Analyzing Emoji Interpretation in Software Artifacts

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***Abstract*—Emoji are ideograms and smileys used in electronic messages and web pages. Emojis exist in various genres, including facial expressions, common objects, places and types of weather, and animals. Figuring out how emojis are interpreted in the context of software development artifacts would be beneficial for developers to improve communication. Emojis are becoming increasingly commonly used in software development artifacts. It is important to understand how their usage can impact communication between developers.**

***Index Terms*—Emojis, eye tracking, sentiment, development artifacts.**

I. Introduction

The GitHub pull request structure has become a core pillar of the software development process. The tone of a of a pull request or a code review makes a massive difference between whether something is accepted or not, and whether a contributor is more likely to work on the same project.

As a developer, communication through electronic messages has become the norm. Part of this communication includes emojis which are ideograms and smileys. Emoji use in software development artifacts has become increasingly common. Therefore, understanding how emojis affect the tone of text in the context of a pull request is extremely useful to help programmers manage their tone, leading to a better working environment and better communication.

This study is an extension of the pilot study conducted by Park et al. [17]. This study investigated how emojis are read and perceived by developers and how that compares to sentiment analysis tools. The main problem this study addresses is that developers express sentiment through software artifacts, but there is a lack of understanding about how this sentiment is perceived by tools. Other studies have looked at how emojis affect the sentiment of pull requests. However, no other studies until Park et al. have involved an eye tracker within this process. An eye tracker gave insight into how often emojis were looked at throughout the process of reading a pull request. This could give information about how emojis could impact a developer's sentiment. This study will follow a similar data collection methodology and data post-processing, but we will examine how emoji presence will impact the confidence of the developer when assessing the sentiment of pull requests.

The paper makes the following contributions.

- Studies the effect of emoji on developer sentiment within GitHub pull requests.
- Analysis of how emojis impact a humans' confidence of a development artifact's sentiment classification

The paper is organized as following. Section II discusses the related work in the area of eye tracking and emoji sentiment. Section III goes over the Research Questions and their motivations. Section IV discusses our hypotheses for our two research questions. Section V goes over the Study Goal, the Data Set we used, and our Study Methodology. Section VI goes over data processing. Section VII goes over the paper's threats to validity. Section VI goes over the results and analysis of the study. Section IX talks about conclusions and future work for the study.

II. Related Work

This section presents related work in the area of sentiment analysis with emoji usage. We examine how emojis and sentiment exist in the general domain, in Software Engineering, and in social media settings. This includes background information about how emoji use can impact sentiment and how emojis are comprehended in different situations.

A. How Emoji Presence can Impact Sentiment

[19] studied how the position and implied emotion of an emoji in a neutral, narrative sentence would impact a participant's perception of the sentence tone and how it may impact the participant's eye movement. It was found that if an emoji was at the end of the sentence, the participant took longer to read it, suggesting that the participant re-contextualized the sentence with the emoji in mind. It was also found that the emoji did not impact the sentence emotion assessment.

Kimura et al. [11] This paper discusses the automatic construction of an emoji sentiment lexicon. They mention that emojis have been used to express users' sentiments and emotions in text-based communication. In order to analyze sentiment of users' posts, an emoji sentiment lexicon with positive, neutral and negative scores has been made with use of manually labeled tweets, but there are less emojis in the lexicon than there are currently existing emojis and expanding the lexicon takes a lot of time and effort. Therefore, they proposed to extract sentiment by calculating the frequency between the sentiment words and each emoji. Their experiments conducted on a collection of tweets showed high correlation between the original lexicon and the automatically constructed lexicon for three sentiment categories.

Wiseman et al. [23] This paper discusses the use of emojis in communication and how they are used in highly personalised and secretive ways. They showed that emojis are re-purposed for meanings other than their intended use almost like an inside joke. They present the reasons for why some emoji get used and explore why emojis get re-purposed. They discussed how the form of re-purposing in the context of intimate and personal sentiments must be considered in emoji-based sentiment analysis.

