Emotional Contagion: From Streamers' Facial Expressions to Twitch.tv Chat

Simonas Budėjis
University of Twente
PO Box 217, 7500 AE Enschede
the Netherlands

ABSTRACT

Live streaming is becoming a more popular media entertainment form each year. It enables real-time communications among the viewers and the streamers. By interacting with the streamer, viewers express, among other things, their emotion through text messages and emotes. On the other hand, by interacting with the viewers, streamers express a variety of emotions verbally and through facial expressions. Subsequently, the other party might experience and express similar emotions as well. This phenomenon is called emotional contagion. In this research, I analyze the emotions of streamers' facial expressions and then study the correlation with the sentiment in the preceding and subsequent chat messages of their viewers on the platform Twitch.tv. This study finds weak correlations between the emotions of streamers' facial expressions and the sentiment of viewers' chat messages. I conclude this paper by discussing the results in more detail and giving directions for future work.

Keywords

Emotional Contagion, Sentiment Analysis, Facial Expressions, Live Stream, Twitch.

1. INTRODUCTION

During the last decade, live streaming has been growing rapidly as a new form of online media entertainment. Surrounded by popular giants such as Twitch, YouTube, Facebook Gaming and others, the live streaming industry is becoming more attractive as a career path choice to people of different genders, cultures, and ethnicities each year. This in turn increases the interest and audience traffic towards live streaming platforms even more. In the last year alone, the number of hours watched on Twitch has increased drastically. In March 2020, the number of hours watched equated to over 1.2 billion, while in April 2020 the number jumped to over 1.7 billion hours. Over one year later, in May 2021, this number increased to over 2.3 billion [16]. One of the explanations for such a jump in the number of watched hours could be the COVID-19 pandemic and the quarantine measures imposed by the governments which many people find difficult to deal with [1]. Previous research by de Wit et al. shows that Twitch helps people cope during difficult times [2]. Moreover, past studies also indicate the existence of strong emotional connectedness that viewers experience while participating in live streaming [6, 15, 18, 19].

The connection between the streamer and the audience is perhaps one of the greatest aspects of live streaming. Viewers can interact with the streamer by sending messages in the chat, donating money to the streamer, subscribing to the channel and by other platform-related means. The real-time communication between streamers and their viewers allows for the exchange of emotional states, which subsequently makes it possible for the other party to experience the same emotion. This relationship between the emotional states is known as emotional contagion [3]. Past studies have reported that emotional contagion occurs in other social media platforms such as Twitter and Facebook [4, 10]. Guo and Fussell [7] argue that studying the viewer-streamer sentiment relationship can assist in understanding how live streaming shapes people's behavior.

1.1 Problem Statement

Research on the emotional exchange between streamers and their viewers, and emotional contagion in live streaming is scarce. The only study on emotional contagion in a live streaming environment is done by Guo and Fussell [7], where the focus was put on streamers' utterances (verbal expressions). Because streamers express their emotions through their body language as well, mainly facial expressions, I believe that this is the right next direction to take when studying emotional contagion in live streaming. Studying this phenomenon further should provide interesting insights into the connections between streamers and their audiences. Furthermore, some implications for novel streamer-viewer interaction systems might be discovered as well.

1.2 Objective and Goals

In this research, I will extend on the previous study of emotional contagion in a live streaming environment [7]. This study will analyze the streamers' emotions expressed in facial expressions. The results will then be compared to the sentiment in the preceding and subsequent chat messages from their viewers.

The research question to be answered at the end of this study:

- What is the correlation between the sentiment expressed in live streamers' facial expressions and the sentiment in their viewers' messages?

Two sub-questions will be used to answer the research question:

1. What is the correlation between the sentiment expressed in live streamers' facial expressions and the sentiment in their viewers' *subsequent* messages?
2. What is the correlation between the sentiment expressed in live streamers' facial expressions and the sentiment in their viewers' *preceding* messages?

The goal of this study is to extend the scientific literature with new knowledge and insights on emotional contagion in a live streaming environment, mainly Twitch platform. Due to my own previous experience in interacting with live streaming, I expect that the sentiment of streamers' facial expressions will not be strongly correlated with the sentiment of chat messages.

35thTwente Student Conference on IT, July 2nd, 2021, Enschede, The Netherlands. Copyright 2021, University of Twente, Faculty of Electrical Engineering, Mathematics and Computer Science.

2. RELATED WORK

2.1 Live Streaming and Social Interaction

The live streaming environment is not limited to the broadcast and consumption of live media content. In recent years, social interaction between the streamers and their audiences has been a quite popular research direction. Scheibe et al. [14] explored the concept of Social Live Streaming Services that highlights the interactive part in live streaming, especially the audiences' participation. While this participation has been further studied from several different angles, most research, however, focuses on various engagement styles in live streaming and viewers' motivations for interacting with their favorite live streaming communities [8, 12, 15, 17-19].

