Investigating the Influence of Users Personality on the Ambiguous Emoji Perception

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Abstract

Emojis are an integral part of Internet communication nowadays. Even though, they are supposed to make the text clearer and less dubious, some emojis are ambiguous and can be interpreted in different ways. One of the factors that determine the perception of emojis is the user's personality. In this work, I conducted an experimental study and investigated how personality traits, measured with a Big Five Inventory (BFI) questionnaire, affect reaction time when interpreting emoji. For a set of emoji, for which there are several possible interpretations, participants had to determine whether the emoji fits the presented context or not. Using regression analysis, I found that conscientiousness and neuroticism significantly predict the reaction time the person needs to decide about the emoji. More conscientious people take longer to resolve ambiguity, while more neurotic people make decisions about ambiguous emoji faster. The knowledge of the relationship between personality and emoji interpretation can lead to effective use of knowledge of people's characters in personalizing interactive computer systems.

1 Introduction

Emojis have become incredibly popular on the Internet (Kralj Novak et al., 2015; Pavalanathan and Eisenstein, 2015). One reason for that is that text messaging is one of the most common communication channels now. But yet being convenient and enabling communication at a distance, text communication is not as expressive as live speech (Lengel and Daft, 1984). Since we can read the text with different intonations, text messages can be easily misunderstood. Emojis, which are pictograms depicting human faces, gestures and objects, partially solve this problem by augmenting text with emotional awareness cues.

However, despite being the visual representation, emoji can have the same ambiguity as words at the lexical meaning level (Prada et al., 2016; Cunha et al., 2020). Even though usually emoji are used within the context, which in theory should work well in both directions: emoji complement and resolve the ambiguity of the text, and the emoji itself in conjunction with the text should not cause difficulties in interpretation, it doesn't always work. And for different reasons, the same emoji can be interpreted differently by different people.

One of the plain explanations is that emoji rendering is specific to different operating systems, for example, for Apple and Google smartphones, and the same emoji can look quite different on different devices. Moreover, operating systems update rendering with newer versions and even users of the same device and platform may see slightly different emojis depending on whether they have updated their software or not. Finally, emojis diverge on different platforms. For example, Facebook uses a fairly specific rendering, quite different from the basic one. Of course, this affects how people perceive the same emoji and can have an impact on communication (Miller et al., 2017).

However, the perception of emojis can depend not only on the technical characteristics of the device but also on the person using them. Research shows that how a person interprets emojis is influenced by age, gender, cultural background (Barbieri et al., 2016; Jaeger et al., 2017; Wolf, 2000). But most studies address the issue of flattering differences at the level of group characteristics, and not many research analyze the influence of user personality on the interpretation of emoji. The existing ones mainly analyze emojis isolated from the context (Völkel et al., 2019). While taking into account that we usually see emojis as complementary to the text, it is important to analyze them within the context.

Thus, in this work, I'm trying to touch on this gap, and understand if there is a connection between the personality of the user and the way he

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perceives emoji within the text context - in the form in which we usually see emoji. So my research question is: *Do personality traits have an impact on how people perceive ambiguous emojis in context?*

To address these questions, I conducted an experimental study in which I presented people with ambiguous emoji, for which two more or less equivalent contexts are possible, and measured the time it took for them to decide whether the presented emoji fits the context or not. The participants then completed a BFI survey to determine their personality profiles. Finally, using regression analysis, I tested if there is a significant effect of different personality traits on reaction time when resolving emoji ambiguity.

My results show that conscientiousness and neuroticism significantly predict the reaction time the person needs to decide about the emoji. More conscientious people take longer to resolve ambiguity, while more neurotic people make decisions about ambiguous emoji faster. The interaction with the context presented affects the impact of both conscientiousness and neuroticism on the reaction time.