Wu et al. [24] talks about sentiment classification through high quality sentiment lexicons. These lexicons are able to cover a large number of sentiment words. The sentiment words have the potential to improve the performance of neural sentiment classifications. The authors proposed two approaches to exploit these sentiment lexicons to enhance sentiment classification. They included using the sentiment lexicons to learn sentiment-aware attentions and sentiment-aware word embeddings.

Zhenpeng et al. [2] talks about how emojis can be an unreliable source of sentiment because they can vary widely based on the context that surrounds it. For example, the ship emoji may have a different context in software engineering and outside of software engineering. Therefore, the researchers came up with a learning approach to the problem that will adapt to the sentiment of various emoji within the context of software engineering. This approach was able to gain better sentiment analysis results without manual tagging of emoji sentiment based on context.

Völkel et al. [21] talks about how emojis are used as non-verbal cues in texting, but they can also lead to misunderstandings since they can also have an ambiguous meaning. They run a study on the influence of a person's personality on their understanding of emojis. They presented the participants of the study with a short text chat and asked the participants to add emojis to the texts. They found that personality influenced the choice of emojis.

B. How Emojis are Comprehended

Howman et al. [9] used eye-tracking to gain insight into processes used in emoticon comprehension. They focused on younger (18-30) and older (65+) participants and looked at their eye movements when interpreting comments that could be interpreted as sarcastic. They found that participants read the text faster when an emoji was present, but spent longer re-reading the surrounding text. This suggest that more time was spent understanding how the emoji gives context to the sarcastic nature of the text. They also found that age or other perceiver-related factors may play a role in how emojis are interpreted.

Barach et al. [1] examined how emojis are processed when they are part of a block of text. It is not known if emojis are registered and processed the same as words while reading. Eye-tracking was used to see if a sentence with an actual word versus a sentence with the emoji equivalent of a word was read differently. An example of this is using the word coffee in a sentence and then using the coffee emoji in the same sentence. They also used incongruent emojis in sentences. It was found that congruent emojis were fixated on less than incongruent emojis. They were also more often skipped, suggesting it is read more similarly to a word.

Chen et al. [3] looked at how sentiment is interpreted in the context of software development using emojis. Software can be used to detect sentiment, but it is often not reliable in the context of software tasks. In this paper, researchers used emojis as a way to self-report labels of sentiment. It suggested that emojis are a more viable tool for sentiment analysis in the context of software engineering tasks.

Liebeskind et al. [12] talks about trying to predict the most likely emoji given a short text as input. They extracted a Hebrew political dataset of user comments for emoji prediction. They then looked at n-gram representations for emoji classification. They found that word embedding is not optimal for this task and n-gram representation performs better for the emoji prediction in the Hebrew political domain.

Herring et al. [8] talks about how age can change the meaning received from emojis. Participants that were 31 or older often did not understand the function of the emoji in context, and instead interpreted the emoji literally. While younger participants understood the purpose of an emoji in a specific context. There is also a gender gap – older men tend to harbor resentment towards emojis and not understand their use, while younger women tend to understand how an emoji was used conventionally.

Cohn et al. [4] examined how emojis are processed when they are substituted for actual words in a sentence. This is applicable to our study as many of the emojis in pull requests are used as word substitutions. They found that there was a processing cost when the emojis were read, since they were images compared to words, but there was no difference in comprehension between words and the emoji equivalent of that word. It suggests that text and emojis can be integrated equally into expressions, despite the time cost.

C. Emoji Sentiment in Software Engineering Domain

Lu et al. [14] examined how emojis are used in a software engineering domain. For their study, they looked at how emojis are used in GitHub. They found that sentimental usage is the the reason for emojis being used in issues, pull requests, and comments. For READMEs, emojis were found to be used mostly to emphasize details.

Park et al. [17] completed a pilot study that examined how developers' perceived sentiment of pull requests with emoji compared to the output of sentiment analysis tools. It differs from Lu et al.'s work as it included eye-tracking data and was held in a more realistic developer setting. They found that sentiment analysis tools did not often match that of developers for negative sentiment pull requests. They suggest this is because the tools could not accurately interpret what the emoji was supposed to represent or do for the tone of the pull request. They also further support the notion that sentiment analysis tools tend to work best for the domain that they are written and trained for.