2.2 Engagements, Motivations and Effects

2.2.1 Motivations for Tipping

Wang et al. [12] studied the reasons for viewers' tipping behavior on Chinese platforms. In their paper, the authors included snippets of survey respondents' answers to a questionnaire. The snippets encompass several different motivations of viewers for tipping their favourite streamers. The authors conclude that the main reasons are the appreciation for live streaming content, the interaction with the streamer, learning new things and providing support for the streamer. Some of the reasons, such as interaction with the streamer and providing support, hint towards the connection that viewers feel towards the streamer. The paper also studies the effect of the design of digital gifts on the interaction between streamers and their audiences. The conclusion is made that viewers tip the streamers while they are watching the live stream and gift-giving is becoming a medium for interacting with the streamers.

Research by Wohn et al. [18] studied viewers' emotional, instrumental and financial support provisions for live streamers. The study finds six themes that explain viewers' motivations for providing support for the streamers: paying for entertainment, helping streamer to sustain and improve their content, compensation for learning, emotional attachment, desire for interaction and helping solve offline social issues. The study also finds that para-social interaction is a factor, which is most strongly, among others, associated with the provision of all three different types of support. This indicates that viewers provide support to the streamer due to the one-sided relationship that they experience, albeit the response by the streamer is not explored.

2.2.2 Other Types of Motivations

There are several papers that further examine the motivations of viewers' involvement in a live streaming environment. Uses and Gratifications (UG) theory has been one of the most frequently adopted theories to study five distinct types of motivations: cognitive, affective, personal-integrative, social-integrative and tension release [8, 15, 17, 19].

Yang [19] studied Chinese viewers' motivations for participating and engaging with live streams by adopting the UG theory. The study concluded that personal-integrative, tension release, affective and cognitive needs had positive significance on Chinese viewers' motivations to watch various live streaming contents. Personal-integrative needs refer to one's credibility, respect, status, confidence and stability, while tension release refers to escapism and diversion. Furthermore, affective needs refer to emotional needs and pleasure, while cognitive needs refer to acquiring new information and knowledge.

Coping with difficult periods in life also explains some of the viewers' needs to participate in live streaming. de Wit et al. [2] explored whether participation in live streaming communities can help people cope with difficult times in their lives. The study concluded that the nature of the difficult time depends on the viewer and that the majority of cases were related to mental health problems. 82% of survey respondents reported that Twitch can be somewhat helpful. Some of the responses also mention that live stream watching provide them with positive feelings. However, other respondents reported that Twitch can be a dangerous source of social activity, which can worsen the viewers' mental health condition even more.

2.3 Emotional Contagion

Viewers' motivations for interacting with live streams have been explored. One of the more important motivation types for this study is the emotional connection that viewers experience towards the streamer. While understanding the driving factors behind viewers' interaction can be beneficial, streamers' responses need to be studied as well to fully understand the social interaction that takes place in live streaming, especially the exchange between emotional states, i.e., emotional contagion [3].

Emotional contagion is the process when the individuals that observe the change in behavior of another individual, reproduce that behavior as a reflex [3, 13]. It has previously been studied on large social media websites such as Twitter and Facebook [4, 10]. Ferrara and Yang [4] found that on Twitter, positive emotions are more prone to contagion. Furthermore, highly susceptible users are more likely to adopt positive emotions. Data by Kramer et al. [10] shows that textual content alone is a sufficient channel for emotional contagion, which is one of the main ways for interacting with streamers in live streaming.

2.3.1 In Live Streaming

The research on this phenomenon in live streaming environments, where massive amounts of social interaction between the streamers and their audiences take place hourly, has been lacking. Guo and Fussell [7] conducted one of the first studies on emotional contagion in live streaming, on YouTube. The researchers collected video transcripts and by using Vader sentiment analysis tool, analyzed the sentiment in utterances. They further studied the correlation between the positive and negative sentiments in utterances and the same sentiments in subsequent chat messages by using linear regression analysis. Moreover, the correlation between the sentiments in preceding chat messages and the sentiments in subsequent chat messages was studied as well. The researchers concluded that emotional contagion occurs on live streaming and that the preceding chat messages is a stronger predictor of subsequent chat messages than the utterances of the streamer. Finally, researchers suggested that other streamer expressions such as tone, pause and body language be analyzed.

For this research, I chose to conduct a similar study to the one by Guo and Fussel [7]. In this study, I focus on the body language, mainly facial expressions, on the platform Twitch, where many streamers tend to stream with web cameras enabled. I trust that Twitch is an ideal platform for this type of study due to its popularity [16], social interaction focused categories, such as "Just Chatting", and the unique means of communication between viewers and streamers, i.e., through emotes that express great variety of emotions, enrich the chat messages, and can be designed by anybody.

3. METHODOLOGY

3.1 Selection of Streamers

To conduct the sentiment analysis, I first randomly selected 20 live streamers that stream in the English language with no preference for the live streaming category. 10 of those streamers had an average live viewers' number greater or equal than 7000, and the rest had less than 3000. This population of streamers was altered at the later stage of my research due to the dominance of positive sentiment in the early stages of the research. I had collected many samples of positive facial expressions by the streamers early on, and if I were to continue with my initial approach, I would have only kept collecting more and more positive samples, hence the study would have been biased. Therefore, in the later stages of research, the decision was made to select new streamers that partially stream in the "Just Chatting" category, where many of them spend more time interacting with their chat compared to other categories. I have also selected more female streamers due to my own personal observation that they express more emotions. The final streamers' population and selected video IDs can be seen in Table 1.