Thus, the contributions of this work are as follows: First, I try to address the gap in the studies of the link between user personality and emoji interpretation. Second, this study explores how people with different personalities perceive not standalone but emojis in context as we usually see them in text messaging. Finally, to my knowledge, existing research examines the perception of emoji in terms of choosing a qualitative interpretation, while I measure the relationship between personality and perception of emotional ambiguity by measuring reaction time.

2 Theoretical Background

2.1 Why do we use emoji?

When we speak in person, our language is enriched with non-verbal cues such as facial expressions, gestures and intonation (Burgoon et al., 2010). However, text messaging, despite its advantages as the ability to communicate at a distance and respond at a convenient time, is devoid of a non-verbal communication channel. From this, the sender and the recipient can intonate and interpret the same text in different ways, which can cause misunderstanding (Aoki and Woodruff, 2005). One possible way to mitigate this problem is by using emoji - pictograms that reflect facial expressions, gestures, or objects (Derks et al., 2008). They can serve as a replacement for gestures or emotions of the interlocutor and thereby make the text less ambiguous.

Lo discovered that the same text could be understood in different ways, depending on which emoticon is placed after it (Lo, 2008; Walther, 2011). Walther and D'Addario, on the one hand, found that, in general, the emotional colouring of the text itself is more important for interpretation than the emoticons. However, in the case of emoticons displaying negative emotions, the interpretation of the text changed significantly (Walther, 2011).

Thus, among the most common reasons found as the result of qualitative research, people use emojis to heighten the emotional colouring of the text (Hu et al., 2017). Another reason is to clarify the tone of the initially neutral message. For example, as a result of interviewing people, Cramer et al. found that people can add "heart" or "kiss" to add a romantic context to the neutral message ("See you 😘") (Cramer et al., 2016). Sometimes emojis add situational meaning, for example, "I am travelling to Germany next week ✈️," explaining that person will go to Germany by plane (Kaye et al., 2016). Another common reason to use emojis is to lighten the tone of the message and make people perceive aggressive messages more positively (Kaye et al., 2016; Rodrigues et al., 2017). Lastly, a few studies mention the emoji's function as referring to shared memories and jokes and increasing intimacy and closeness between people (Kaye et al., 2016; Kelly and Watts, 2015; Rodrigues et al., 2017).

2.2 Lexical Ambiguity

The phenomenon of lexical ambiguity, when a single word has multiple meanings, is quite common in the language (Beekhuizen et al., 2021). It is a natural feature of any language allowing the expression of multiple concepts within a limited vocabulary (Youn et al., 2016). Since humans are able to effectively decode this ambiguity and process multiple senses of a single word, research on lexical ambiguity occupies one of the key places in the cognitive sciences of language.

Despite the fact that emoji should be more univocal (Prada et al., 2016; Cunha et al., 2020), since they are a visual representation of concepts, ambiguity occurs in them too (Kralj Novak et al., 2015). In written text, emojis perform the function of replacing non-verbal communication methods such as facial expressions and gestures. And, given this essence, most often, emojis are used not separately but within the context, in which they should be perceived as a whole (Bavelas and Chovil, 2000). In the same manner, as we perceive the interlocutor, who gestures and expresses emotions during speech.

The problem of emoji ambiguity is approached from different angles. There are several dictionaries constructed with the aim of collecting a base of meanings associated with emoji and potentially disambiguating them. For example, Wijeratne et al. created a semantic tool, EmojiNet, allowing systems to link emojis with their meaning in context, which was successfully tested on disambiguating context in Twitter (Wijeratne et al., 2016, 2017). They also looked at the 25 most commonly misused emojis when applying the emoji sense disambiguation algorithm. In a similar manner, Novak and colleagues came up with a sentiment vocabulary for emoji based on the representations of tweets in which emoji appear (Kralj Novak et al., 2015). However, Miller argues that such solutions are not effective because people often disagree on the interpretation of the same emoji (Miller et al., 2017).