Lou et al. [13] used sentiment analysis based on long short-term memory to analyze emoji sentiment. They addressed the limitation that most sentiment analysis tools consider the emoji separately from the rest of the text instead of as a unit. Their approach emoji based sentiment analysis with attention networks.

D. GitHub & Sentiment in Software Engineering domain

Huq et al. noted how the emotion or sentiment of a developer can have an impact on the developer's performance, and in turn, the software product. With this in mind, they studied how sentiment is different between regular bugs and Fix-Inducing Changes (FIC). To do this, they analyzed the sentiment of pull requests from 6 popular GitHub repositories and analyzed its sentiment using a software engineering domain sentiment tool: SentiStrength-SE. They found that FICs tend to contain more negative sentiment versus regular commits. Also, commits that come before an FIC are more likely to show more emotion. In addition, they found that too many positive emotions in discussion may lead to code that contain bugs, possibly because too much positive sentiment or praise can lead to overconfidence or carelessness from the developer. Overall, they show that sentiment and developer behavior can have relationships between one another.

Limeira de Lima Júnior et al. [5] used a Random Forest classifier to attempt to determine, out of 3 developers tagged on a pull request, which of the three developers would actually review the pull request. The model would output a percent likelihood that the predicted developer would be the one that reviewed the pull request. Out of 3 developers, that percentage varied from a low of 47.33% to a high of 95.47%.

Zhewei et al. [10] look into how professors can use pull request bots to provide valuable feedback to students without having to manually go through every pull request that a student submits. There were 3 bots used in the study that helped detect issues, display test results, and remind students to fix issues. 70% of students in this study found the feedback they received on these pull requests helpful, and showed that bots can provide a higher amount of feedback to students in a timely manner than busy professors.

Pletea et al. [18] talks about application security discussions on GitHub and the atmosphere of those discussions. They mined several discussions from Pull Requests and commits and found that security discussions make up around 10 % of all discussions on GitHub. They also found that more negative discussions are used in security-related discussions than any other discussion on GitHub. They stated that this emphasizes the importance of training developers to reduce frustration and improve project atmosphere.

E. Emoji & Sentiment in Online Social Interactions

[16] Novak et al. studies the sentiment of the 751 most frequently used emojis on Twitter. They computed the sentiment of emojis from the sentiment of the tweets they were in. They found that the most common emojis used were the ones with a positive sentiment. They also found that emojis tended to appear toward the end of tweets, and the sentiment was higher the further the emoji was towards the end.

Debnath et al. [6] decided to look into the information lost when removing an emoji from a piece of text in the context of NLP. To do this, they decided to use a Twitter API, and find a bunch of tweets with emojis relating to a specific topic. Once they did that, they split everything into two datasets – the original tweet with the original emoji, and a new tweet with a similar emoji. They found that any sentiment related algorithm ended up performing better with the original emojis rather than the similar emojis, suggesting that emojis are useful for determining user sentiment and thus hold sentimental information.

Wijeratne et al. [22] This paper discusses a comprehensive analysis of the semantic similarity of emojis through models which utilize machine learning on emoji meanings and descriptions. They used multiple training corpora from Twitter and Google News in order to develop and test models to measure each emojis similarity. They evaluated their work by using a data set which assigned human annotated semantic scores to 508 pairs of emojis. They presented a real world use case on emoji embedding models using sentiment analysis and showed that their model outperforms other embedding models too.

Tomihira et al. [20] This paper discusses the use of emojis and how they are effective in expression emotion in sentences. They found that sentiment analysis in natural language processing uses learning by manual labeling of sentences. They propose a new model that learns from sentences which use emojis as labels and collected tweets from Twitter as the corpus. They run the model and compare based on EncoderDecoder Model of Recurrent Neural Network and Convolutional Neural Network. They found that emojis are effective in expression emotions of tweets.