3.2 Collection of Videos and Messages

The next step is to select Videos on Demand (VODs) for each streamer and collect the chat messages. After the streamer finishes their live broadcast, the content is saved in video format that is accessible to anyone, unless the streamer had put restriction on access. Each VOD has a unique ID that can be used to request chat messages via Twitch API. The contents and timestamps of the messages from a single video are then saved in a CSV file. The example can be seen in Figure 1.

3.3 Assigning Sentiment Values to Twitch Emotes

After collecting the chat messages, the enabled emotes on the streamer's channel need to be evaluated. In this research, to analyze the sentiment of arbitrary blocks of text, I am using Node.js *sentiment* module which uses AFINN-165 wordlist [5] and (Unicode) Emoji Sentiment Ranking [9], making it suitable for social media use. The module was chosen because AFINN-165 contains the most recent wordlist with 3382 entries, and the module itself contains a feature for overriding and adding new entries to the wordlist.

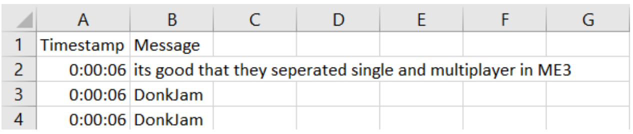
The module analyses each word separated by whitespace and other punctuation signs in a block of text independently. The words that are part of the wordlist have sentiment integer values assigned to them ranging from -5 (most negative) to 5 (most positive). After the analysis, the module outputs the total score of a block of text and the value of each word. The example can be seen in Figure 2.

For the facial emotion analysis, I am using Microsoft Azure Face API, which is also available as a Node.js module. Research shows that Face API is one the best tools for analyzing non-standardized facial expression images that may include poor lighting, confusing camera angles and room settings for the algorithm [11]. Because this module outputs the values ranging from 0 to 1, I re-scale the sentiment values of blocks of text between 0 and 1 as well. The example can be seen in Figure 2.

As mentioned previously, one of the features of the *sentiment* module is the use of additional words that are not part of the original wordlist. I have used this feature to assign sentiment values to global emotes offered by Twitch, global 3rd-party emotes offered by FrankerFaceZ and BetterTTV, channel-enabled emotes by the aforementioned 3rd-party services and the subscriber-only channel emotes. This is because emote-use is a large part of Twitch culture. Viewers use emotes to enrich their messages and express certain emotions. If the emotes are not valuated, the message becomes more neutral, according to the sentiment analyzer. In total, I have evaluated 969 unique emotes, all of which extend the original wordlist before the analysis. The example can be seen in Figure 3.

Table 1. Streamers and Video IDs

Streamer	Video IDs
trainwreckstv	1024966193, 1028860052
ninja	1037051767
otzdarva	1031431251
huskers	1034903476
elajjaz	1037993152
nymn	1050718401
fanfan	1050597035
wolfabelle	1049595917
pixelsmixel	1048566226
badgalshay	1041509320
jimmy_broadbent	1028194377
sweet_anita	1050805776
kandyland	1052866839



	A	B	C	D	E	F	G
1	Timestamp	Message					
2	0:00:06	its good that they seperated single and multiplayer in ME3					
3	0:00:06	DonkJam					
4	0:00:06	DonkJam					

Figure 1. Sample of the collected chat messages

Figure 2. Sentiment analysis of arbitrary text and re-scaling

Figure 3. Sentiment values assigned to arbitrary emotes

3.4 Collection of Facial Expressions' Timestamps

3.4.1 Sentiment Streaks

After the channel emotes have been evaluated, the next (useful but not mandatory) step is to search for sentiment streaks in the previously retrieved chat messages. Sentiment streaks can assist in finding the timestamps where the streamer is expressing a positive or negative emotion and the viewers are reacting in a similar fashion (note: streamer messages are not considered). If 5 or more chat messages in a row are classified as positive (e.g., positive sentiment value of a message is 0.8), then this could be classified as a sentiment streak.

3.4.2 Manual Search

The goal of sentiment streaks is to find certain facial expressions by the streamer with the help of their chat messages programmatically. At the start of this research, I relied on sentiment streaks to find relevant timestamps. However, I have soon realized that most of the time sentiment streaks are not helpful in finding any unique facial expressions by the streamers, i.e., while there are existing streaks, the streamers' facial expression remains unchanged. Because of this, towards the end of my research, I have only relied on manual search by just fast-forwarding VODs.

In this research, I have aimed to collect 15 timestamps from each streamer's VODs where the streamer makes a different facial expression from their casual one. The timestamps have been assigned an ID which is used to match the images in the final analysis step. The data is saved in a CSV file.