2.3 Perception of emojis

There can be several reasons for the fact that people can interpret the same emoji in different ways. Some of them are technical in nature and are related to the essence of emoji as such. Emojis are Unicode icons, and the way they are displayed depends on the operating system, its version and the platform on which they are used (Miller et al., 2016; Davis and Holbrook). So, for example, emoji in Apple and Android can be significantly different. Moreover, with software updates, manufacturers update emoji as well, so even people with the same phones but with an updated and not updated OS version can see different displays of the same emoji. Finally, there are platforms like Facebook that have their own emoji renderings (Miller et al., 2017).

Apart from technical factors, there are also human-related factors. Tigwell and Flatla found that users can perceive the sentiment of emoji differently even when they are shown on the same device and platform (Tigwell and Flatla, 2016). The way a person interprets emojis was found to be influenced by age (Jaeger et al., 2017; Koch et al., 2022). Herring et al. show that people over 30 have a tendency to interpret emojis too literally and younger people understand them in a more conventional manner (Herring and Dainas, 2020). Regarding gender, females have generally more positive attitudes towards emojis use (Chen et al., 2018), and females use more variations of emojis (Prada et al., 2018), mostly to express positive feelings such as support and joy. Males in general use emotions more to express teasing and sarcasm (Wolf, 2000). Finally, miscommunication in emojis can also be explained by cultural factors, and emojis can be interpreted differently in regards to the socio-geographics of a country. Barbieri et al. found that people from the UK and Spain have disagreements in the interpretation of weather-related emojis, and people from the UK and the USA perceive emoji related to holidays differently (Barbieri et al., 2016).

2.4 User personality and emoji use

The above-mentioned studies, explore differences in perception at the group level, and there is currently not a lot of research addressing the difference in emoji perception at the individual level. This aspect may be quite important because it is known that personality affects the way people express themselves, raising the assumption that it may also influence how people interpret emotions (Campbell and Rushton, 1978; Costa and McCrae, 1980). Li et al. examined the influence of personality traits on patterns of emojis usage in Twitter (Li et al., 2018). To assess the users personality profiles, for each user, authors analyzed which words people use in tweets and found clear patterns of the emoji use specific to different personality traits. They found that people with high scores on neuroticism tend to use emojis to express exaggerated emotions. Extraverts and conscientious users use more positive than negative emojis. Finally, in general, emotionally unstable and agreeable people use more emojis overall.

Marengo et al. explored the relationship between personality and the use of emojis in a different way (Marengo et al., 2017). They presented participants with a set of 91 emojis and asked to self-identify with them. They found a positive correlation between the use of a blushing smiley and agreeableness, as well as that extraversion, is associated with positive emojis. Lastly, emojis with negative sentiment showed a negative correlation with emotional stability.

Finally, Völkel et al. studied the link between user personality and emoji interpretation in context (Völkel et al., 2019). They measured the personality profile of people with the Big Five Inventory - a model that describes the emotional and behavioural tendencies of people in five dimensions (John and Srivastava, 1999). The model covers (1) Openness, related to willingness to try new things, (2) Conscientiousness - a tendency to show self-discipline, (3) Extraversion, which means the enjoyment from interaction with other people, (4) Agreeableness - valuing high getting along with others, and (5) Neuroticism - a tendency to feel and express negative emotions. Participants were shown a concrete message context and had to add an appropriate emoji to it. Then authors ran a generalized linear regression fitting BFI personality scores as predictors and counts of specific emojis as dependent variables. Authors claim that the choice of emojis is influenced by personality traits but do not point out specific links between personality traits and emojis using patterns.

In this work, I try to step back and explore the link between perception emoji and personality traits by analyzing how people with different personality profiles resolve ambiguity in emojis.

3 Methodology

3.1 Experiment

To test the impact of peoples BFI profile on the time they need to decide whether an emoji is suitable for the context or not, I conducted a reaction time experiment. The design was inspired by Jack Yates, who explored priming by dominance in ambiguous words by measuring reaction times participants needed to determine whether the presented word was ambiguous or not (Yates, 1978). Following his procedure, I presented participants with a short sentence followed by emoji and asked them to choose if the emoji was suitable for the context or not. For each sentence, I measured the time it took for the participants to make a decision. In the following subsections, I present a more detailed description of stimuli selection and experiment design.