Kimura et al. [11] This paper discusses the automatic construction of an emoji sentiment lexicon. They mention that emojis have been used to express users' sentiments and emotions in text-based communication. In order to analyze sentiment of users' posts, an emoji sentiment lexicon with positive, neutral and negative scores has been made with use of manually labeled tweets, but there are less emojis in the lexicon than there are currently existing emojis and expanding the lexicon takes a lot of time and effort. Therefore, they proposed to extract sentiment by calculating the frequency between the sentiment words and each emoji. Their experiments conducted on a collection of tweets showed high correlation between the original lexicon and the automatically constructed lexicon for three sentiment categories.

Mastumoto et al. [15] talks about sentiment analysis from tweets based on emoji's category. They mention that there are existing studies about sentiment analysis focused on emotional expressions included in a sentence but there are many types of emotional expressions like internet slang which cannot be constructed on the emotional expression dictionary. Since these studies use a corpus and machine learning, the performance is dependent on the annotations. The authors use categories which are expressed as emojis as sentiment labels to annotate and train word embedding features in neural networks.

III. Research Questions

We now present the three research questions studied in this paper.

RQ1: How does an emoji impact the sentiment of text, specifically in GitHub pull requests?

RQ2: Can an emoji impact a participant's confidence of sentiment classification of a given sentence?

RQ3: Do participants fixate on an emoji longer than the text when reading through a pull request?

GitHub pull requests are a significant way that developers communicate and show sentiment in the development process. Because emojis are becoming more integrated in development tools RQ1 will work to see if their usage can impact a developer's interpretation of the pull request they are reading.

RQ2 is significant as it would give insight into how emojis can impact developer behavior and confidence. If emojis tend to make a reader more or less confident in the message's meaning, it could have implications for how developers communicate.

As eye gaze data have given information about developer behavior and perception in previous studies, RQ3 seeks to understand if developers look at emojis more when trying to understand the sentiment of a pull request.

IV. Hypotheses

We believe that emojis will affect a person's sentiment attached to the text. We also believe that a user would look at emojis for longer than normal text.

V. Study Design

TABLE I
Pull Request Information

PR ID	Emoji Present	Number of Emoji
894	Yes	4
2291	Yes	1
2785	Yes	13
346	Yes	1
2502	Yes	5
408	Yes	2
1926	Yes	2
415	Yes	1
7789	Yes	2
4973	Yes	2
3241	Yes	1
685	Yes	1

A. Study Goal

The goal of our study is to determine how an emoji impacts the sentiment of text, specifically in GitHub pull requests.

B. Data Sets and Pull Request Selection

The study includes 12 pull requests from open source projects maintained on GitHub. Pull requests were chosen based on their length and the number of emojis within them. Short pull requests were chosen to avoid participant fatigue when reading through a pull request, especially considering participants needed to keep their head still throughout the study.

To remove the emojis from the pull requests, we will be using a TamperMonkey script that will remove every instance of the ”g-emoji” tag, and every instance of an image with the ”emoji” class from the GitHub pull request webpage.

C. Eye Tracking Equipment and Environment

The Tobii Pro TX300 eye tracker was used to track each participants' eye movements while they completed tasks. The eye tracker was set to run at 60Hz. Additionally, the iTrace Core server and the iTrace Chrome plugin were used to track the participants' eye gaze and location on the screen.

D. Participants

Our study included 6 participants that were recruited all from the same Eye Tracking course at the University of Nebraska-Lincoln. All participants are upperclassmen or graduate students in the Computer Science or Software Engineering majors at the University of Nebraska-Lincoln. Of these 6 participants, 3 were male and 3 were female. The ages of our participants ranged from 21 years old to 24 years old. Of our participants, 4 participants answered they were confident with pull requests, while 2 answered they were not. Additionally, 4 of the participants answered that they did not review pull requests often, while 2 of the participants answered that they reviewed pull requests frequently. One of the participants was a graduate student, while the rest were undergrads.