3.5 Collection of Screenshots

After collecting 15 timestamps from one streamer's videos, the next step is to collect screenshots of facial expressions for the face analysis with matching IDs discussed in the previous step. As mentioned previously, I am using MS Azure Face API for face analysis. The software analyses the image and searches for faces. If it is unable to detect any faces, it does not return any results. The analysis can return emotion values ranging from 0 to 1, where 1 is distributed similarly as in Figure 2, for the following emotions: happiness, anger, contempt, disgust, fear, sadness, neutral, surprise. In my analysis, I aimed to get a similar output as I do with text analysis, i.e., an object with positive, negative and neutral values. Hence, I sum the values of several emotions to obtain the desired emotion. The re-classified emotions can be seen in Table 2.

3.6 Final Analysis

3.6.1 Part 1

The data collected in previous steps now need to be joined together. This is done in several steps:

1. The collected screenshots are analyzed with Face API and the emotion values for each of the 15 timestamps are acquired,
2. The messages that were sent up to 15 seconds *after* the timestamp are collected. This time range was selected because some viewers tend to react to the stream and send their message in the chat more quickly than the others. I assume that in 15 seconds, viewers will have reacted to the expression. This also allows for more message samples, which is more representative of the viewers' population, and increases the accuracy of the data,
3. The sentiment values of each message are obtained and averaged out for a single timestamp. The process is repeated for all 15 timestamps,
4. The analysis of facial expressions is then paired to the corresponding (averaged) analysis of chat messages,
5. All information is then stored in a CSV file which is named after the streamer's username and an indicator of whether the file contains analysis for subsequent messages or preceding messages. In this case, the analysis was done on subsequent messages,
6. The whole process is then repeated from step 1 to analyze the messages 15 seconds *before* the timestamps and to acquire preceding messages' analysis.

Example output can be seen in Figure 4.

3.6.2 Part 2

Once the data is saved in CSV files, all subsequent messages' analyses are joined into a single file, as well as the preceding messages' analyses into a separate single file.

Finally, linear regression analysis is made. Just like in the study by Guo and Fussell [7], I study the correlation values. For this, I make use of CORREL function in Microsoft Excel software to obtain Pearson's correlation coefficient values between each sentiment. First, the dependent variable is sentiment of subsequent messages (*Messages*), second, the dependent variable is sentiment of streamers' facial expressions (*Face*).

Table 2. Re-classified Face API emotions

Emotion (re-classified)	Face API Emotions
Positive	Happiness
Negative	Anger, Contempt, Disgust, Fear, Sadness
Neutral	Neutral, Surprise

	A	B	C	D	E	F
1	Face			Messages		
2	Positive	Negative	Neutral	Positive	Negative	Neutral
3	0.002	0.148	0.85	0.1341	0	0.1736
4	0.022	0.284	0.694	0.2144	0.0546	0.2573
5	0.009	0.382	0.609	0.0721	0.0095	0.3469
6	0.015	0.417	0.567	0.1488	0.2675	0.2679
7	0	0	1	0.1507	0.0016	0.2049
8	0.02	0.078	0.901	0.2417	0.0125	0.3458
9	0.024	0.847	0.129	0.277	0.0444	0.1119
10	0.698	0.247	0.055	0.2667	0	0.3333
11	0.002	0.26	0.738	0.2143	0.0321	0.1107
12	0	0.133	0.866	0.1487	0.1032	0.2935
13	0	0.184	0.814	0	0.0583	0.275
14	0.178	0.047	0.775	0.4003	0	0.2247
15	0.469	0.114	0.417	0.3005	0.1767	0.3895
16	0	0.166	0.834	0.1845	0.0357	0.2083
17	0.109	0.269	0.622	0.0985	0	0.2651

Figure 4. Sample output of Part 1 of Final Analysis. If preceding messages are analyzed, dependent variable is Face, otherwise Messages

Table 3. No. of dominant sentiments in subsequent messages analysis

Dominant Sentiment	n (Face)	n (Messages)
Positive	95	65
Negative	16	7
Neutral	69	108

Table 4. No. of dominant sentiments in preceding messages analysis

Dominant Sentiment	n (Face)	n (Messages)
Positive	94	80
Negative	17	4
Neutral	68	95

4. RESULTS

4.1 Dataset

4.1.1 Quantities

For the subsequent messages' analysis, 183/195 images were successfully analyzed by Face API (refer to 3.5), as well as 5376 chat messages by *sentiment* module. 3 of those images had no text sentiment analysis values matched due to no messages being sent in 15 seconds timespan, leaving with 180 samples total.

For the preceding messages' analysis, the same 183/195 images were analyzed, with 5100 chat messages. 4 of those images had no text sentiment analysis values matched, leaving with 179 samples total.

4.1.2 Dominant Sentiments Analysis

The dominant sentiments per sample and their quantities can be seen in Tables 3 & 4. In subsequent messages' analysis, where the dependent variable is *Messages*, 95 images are classified as mostly positive, 16 as mostly negative and 69 as mostly neutral. As for the average sentiments of subsequent messages, 65 are classified as mostly positive, 7 as mostly negative and 108 as mostly neutral. In preceding messages' analysis, where the dependent variable is *Face*, 94 images are classified as mostly positive, 17 as mostly negative and 68 as mostly neutral. As for the average sentiments of preceding messages, 80 are classified as mostly positive, 4 as mostly negative and 95 as mostly neutral.

