interest, and it may not be possible for us to use Td (time dummies) and Fe (fixed effects). Instead, OLS is a clear and straightforward method for analyzing the relationship between variables. It helps find the model's coefficients, the residuals, and various statistical measures such as the R-squared value and p-values of the coefficients.

By carefully examining the data in the table, we found eight different emotions – happiness, sadness, neutral, anger, contempt, disgust, surprise, and fear. We want to investigate how emotions would impact the understanding of the educational video content and compare other emotions to see which emotion would have the most significant impact. In our A/B test, we controlled for the factors of age, gender, and a constant value; we calculated and compared the accuracy of pre-quiz and post-quiz scores to determine the degree of understanding of the video content. Generally, we implemented two experiments to define the participants' emotions, so our study carried out two OLS models. The first OLS model uses the emotion by machine recognition of facial expressions in each frame, in which case we calculated the average emotion frame of each participant to analyze. The second OLS model uses self-reported emotion from the participants, which was their subjective interpretation of their current emotional status. We then compared the eight emotions in each OLS model to find the coefficient corresponding to each emotion and explain it in turn.

Overall, our study aims to use the A/B test to determine if there’s a causal effect between emotions and the understanding of video content. If not, we aim to use the coefficients to analyze how much degree each emotion impacts the participant’s understanding. In our experiment, each participant is our unit of analysis, people with each emotion are our treatment group, and their ages, gender, and other constant factors are the controlled group. We compared eight emotions in the same context to see how different emotions impact the effectiveness of understanding an educational video. Unlike observational studies, an A/B test with data analysis can be used to test hypotheses about user behavior, allowing researchers to make more accurate assumptions, and it helps figure out which variable is more effective at achieving a particular goal. In our study, the A/B test provides us with coefficients to specify the degree of impact of each emotion; it can be effective for researchers to offer potential suggestions in future studies. For example, if researchers want to achieve a higher quiz correct rate, they can reference the result in our experiment and encourage participants with specific emotions to do the test.

However, it is worth noting that a variety of factors can influence the relationship. Some covariates, like family education and race, can impact the outcome of the data collection process. For instance, family education, which refers to the level of education achieved by a participant’s parents or guardians, can be a potential factor in understanding video content. On average, participants whose parents have higher levels of education tend to have higher scores and more knowledge compared to participants whose parents have lower levels of education. Additionally, parents with higher levels of education may be more likely to provide more resources and access to support their children so that the participants may get higher scores on the quiz. Although we can monitor the outcome variable (post-quiz and pre-quiz scores) in the experiment, some moderator variables can also change the outcome. Specifically, what can be learned is not the same for someone who always watches online educational videos and those who do not.

Overall, A/B testing is an essential tool for understanding how different variables impact the effectiveness of another variable by comparing options in the same context. It helps validate assumptions, make informed decisions, and provide guidance.

3. Result obtained

The figure below shows the statistical results of the OLS model with all emotions with their detection confidence for the given faces, including happiness, sadness, neutral, anger, contempt, disgust, surprise, and fear, and the ages, gender, and a constant value are the controlled features. Since the sample size is relatively small (61 samples), the significant level p-value is expected to be larger than the normal chosen value (0.05), which is 0.1 in this case. We can see that the only significant feature is the fear emotion, which is totally negatively correlated to the quiz result, this is intuitive because once scared by the video, people can hardly remember the knowledge learned or think carefully and deeply about the problem, similarly, when a person is angry, it would be negatively correlated to the results, but compared with fear, the effect is quite slight. Surprisingly, the result shows that whether one is happy or sad would not affect the quiz result as they have a very low p-value(nearly 0), even though the happiness emotion is positively related to the result while sadness is negative, however, it may be caused by the misidentification of the emotion identification machine. Furthermore, it can be found that when people's moods fluctuate, but not violently, it could have a positive effect on the quiz results, this trend can be seen in contempt, disgust and surprise emotions, whose absolute p-value are less than fear but all positive. On the other hand, if one has no emotional fluctuation at all, she/he may not be attracted by the video and therefore not learns it well, this can be seen by the emotion neutral, which is largely negatively related to the quiz result, and its p-value is even more negative than the fear.