TABLE II
Participants

ID	Gender	Degree Pursuing	Pull Request Familiarity	Pull Request Review Frequency
1	F	Masters	2	2
2	M	Bachelors	4	4
3	M	Bachelors	5	2
4	F	Bachelors	4	2
5	M	Bachelors	5	3
6	F	Bachelors	3	2

E. Methodology

During our user study, our users were asked to read 12 GitHub pull requests while sitting in front of a Tobii TX300 eye tracker. First we had them answer a questionnaire about their age, gender, what degree they were pursuing, their familiarity of pull requests, and how often they review pull requests. After completing the questionnaire, we had them sit down in front of the eye tracker and calibrate the tracker. Once the calibration was completed we pulled up a pull request on the screen and had them read through it. Once they read the pull request, they answered questions about their perceived sentiment of the pull request along with their confidence of their perceived sentiment. We wrote a script for the chrome extension TamperMonkey to remove emojis from alternating pull requests. A test user will alternate between reading an pull request that has an emoji and reading an pull request that does not have an emoji. After they completed the 12th pull request, they were presented with another questionnaire asking them their overall confidence of their sentiment analysis.

F. Study instrumentation

Before starting the eye tracking portion of the study, we had the user answer a questionnaire regarding their familiarity with GitHub Pull Requests and how often they reviewed GitHub Pull Requests. This questionnaire used the 5-item Likert scale from strongly disagree to strongly agree. The questionnaire also included questions about their age, gender, and highest academic degree achieved.

TABLE III
DEPENDENT VARIABLES

RQ1	ArtifactSentiment	The GitHub pull request's perceived sentiment value.
RQ2	SentimentConfidence	The participant's confidence in the sentiment.
RQ3	FixationDuration	How long the participant fixated on an AOI.

VI. ANALYSIS AND RESULTS

A. Post Processing

Each of the 12 pull requests that the developers looked at had two CSV files associated with them. One CSV file was from the Chrome plugin and the other was from the iTrace server. These CSV files were downloaded and used in the I-VT fixation filter [7]. This filter took each of the raw gazes in the files generated after each task and determined what developers were looking at and detected fixations.

We can use this information to answer our study goal in two ways. First, we can compare the questions on sentiment between users who saw an emoji for that specific pull request and users that did not see an emoji. This will allow us to pinpoint if an emoji shifted the sentiment of the text more towards the sentiment of an emoji. Second, we can use the eye tracking data to see at what point, if any, the user looked at the emoji and for how long. If a user looks at the emoji for a long duration, then we can reasonably assume that they used the emoji as context to read through the pull request. If a user does not look at the emoji at all, then they did not factor it in when determining the sentiment of specific text.

B. RQ1: Results

We found that emojis tend to have a positive impact on the overall sentiment of a pull request. The average sentiment for a pull request with an emoji was 3.69, while the average sentiment for a pull request without an emoji was 3.19. There were only 2 pull requests with emojis in which participants rated the sentiment as negative, compared to 5 where there were not emojis. Plus, there were significantly more positive and very positive responses in pull requests with emojis (21) compared to pull requests without emojis (10) as seen in in figure 2. Something to note is that there was only 1 pull request where the sentiment with the emoji was lower than the sentiment without the emoji. Table IV shows the emojis that were fixated on during the pull requests and the participant's given sentiment of that pull request. It shows that the sentiment is never below neutral which goes along with the average sentiment of a pull request with an emoji being higher than a pull request without an emoji. The average sentiment of the PRs where users fixated on emojis was 3.8, which is above the average sentiment for pull requests with emojis. This suggests that the more that the user fixates on an emoji, the more likely they are to rate the pull request that contains that emoji positively.