4.1.2.1 Subsequent Messages Dataset

With further analysis of subsequent messages dataset and *Messages* sample, it is found that in the sample of 65 positive ones, 45/95 (47.37%) correspond to the sentiment in facial analysis, 20/95 (21.05%) do not correspond and 30/95 (31.58%) are classified as a neutral sentiment (expected 30 more positives according to *Face* sample but got neutral). In the sample of 7 negative ones, 1/16 (6.25%) correspond to the sentiment in facial analysis, 6/16 (37.50%) do not correspond and 9/16 (56.25%) are classified as a neutral sentiment (expected 9 more negatives according to *Face* sample but got neutral). In the sample of 108 neutral ones, 53/69 (76.81%) correspond to the sentiment in facial analysis, 16/69 (23.19%) do not correspond and the rest of the sample (N = 39) contains classifications that were expected as positive or negative but got classified as neutral.

The results indicate that 76.81% of the times, neutral messages are followed by neutral facial expressions, which is quite often. Less than half of the time (47.37%) positive messages are followed by positive facial expressions, which does not indicate a strong emotional contagion in positive sentiment. Only 6.25% of the time, negative messages are followed by negative facial expressions which indicate almost none of the emotional contagion for this sentiment. 39 times (21.67%) neutral messages are followed by positive or negative sentiment in streamers' facial expressions, indicating that the chat's reaction does not change.

4.1.2.2 Preceding Messages Dataset

With further analysis of preceding messages dataset and *Face* sample, it is found that in the sample of 94 positive ones, 53/80 (66.25%) correspond to the sentiment in preceding messages, 27/80 (33.75%) do not correspond and the rest of the sample (N = 14) contains classifications that were expected as neutral but got classified as positive. In the sample of 17 negative ones, 0/4 (0.00%) correspond to the sentiment in preceding messages, 4/4 (100.00%) do not correspond and the rest of the sample (N = 13) contains classifications that were expected as neutral but got classified as negative. In the sample of 68 neutral ones, 43/95 (45.26%) correspond to the sentiment in preceding messages, 25/95 (26.32%) do not correspond and 27/95 (28.42%) are classified as positive or negative (expected 27 more neutrals according to *Messages* sample but got positive or negative).

The results indicate that 66.25% of the time, positive facial expressions are followed by a positive chat, meaning that the positive chat affects the positivity of the streamer. 0.00% of the time, basically never, negative facial expressions are followed by negative chat, which suggests that there is no emotional contagion on negative sentiment. 45.26% of the time, less than half, the neutral facial expressions are followed by the neutral chat messages. Although this number, in the real world, may be a lot higher due to mostly neutral chat and mostly neutral streamers, these are the results of my analysis. Finally, 7.82% of neutral facial expressions were followed by positive chat, indicating that the streamer did not express the positive emotion expressed by chat, and 7.26% of neutral facial expressions were followed by negative chat, also indicating that the streamer did not express the negative emotion which was expressed by chat previously.

4.2 Correlation Analysis

The Pearson's correlation (R) and coefficients of determination (R-Square) between each sentiment in *Face* and *Messages* is analyzed. Correlation coefficients indicate the strongness of the relationship between two variables, while R-Square indicates the proportion of variance of the dependent variable that is explained by the independent variable. Furthermore, a two-tailed T-test is used to study the statistical significance of the correlation between variables, where H0: "The correlation of variables is not statistically significant". The relevant Figures are 5 & 6.

The results indicate that in both cases, the variables are not strongly related to each other. The p-values that deem matching correlation values statistically significant due to the T-test (null hypothesis rejected) are highlighted in green, while the insignificant ones (failed to reject the null hypothesis) are highlighted in red. The correlation results are discussed in further sub-sections.

Face \ Messages	Positive	Negative	Neutral	
Positive	16.17%	3.51%	-24.82%	
Negative	-3.26%	-2.79%	11.73%	R
Neutral	-16.92%	-2.51%	22.18%	

Face \ Messages	Positive	Negative	Neutral	
Positive	2.62%	0.12%	6.16%	
Negative	0.11%	0.08%	1.38%	R-Square
Neutral	2.86%	0.06%	4.92%	

Face \ Messages	Positive	Negative	Neutral	
Positive	$p < 0.05$	$p > 0.1$	$p < 0.001$	
Negative	$p > 0.1$	$p > 0.1$	$p > 0.1$	p-values
Neutral	$p < 0.05$	$p > 0.1$	$p < 0.01$	$\alpha = 0.05$, df = 178