	Dependent variable:
	correct_post_quiz/8 - correct_pre_quiz/2
emot_anger	-0.274
	(0.440)
emot_contempt	0.322
	(0.212)
emot_disgust	0.414
	(0.818)
emot_fear	-2.258*
	(1.166)
emot_happiness	0.049
	(0.115)
emot_neutral	-3.923
	(2.425)
emot_sadness	-0.064
	(0.156)
emot_surprise	0.156
	(0.179)
age	0.001
	(0.004)
gendermale	-0.097
	(0.090)
Constant	3.869
	(2.389)
Observations	61
R2	0.191
Adjusted R2	0.029
Residual Std. Error	0.318 (df = 50)
F Statistic	1.177 (df = 10; 50)
Note:	*p<0.1; **p<0.05; ***p<0.01

In order to see the effect on the quiz results of each emotion separately, we also run the OLS model with only each emotion as an independent variable, and ages, genders and constants are still controlled variables.

By looking deeper into the emotion fear, from the results of the OLS model with only fear emotion as the independent variable, we can see that the p-value is still significant and negatively related to the result. Although the absolute p-value is smaller than the previous results(-1.68/-2.25), the fear emotion still has a very big effect on the result, and other emotions may weaken this effect. And the similar phenomenon is shown in the OLS model with only neutral emotion, in which the p-value is reduced from -3.9 to -2.8.

Then by looking into the emotion of anger, we can see that, previously the p-value was -0.274, which is negatively related to the result, now it is 0.03, which has nearly no effect on the quiz results. It shows that only anger emotion may have little influence on peoples' learning, but with other emotions, it may have some combined effect. Similar trends can be seen in emotional surprise.

What is more, in some emotions like contempt, disgust, sadness, and happiness, there is no significant change in their p-values in the new OLS models, which means for these emotions, the co-effect from other emotions is trivial(contempt and disgust) or the p-values are really small to influence the result or other variables(sadness and happiness).
OLS model with self-reported emotions:

The figure below shows the statistical results of the OLS model with all self-reported emotions with their detection confidence for the given faces, including happiness, sadness, neutral, anger, contempt, disgust, surprise, and fear, and the ages, gender, and a constant value are the controlled features.

	Dependent variable:
	correct_post_quiz/8 - correct_pre_quiz/2
emot_anger	-0.274
	(0.440)
emot_contempt	0.322
	(0.212)
emot_disgust	0.414
	(0.818)
emot_fear	-2.258*
	(1.166)
emot_happiness	0.049
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emot_neutral	-3.923
	(2.425)
emot_sadness	-0.064
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emot_surprise	0.156
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Constant	3.869
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We can see that the only feature with a significant p-value is happiness, which means when one really enjoys learning, he/she can learn the video well, but that joy doesn't necessarily show on the face. And when one is angry, the video may leave he/she a deeper impression, which could have a positive relation to the quiz result.

As for other emotions, the p-values are all about 0, which means that some relatively less intense emotions will not have a great impact on the results, although those emotions may be misrecognized by the AI to be other emotions like neutral.

4. Conclusions

Our research is mainly about the influence of emotion on comprehension ability. The specific implementation is divided into two parts. The first part uses the emotion emot_xxx detected by AI as our independent variable, and the second part uses the emotion self_raw_xxx of the participants' own report as our independent variable. The reason for this distinction is that the emotion detected by AI requires video data, and the data size is small, while the latter does not require video data, and the amount of data is large.

In the first part of the study, after controlling for age and gender, we only observed that the emot_fear variable had a significant negative impact on comprehension, and the other variables had no significant impact. In the second part of the study, again only self_report_fear had a significant negative effect on comprehension.

As mentioned in the introduction, negative emotions such as Fear have a negative impact on learning (comprehension), and the specific performance is that negative emotions may reduce the time for people to learn. Therefore, when the participants watched the video and showed fear emotion, he/she may be avoiding the video.

Unlike what was mentioned in the introduction, positive emotions such as Happiness have no significant positive impact on learning in the current results. We think that there may be some flaws in the experimental design. According to our analysis, the experimental workflow can be improved in several aspects as follows:

1. The independent variables selected in this study are mainly the emotions of the participants, among which the emot_xx variable is image recognition completed by AI. Therefore, participants are required to turn on the video. However, among all the more than 200 participants, only a small number of participants have collected video data. The reason may be: some participants are unwilling to open the video; there is an error in collecting the video. Due to the small amount of data, the experimental results may deviate from the real situation. Hope to have the opportunity to obtain more data for further analysis.

2. The dependent variable selected in this study is mainly the degree of understanding of the video. How to measure it effectively has troubled our team. In the end, we chose the difference between the correct rate of the two quizzes before and after as the measure of video

understanding. However, the number of pre-quiz and post-quiz questions are 2 and 8 respectively, which is quite different, which may lead to a certain chance of the difference in the correct rate. If you can adjust the number of questions before and after the same, for example, 5 questions, it may further increase the credibility.

5. References

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