3.2 Selection of the stimuli

There were 3633 emojis in the Unicode system by September 2021, when this work was started. I concentrated on emojis that represent either emotions or hand gestures since this study concentrates on the emotional expressiveness in communication and based on the claim that people with different personality types express and interpret emotions in different ways (Campbell and Rushton, 1978; Costa and McCrae, 1992). To make a set of ambiguous emojis stimuli, I assessed the Top 150 Twitter emojis in September 2021 [1] and chose those that fall into the Smileys People category. This resulted in a set of 74 emojis. Emojipedia [2] and Dictionary [3] provide interpretation and examples of the context of the use of emojis. For each emoji from my set, I looked through their pages on these sites and selected those for which at least two meanings were presented. As a result, I got a set of 23 emojis with several interpretations possible (Appendix 1). I used the renderings used in WhatsApp on the iOS operating system.

3.3 Context creation

For each emoji, I came up with two contexts, adapting those presented on the Emojipedia and Dictionary so that they are appropriate for the experiment. The goal of adaptation was to minimize the influence of the structure of the text on the reaction times. Hence all sentences were short (no more than 32 characters with a maximum variation of 2 words between sentences), affirmative, without punctuation and any professional terms, and in plain English (Appendix 1). For instance, I converted the example from Dictionary: *"This guy has been taking pics of his gf for like 30 minutes and hes being so patient with her omg so cute 🥺"* to *"This kitten is so cute 🥺"* so that the length of the sentence and slang language do not affect reading and reaction time. The contexts were treated as more or less equally probable, and none of them was treated as priming.

3.4 Experimental design

The experiment had the following procedure. The participants were given the task to read the sentence and answer the question of whether they think the emoji at the end of the sentence suits it or not. Each member rated a complete set of emojis. However, for counterbalancing purposes, the participants were randomly split into two groups and received emojis with different preceding contexts. In order to control the sequence effect, assuming that participants might experience fatigue or confusion after specific stimuli, the stimuli were presented

[1] https://emojitracker.com
[2] https://emojipedia.org
[3] https://www.dictionary.com

in random order. Stimuli appeared one after another, each on a separate page. To make a decision, participants had to select an option ("suitable"/" unsuitable") and then click the "Next" button. The experiment was conducted on the PsyToolkit platform (Stoet, 2010, 2017).

To make sure that the participants actually read the stimuli and did not just randomly select the answers, three filler questions were added, in the form of yes/no questions, asking about the content of the previous sentence.

3.5 Questionnaire

Participants' personality traits were assessed with the Big Five Inventory Questionnaire (John and Srivastava, 1999). I used the traditional full version of the inventory, consisting of 44 questions measuring (1) extraversion, (2) agreeableness, (3) conscientiousness, (4) neuroticism, and (5) openness. Participants had to choose to which extend the statements aimed to estimate different personality traits apply to them on a 7-point Likert scale.

In the end, I collected socio-demographic information about the participants, including gender, age, country of birth and residence, level of English proficiency. Also, I asked users to indicate from which device they took the survey.

3.6 Participants

I recruited participants from the same age group (18-27) and country of birth (Russia) to minimize the impact of these variables on outcome. The rationale behind such restrictions was that cultural factors could influence how people interpret emojis (Barbieri et al., 2016; Lu et al., 2016), and that people of different ages use emojis differently (Herring and Dainas, 2020; Koch et al., 2022). Moreover, participants were asked to indicate their level of English proficiency, and participants with language levels below intermediate were filtered out. Participants were recruited through the university mailing list and social media. One voucher for 1000 rubles was drawn among the participants.