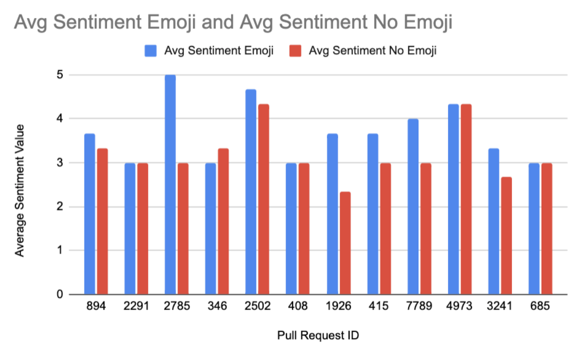

Fig. 1. Average Sentiment of Each Pull Request

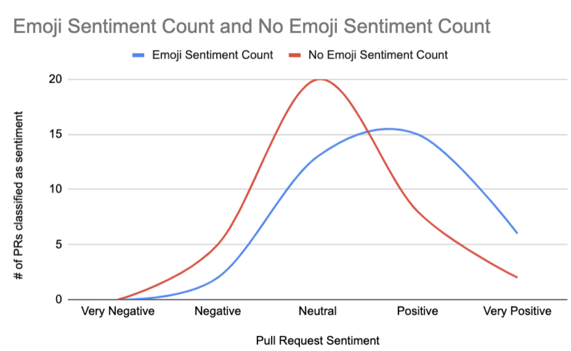

Fig. 2. Number of Responses for Each Sentiment Response Type

C. RQ2: Results

We found that emojis did not impact a participant's confidence of sentiment classification of a given sentence. If anything, emojis caused participants to be less confident in their sentiment. The average confidence for a pull request with an emoji was 3.97, while the average confidence for a pull request without an emoji, was 4.11. This could be due to the fact that GitHub uses custom emojis along with

TABLE IV
EMOJIS FIXATED ON AND RELATED SENTIMENT

Participant	PR ID	Emojis Fixated On	Sentiment
5	346	💃	Neutral
5	408	😅	Neutral
6	2785	😆	Very Positive
6	2502	😎, 👍	Positive
6	7789	😝	Positive

standard emojis, and the participants might have not known the meaning of the custom emojis. Another interesting thing to note is that no participant stated that they were not confident in the sentiment of text, with the lowest number being put by any participant being a confidence rating of 3 out of 5.

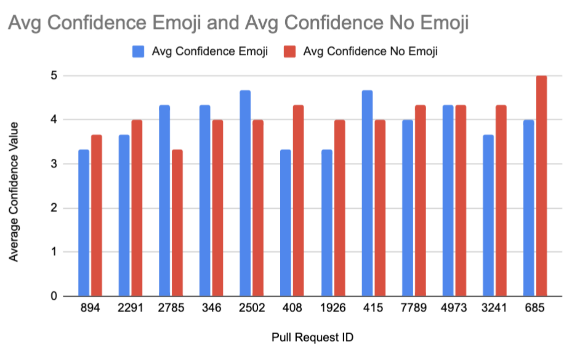

Fig. 3. Average Confidence of Each Pull Request

D. RQ3: Results

The eye tracking data we collected showed that participants did not fixate on emojis for longer than natural text of the pull requests. We did notice that when the participant would be looking at an emoji, the eye tracker would bounce their gaze between the text surrounding the emoji and the emoji, resulting in raw gaze data as seen in 4 that wasn't completely accurate which affected the fixations as seen in 5. We believe that this could have impacted the conclusions we were able to make from this data and that expanding this study in the future may offer different results.

VII. THREATS TO VALIDITY

One threat to construct validity is that the results can be up for interpretation depending on how the users answer questions about the sentiment of a specific GitHub pull request. A threat to external validity is that we were only able to analyze the data from two participants in the study. An additional threat to external validity would be that we recruited students from an eye-tracking course, along with running this study on members of our project.