Figure 5. R, R-Square and p-values of subsequent messages analysis

4.2.1 *Subsequent Messages*

4.2.1.1 *RQ Sub-Question 1*

The correlation coefficient results indicate four positive relationships: positive sentiment in *Face* has a relationship with positive and negative sentiments in *Messages*, while neutral sentiment in *Messages* has a relationship with negative and neutral sentiments in *Face*. Positive relationships indicate that the change in the dependent variable *Messages* is in the same direction as the independent variable *Face* (i.e., if *Face* increases, so should *Messages*). Out of the four positive relationships, two are statistically significant at $\alpha = 5\%$, which indicates that there is a 5% probability that a mistake is made by rejecting the null hypothesis. The rest of the relationships are negative, meaning that the change in the dependent variable *Messages* is in the opposite direction as the independent variable *Face* (i.e., if *Face* increases, *Messages* should decrease). Out of the five negative relationships, two are statistically significant. To conclude, positive sentiment in *Face* can be a good predictor for positive and neutral sentiments in *Messages* (i.e., the more positive the *Face*, the more positive and less neutral the *Messages* should be), and neutral sentiment in *Face* can be a good predictor for positive and neutral sentiments in *Messages* (i.e., the more neutral the *Face*, the less positive and more neutral *Messages* should be). Finally, it is important to note that because the correlation values are smaller than 0.3, this indicates a small correlation, and as the value approaches 0, the correlation becomes weaker.

4.2.1.2 *R-Square*

R-Square indicates the proportion of variance of the dependent variable that is explained by the variance of the independent variable. From the results, it is seen that 6.16% of the variance in *Messages* neutral sentiment is explained by the variance in positive sentiment in *Face*. The results go hand in hand with the rest of the tables in Figure 5. It can be concluded that the neutral sentiment in *Messages* is most strongly correlated to the positive and neutral sentiments in *Face*, which suggests that after a neutral and positive facial expression by the streamer, the majority of chat messages had a change in neutral sentiment (i.e., they became more or less neutral).

Face \ Messages	Positive	Negative	Neutral	
Positive	15.45%	16.83%	-22.50%	
Negative	-6.15%	-1.23%	19.14%	R
Neutral	-14.50%	-18.95%	15.22%	

Face \ Messages	Positive	Negative	Neutral	
Positive	2.39%	2.83%	5.06%	
Negative	0.38%	0.02%	3.66%	R-Square
Neutral	2.10%	3.59%	2.32%	

Face \ Messages	Positive	Negative	Neutral	
Positive	$p < 0.05$	$p < 0.05$	$p < 0.01$	
Negative	$p > 0.1$	$p > 0.1$	$p < 0.02$	p-values
Neutral	$p > 0.05$	$p < 0.02$	$p < 0.05$	$\alpha = 0.05$, df = 177

Figure 6. R, R-Square and p-values of preceding messages analysis

4.2.2 *Preceding Messages*

4.2.2.1 *RQ Sub-Question 2*

The correlation coefficient results indicate four positive and five negative relationships, surprisingly in the same sentiment pairs as in subsequent messages analysis. This may suggest that studying correlation from these two different angles bear little significance. On the other hand, this might also suggest that the emotion that streamers express due to chat messages is very similar to the sentiment of chat messages due to streamer's facial expressions, which means that the reactions by both parties are very similar, indicating a good emotional connection. In any case, the results show that six out of nine relationships are deemed statistically significant, which indicates that the various sentiments in chat messages have a significant linear relationship with subsequent emotions expressed by the streamer, more so than in subsequent messages' analysis. This suggests that the effect of preceding chat messages on streamers' emotion is more significant than the effect of streamers' emotion on subsequent chat messages. The neutral sentiment in *Messages* can be a predictor for all sentiments in *Face* (i.e., the more neutral the *Messages*, the less positive, more negative and more neutral the *Face* should be), while the negative sentiment can predict positive and neutral sentiments in *Face* (i.e., the more negative the *Messages*, the more positive and less neutral the *Face* should be). Positive sentiments are also significantly related (i.e., the more positive the *Messages*, the more positive the *Face* should be). The correlation coefficients, however, are similarly as small as in subsequent messages analysis, indicating a small correlation.

4.2.2.2 *R-Square*

From the results, it is seen that 5.06% of the variance in *Face* positive sentiment is explained by variance in neutral sentiment in *Messages.* This could suggest that the change in positive facial expression by the streamer precedes neutral messages, meaning that the change in the positive reaction of the streamer is not triggered by the positive or negative chat but rather something else that they are doing. This is similar to the negative reactions: 3.66% of the variance in *Face* negative sentiment is explained by variance in neutral sentiment in *Messages*, indicating that the change in negative sentiment of the streamer is not explained by positive or negative chat. 3.59% of the variance in neutral streamer reactions is explained by variance in negative chat messages, which suggests that streamers may react more or less neutrally to negative messages.

5. DISCUSSION

5.1 Results

The correlation has been analyzed, and the research question has been answered by discussing two sub-questions and with supporting Figures 5 & 6. The results match my initial expectations of low correlation values, which prove that facial expressions alone are not sufficient to fully understand and continue studying emotional contagion in a live streaming environment. The results match the previous findings of evidence of emotional contagion in live streaming by Guo and Fussell [7]. In their study, the researchers found that preceding chat messages, as well as streamers' utterances, can predict the sentiment of the subsequent chat messages. In this study, I explored the correlation between positive, negative and neutral sentiments in *Face* and *Messages* variables and discussed their relationships. Even though the correlation coefficients are small, suggesting that the sentiments are not strongly related, some of the relationships are proven to be statistically significant and thus, cannot be ignored. I find that positive and neutral emotions in streamer's face can predict the positivity and neutrality of subsequent chat messages. Moreover, I also find that positive, negative and neutral sentiments of chat messages can predict some of the emotional changes of the streamer.