I indicated the number of participants using the G*Power tool (Faul et al., 2007). An a priori analysis showed that I would need 138 participants if I hypothesize a large effect size of f2 = 0.15 and aim for statistical power of 0.95. I got 147 participants in total, 32 males and 115 females with a mean age of 24.

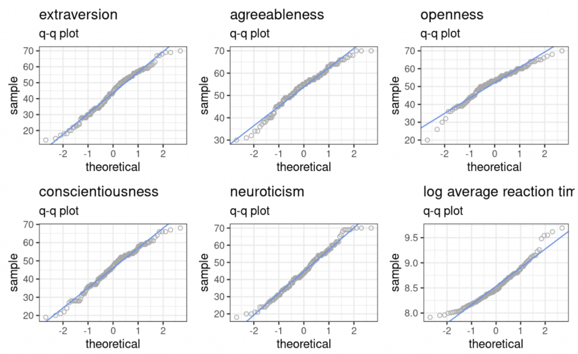

Figure 1: Quantile-Quantile plots for BFI scores and the logarithm of average reaction time.

3.7 Measures

The Reaction Time in the experiment was measured in milliseconds. For each participant, the average reaction time between all emojis was found. The average reaction time was not normally distributed, and I used its logarithm in further analysis. Two participants with outliers in reaction times were deleted from the sample.

For each personality trait from the BFI questionnaire, points for questions on the single construct were aggregated. Figure 1 shows the QQ-plots of personality traits and logarithmic average reaction times in my sample. For all BFI traits, I performed correlation analysis (Appendix 2). All correlations are below the level of 0.5, so I used all the variables in the analysis.

3.8 Model

I used the generalized linear regression models with an average reaction time as the dependent variable and BFI Traits and context as predictors (Stachl et al., 2017; Völkel et al., 2019). The study is exploratory, and I commuted several models. I ran separate models for each trait, adding the context as an interaction variable, and then made an aggregated model with all traits as predictors. I used the significance level of = 0.05. For the model comparison, I calculated R2, Adjusted R2, and Performance Score.

4 Results

In this section, I report the results of regression models (Makowski et al., 2021). I got statistically significant results for the (1) model predicting the reaction time with conscientiousness and context as an interaction, (2) model predicting the reaction time with neuroticism and context as an interaction, and (3) model with all BFI scores as predictors. The separate models with agreeableness, openness and extraversion and context as a predictor were statistically insignificant. In the following subsection, I describe the model performances in more detail. I provide the output of the models in Appendix 3.

4.1 Conscientiousness

The first model I fitted was a linear model (estimated using OLS) to predict the log of average reaction time with BFI conscientiousness score and context. The model explains a statistically significant and weak proportion of variance *(R2 = 0.08, F(3, 135) = 3.93, p = 0.010, adj. R2 = 0.06).*

Within this model:
- The effect of conscientiousness is statistically significant and positive
- The effect of the context is statistically significant and positive
- The interaction effect of the context on conscientiousness is statistically significant and negative

Overall: from the model, we can see that the more conscientious the person is, the more time it takes for him to decide about the ambiguity of the emoji. However, in the case of this model, the context itself affects the reaction time more strongly and also has a negative interaction effect on conscientiousness.

4.2 Neuroticism

With a second model I predicted log of average reaction time with BFI neuroticism score and context. The model explains a statistically significant and weak proportion of variance *(R2 = 0.08, F(3, 135) = 3.84, p = 0.011, adj. R2 = 0.06).*

Within this model:
- The effect of neuroticism is statistically significant and negative
- The effect of the context is statistically non-significant and negative
- The interaction effect of the context on neuroticism is statistically significant and positive

Overall: from this model, we can see that the more neurotic the person is, the more quickly he resolves the ambiguity in emoji, and the neuroticism is the most strong predictor in this model, but the context also plays a role as a positive interaction effect on the neuroticism.