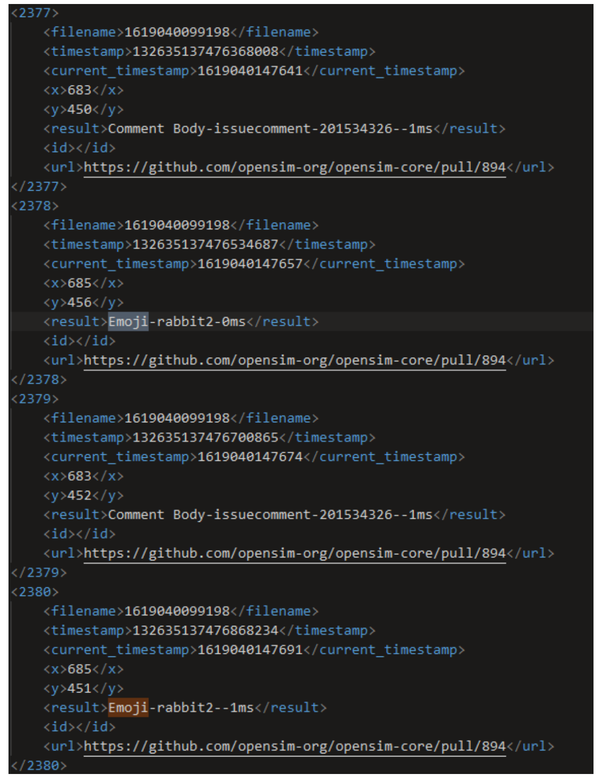

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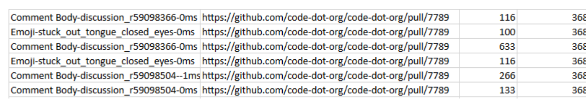
Fig. 4. Raw gaze data bouncing between emoji and surrounding text



Comment Body-discussion_r59098366-0ms	https://github.com/code-dot-org/code-dot-org/pull/7789	116	3680
Emoji-stuck_out_tongue_closed_eyes-0ms	https://github.com/code-dot-org/code-dot-org/pull/7789	100	3681
Comment Body-discussion_r59098366-0ms	https://github.com/code-dot-org/code-dot-org/pull/7789	633	3682
Emoji-stuck_out_tongue_closed_eyes-0ms	https://github.com/code-dot-org/code-dot-org/pull/7789	116	3683
Comment Body-discussion_r59098504--1ms	https://github.com/code-dot-org/code-dot-org/pull/7789	266	3684
Comment Body-discussion_r59098504-0ms	https://github.com/code-dot-org/code-dot-org/pull/7789	133	3685

Fig. 5. Fixation bouncing between emoji and surrounding text

TABLE V
PARTICIPANT 5'S AOIS FIXATED ON DURING READ THROUGH OF PULL REQUEST NUMBER 408

Participant	AOI	Duration in milliseconds
5	Comment Body-issue	449
5	Comment Body-issuecomment	2760
5	PRTitle	614
5	Comment Body-issuecomment	2192
5	Username-polita	1032
5	ConfigurationManager.cs	366
5	Comment Body-discussion	498
5	UnchangedLOC	332
5	Comment Body-discussion	849
5	UnchangedLOC	383
5	Comment Body-discussion	949
5	Emoji-sweat_smile	283
5	UnchangedLOC	1462
5	Comment Body-discussion	931
5	Emoji-sweat_smile	2799
5	Username-polita	566
5	Comment Body-discussion	299
5	Username-kevinchalet	566
5	ConfigurationManager.cs	765
5	Comment Body-discussion	3028

VIII. DISCUSSION AND IMPLICATIONS

An individual developer could make an effort to include more emojis in their pull requests to make sure that any con-

TABLE VI
PARTICIPANT 6'S AOIS FIXATED ON DURING READ THROUGH OF PULL REQUEST NUMBER 408

Participant	AOI	Duration in milliseconds
6	PRTitle	631
6	Comment Body-issue	199
6	PRTitle	1463
6	Username-polita	932
6	HeaderAvatarImage-Polita	716
6	Comment Body-issue	1764
6	Comment Body-issuecomment	7684
6	UnchangedLOC	765
6	Comment Body-discussion	499
6	UnchangedLOC	2196
6	Username-kevinchalet	398
6	Comment Body-discussion	1015
6	Username-polita	1265
6	HeaderAvatarImage-Polita	1745
6	Comment Body-discussion	2619

structive feedback comes across in a positive light. Companies could write guidelines on using emojis in pull requests to promote a more positive work environment.

IX. CONCLUSIONS AND FUTURE WORK

This study provided insight into how emojis affect the sentiment of pull requests. Analysis of the results of the study showed that pull requests with emojis were associated with higher sentiment while pull requests without emojis were associated with lower sentiment. The results of this study offer potential future work into how developers perceive emojis in pull requests. This study can be expanded on by increasing the number of participants. Additionally, this study could be ran with a higher number of pull requests evaluated per developer.

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