5.2 Limitations

5.2.1 Dataset

5.2.1.1 Reactions

One of the main issues with the dataset is the abundance of positive reactions from the streamers and the lack of negative ones. To counter this lack of diversity, the initial list of streamers had to be altered and the focus was put on those who partially stream in the "Just Chatting" category. The search for negative emotions in streamers' faces would require much more manual effort and time investment which was not affordable in this research project. One of the explanations for streamers expressing positive emotions most of the time could be because they are creating their own independent communities and trying to have a good time on stream not only for themselves but for their audiences as well. Statistics show that since the start of the COVID-19 pandemic, the traffic on Twitch has increased drastically [16]. This could be explained by people's desires to forget about their own struggles for a while and tune into their favorite entertainers online that bring some positive feeling into their lives [2].

5.2.1.2 Speed of The Chat and Quantity of Messages

For more accurate results, videos with speedy chat (e.g., at least one message per second) are recommended for analysis. In this study, several videos had a chat that I would personally deem slow (less than a single message in 5 seconds), which impacted the final dataset. For instance, when the 15-second timespans and messages were analyzed, some timespans had no messages in them, which is why these samples had to be removed. Others had 1-3 messages due to the subscriber mode enabled, which then left the software to compute the average sentiment values of very few messages. Some others had close to 100 messages, which is more representative of the streamer's audience. When talking about the representation of the audience, it is also important to remember that a small proportion of total stream viewers participate in chat. In future research, it may also be interesting to study the unique participants in the chat.

5.2.2 Discrepancy Between Different Types of Expressions

It is important to recall that different types of expressions (e.g., facial or verbal) can be conflicting. For instance, the streamer may talk about negative subjects, or banter with their friends, and laugh at the same time, which means that they express two different emotions simultaneously. For future research, it would be interesting to study the match between streamers' facial and verbal expressions and their joint correlation with the audience's chat messages.

5.2.3 Streamers Audiences Reactions

Due to my own observations, I believe that it is important to remember that streamers' audiences tend to be a lot more reactive to what is expressed verbally on stream by the streamer or another media type that the streamer is interacting with (e.g., watching videos, other live streams with their viewers, etc.). This also includes the discussed discrepancy between different types of expressions, e.g., if the streamer is making a negative face and is telling jokes, the audience is probably more likely to react positively. Hence, the future multimodal analysis in this field could also include the content type as a variable.

5.2.4 Content and Intensity

The content and its intensity could also be interesting variables to study in future research. This is because viewers may be more reactive to the content, rapid movements and performance (e.g., videogame), instead of the actual streamer. In this study, some of the selected streamers broadcast themselves playing a single game. First Person Shooter and Battle Royale games that require a lot more focus from the streamer, compared to different types of games, due to the intensity will most likely have the streamer focused on the gameplay and collaborating with their teammates. While the streamer expresses very little emotion, their chat may react positively or negatively to the performance of the streamer in a video game instead of what they are expressing verbally or through their body language.

5.2.5 Software

The software used in this research was Microsoft Azure Face API and AFINN-165-based Node.js module. Even though Face API seems to be fit for research of this type [11], the reliability of the text sentiment analyzer needs to be examined. Previous research has used Vader sentiment analysis which is more fit for sentiment analysis in social media [7]. However, in this research, a different sentiment analyzer was used which allowed overwriting and adding new words, together with their sentiment values, to the wordlist.

5.2.6 Emotes

Even though 969 unique emotes have been evaluated in this research, the reliability is lacking because the valuation was performed by a single person. Manual work of this calibre would require a lot more time investment and should be done by multiple persons, preferably with expertise in sentiment analysis and words evaluation.

Moreover, it is important to note that not all relevant (i.e., expressing an emotion) emotes could be fed to the sentiment analyzer. On Twitch, the subscribers of the channels can use premium emotes of that channel in chats of different channels. In this research, I have only evaluated emotes that are enabled on my selected channels. It is likely that some viewers have used emotes from different channels because of their subscription privileges. These unidentified emotes would increase the neutral sentiment of text analysis and contribute to the less reliable results.

6. CONCLUSION

6.1 Summary

This paper extends one of the first studies on emotional contagion in live streaming by Guo and Fussell [7]. In this study, I focus on the analysis of streamers' facial expressions and the correlation with preceding and subsequent messages to find out if the phenomenon occurs on Twitch platform. Positive, negative and neutral sentiments in streamers' facial expressions and chat messages are examined one by one to learn which particular sentiments in streamers' facial expression and viewers' messages have the strongest effects on the sentiments of the opposite variable.

My study finds further evidence that emotional contagion occurs in live streaming. In subsequent messages' analysis, I find out that the positive facial expression by the streamer should positively contribute to the positivity of subsequent messages and negatively contribute to the neutrality of subsequent chat messages. Moreover, neutral facial expressions should negatively contribute to positivity and positively contribute to the neutrality of subsequent messages.