4.3 Extraversion

The model predicting the log of average reaction time with BFI extraversion score and context was not statistically not significant and had a weak proportion of variance *(R2 = 0.03, F(3, 135) = 1.23, p = 0.302, adj. R2 = 4.93e-03).*

Within this model:
- The effect of extraversion is statistically non-significant and positive
- The effect of the context is statistically non-significant and positive
- The interaction effect of the context on extraversion is statistically non-significant and negative

Overall: even though the model is not significant, we still can see a tiny trend that more extraversive people might resolve ambiguity slower. However, the model performance does not allow us to make such conclusions.

4.4 Openness

The model predicting the log of average reaction time with BFI openness score and context was not statistically not significant and had a weak proportion of variance *(R2 = 0.03, F(3, 135) = 1.42, p = 0.240, adj. R2 = 9.06e-03).*

Within this model:
- The effect of openness is statistically non-significant and negative
- The effect of the context is statistically non-significant and negative
- The interaction effect of the context on openness is statistically non-significant and positive

Overall: although this model is also insignificant, we can see a little trend with more open people needing more time to decide about ambiguous emoji, but the model has the too poor performance to draw any conclusions.

4.5 Agreeableness

The last model with a single BFI predictor was the model predicting the log of average reaction time with BFI agreeableness score and context. The model explains a statistically not significant and weak proportion of variance *(R2 = 0.03, F(3, 135) = 1.16, p = 0.327, adj. R2 = 3.50e-03).*

Within this model:

- The effect of agreeableness is statistically non-significant and positive
- The effect of the context is statistically non-significant and positive
- The interaction effect of the context on agreeableness is statistically non-significant and negative

Overall: the model is not significant, though, the trend we can see in it is that the more agreeable the person is, the less time it might take for him to resolve the ambiguity in emoji, but the model is not significant to claim that.

4.6 All traits

Finally, I fitted a linear model to predict the log of average reaction time with openness, conscientiousness, neuroticism, agreeableness, extraversion and context. The model explains a statistically significant and moderate proportion of variance *($R2 = 0.14$, $F(10, 128) = 2.02$, $p = 0.037$, adj. $R2 = 0.07$).*

Within this model:
- The effect of openness is statistically non-significant and negative
- The effect of conscientiousness is statistically significant and positive
- The effect of neuroticism is statistically non-significant and negative
- The effect of agreeableness is statistically non-significant and negative
- The effect of extraversion is statistically non-significant and negative
- The effect of the context is statistically non-significant and negative
- The interaction effect of the context on openness is statistically non-significant and positive
- The interaction effect of the context on conscientiousness is statistically significant and negative
- The interaction effect of the context on neuroticism is statistically non-significant and positive
- The interaction effect of the context on agreeableness is statistically non-significant and positive

Overall: out of this model, we can see that with an increase in conscientiousness score, it takes more time for the person to resolve the ambiguity. On the contrary, the higher score in neuroticism decreases the time it takes for the person to decide about the ambiguous emoji. The strongest predictor in the model is the interaction between the context and conscientiousness, assuming that the effect of conscientiousness on reaction time also depends on the context in which the person sees the emoji.

For all the models, the standardized parameters were obtained by fitting the model on a standardized version of the dataset.

4.7 Best model

Having all the models together, I compared the statistically significant models between each other to identify the best one with the performance R package (Lüdecke et al., 2021). The result is reported in Table 1. Looking at the performance score and adjusted R-squared, we can see that the most powerful one is the model with all BFI personality traits and context as an interaction as predictors.

5 Limitations and Discussion

I ran an experiment to explore whether there is a link between how people perceive ambiguous emojis and their personality traits. With the regression analysis, I found that the scores on conscientiousness and neuroticism serve as significant predictors of how much time does it take for a person to resolve the ambiguity in emoji, with more conscientious people needing more time and more neurotic people needing less time to decide about an ambiguous emoji. For both significant variables, the interaction effect of the context was also significant. Openness, agreeableness and extraversion did not show any significant effect on the reaction time.