On the other hand, in preceding messages' analysis, I find out that neutral chat messages should negatively contribute to positivity and positively contribute to negativity and neutrality in streamer's facial expressions. Furthermore, the negative chat messages should positively and negatively contribute to the positivity and neutrality in facial expressions of the streamer, respectfully. Finally, positive messages should contribute positively to the positive expressions from the streamer.

6.2 Future Work

Future work in the field of sentiment analysis in live streaming should consider the limitations and other variables that could be included in the multimodal analysis (5.2.2, 5.2.3 and 5.2.4). To reiterate, this study has analyzed the facial expressions of live streamers and discovered little correlation with the sentiment of chat messages. By including streamer utterances, tone, body language, content of the stream and other variables into the analysis, more accurate findings on emotional contagion in live streaming can be discovered, hence the relationships of emotional states between streamers and their viewers can be better understood. Furthermore, studying emotional contagion in live streaming should prove to be valuable for the designers of live streaming platforms and the individual communities of live streamers.

7. ACKNOWLEDGEMENTS

I would like to thank my supervisor C. Sallaberry for his great guidance and suggestions throughout this project, students of the Intelligent Interaction track for feedback on my work and finally, the track chair M. Theune for the organization of track meetings and review on the previous version of this paper.

8. REFERENCES

[1] Centers for Disease Control and Prevention. (n.d.). *Mental Health and Coping During COVID-19*. Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/daily-life-coping/managing-stress-anxiety.html.

[2] de Wit, J., van der Kraan, A., Theeuwes, J. Live Streams on Twitch Help Viewers Cope With Difficult Periods in Life (2020) Frontiers in Psychology, 11, art. no. 586975.

[3] Elaine Hatfield, John T. Cacioppo, and Richard L. Rapson. 1993. Emotional Contagion. Current Directions in Psychological Science 2, 3 (1993), 96–100.

[4] Ferrara, E., Yang, Z. Measuring emotional contagion in social media (2015) PLoS ONE, 10 (11), art. no. e0142390.

[5] Finn Årup Nielsen, "A new ANEW: evaluation of a word list for sentiment analysis in microblogs", Proceedings of the ESWC2011 Workshop on 'Making Sense of Microposts': Big things come in small packages. Volume 718 in CEUR Workshop Proceedings: 93-98.

[6] Guan, Z., Hou, F., Li, B., Chong, A.Y.-L., Phang, C.-W. What encourages purchase of virtual gifts in live streaming: Cognitive absorption, social experience and technological environment (2020) 40th International Conference on Information Systems, ICIS 2019.

[7] Guo, J., Fussell, S.R. A preliminary study of emotional contagion in live streaming (2020) Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW, pp. 263-268.

[8] Hilvert-Bruce, Z., Neill, J.T., Sjöblom, M., Hamari, J. Social motivations of live-streaming viewer engagement on Twitch (2018) Computers in Human Behavior, 84, pp. 58-67.

[9] Kralj Novak P, Smailović J, Sluban B, Mozetič I (2015) Sentiment of Emojis. PLoS ONE 10(12): e0144296.

[10] Kramer, A.D.I., Guillory, J.E., Hancock, J.T. Experimental evidence of massive-scale emotional contagion through social networks (2014) Proceedings of the National Academy of Sciences of the United States of America, 111 (24), pp. 8788-8790.

[11] Küntzler, T., Höfling, T.T.A., Alpers, G.W. Automatic Facial Expression Recognition in Standardized and Non-standardized Emotional Expressions (2021) Frontiers in Psychology, 12, art. no. 627561.

[12] Lee, Y.-C., Yen, C.-H., Wang, D., Fu, W.-T. Understanding how digital gifing influences social interaction on live streams (2019) Proceedings of the 21st International Conference on Human-Computer Interaction with Mobile Devices and Services, MobileHCI 2019, art. no. a33.

[13] Panksepp, J.B., Lahvis, G.P. Rodent empathy and affective neuroscience (2011) Neuroscience and Biobehavioral Reviews, 35 (9), pp. 1864-1875.

[14] Scheibe, K., Fietkiewicz, K. J. and Stock, W. G. (2016) "Information Behavior on Social Live Streaming Services," Journal of Information Science Theory and Practice. Korea Institute of Science and Technology Information, 4(2), pp.

[15] Sjöblom, M., Hamari, J. Why do people watch others play video games? An empirical study on the motivations of Twitch users (2017) Computers in Human Behavior, 75, pp. 985-996.

[16] Twitch Statistics & Charts. TwitchTracker. (n.d.). https://twitchtracker.com/statistics.

[17] WAN, A., WU, L. Understanding the Negative Consequences of Watching Social Live Streaming Among Chinese Viewers (2020) International Journal of Communication, 14, pp. 5311-5330.

[18] Wohn, D.Y., Freeman, G., McLaughlin, C. Explaining viewers' emotional, instrumental, and financial support provision for live streamers (2018) Conference on Human Factors in Computing Systems - Proceedings, 2018-April.

[19] Yang, Y. Influences on Livestreaming Usage in China: Contents, Motivations, and Engagements (2020) Lecture Notes in Computer Science (including subseries Lecture

Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12215 LNCS, pp. 133-142.