These results are in line with previous research. Lots of studies demonstrated that people scoring high on neuroticism, even though performing poor on the complex and stressful tasks, show high performance on simple and repeated tasks (Corr, 2003; Oswald et al., 2017; Poposki et al., 2009; Studer-Luethi et al., 2012). In turn, conscientious people tend to overestimate the importance of tasks, which makes their learning times and decision-making slower (Lepine et al., 2006; Martocchio and Judge, 1997; Murray et al., 2014; Studer-Luethi et al., 2012). The importance of context variables as an interaction also supports previous research claiming the importance of semantics for emoji interpretation (Miller et al., 2016, 2017; Tigwell and Flatla, 2016; Völkel et al., 2019).

Considering previous research, I might interpret my results in a way that conscientious people being achievement striving, careful and not impulsive

Name	R2	R2 (adj.)	AIC_wt	BIC_wt	Performance
all predictors	0.1360748	0.0685807	0.0360656	0.0000013	0.6666667
conscientiousness	0.0803673	0.0599310	0.5140960	0.5333301	0.4010676
neuroticism	0.0785988	0.0581233	0.4498385	0.4666686	0.2900979

Table 1: Comparison of statistically significant models

tend to solve any tasks more responsively, read the context carefully and need more time to decide about the meaning of the emoji. Neurotic people being anxious and impulsive, might make their decisions in a less analytic and more emotional and spontaneous way. What is more, trying to minimize the effect of culture on the results, I recruited participants from the same country of origin. However, having that context as an important interaction variable might mean that, first, the semantic wrapping is important in interpreting emoji, but also that people from same countries have similar information resources and patterns of communication. Therefore, one of the contexts might be more intuitive and familiar to them.

The study has several limitations. First, my sample was biased towards females, and since the related work has found that gender can influence the interpretation of the emojis (Chen et al., 2018; Herring and Dainas, 2020; Koch et al., 2022), the analysis might benefit from a more balanced data. Moreover, I did not restrict the users to use the same operational systems, and even though I controlled the renderings of emojis on the experimental platform, people who usually use different operating systems and use different renderings might have some confusion seeing the appearance of emojis to which they are not used to. Finally, to deal with the sequence effects, I showed the emojis randomly, and due to the limitations of the PsyToolkit platform, I was not able to make a Latin Square Counterbalancing remembering the order of emoji for each of the participants. It would be nice to see whether some possibly confusing emoji affect the reaction time needed to decide about the following one.

In this research, I concentrated only on participants' reaction times. Future work might benefit from adding their answers about whether they found the emoji suitable or not. What is more, only by-subject analysis is performed in this study. I performed an exploratory analysis by-item and found noticeably high average reaction times for the following emojis 🤲, 🤭, 😳. Future work will include by-item analysis and explore the difference in reaction times between people with different personalities for each of the emojis, fitting a separate regression model for all of them.

Considering implications, nowadays, smartphones and laptops have become an integral part of our lives, and interactive computer systems are becoming more adaptive, tracking our behaviour and modelling search results based on it, suggesting words and stickers. With a knowledge of how people with different personality traits interpret emojis in different systems and applications can improve the user experience. For example, it is possible to communicate ambiguity by using ambiguous emojis in correspondence between people with different personality profiles, thereby reducing miscommunication. For instance, highlighting emojis, which other person tend to use with different contexts, or suggesting alternative less ambiguous emojis. What is more, the user's personality can be taken to account in the automatic reply systems and chatbots.

6 Conclusion

Because of the spread of text communication methods, emojis became popular, and serve as a kind of replacement for non-verbal emotional cues. This should make the text less ambiguous and eliminate miscommunication. However, different people may interpret emojis in different ways. Few studies explored the relationship between personality and how people perceive emojis. However, most of the existing research concentrates on emojis out of context, while they are usually used as an addition to text. In this paper, I tried to address this gap and investigated how users with different personality traits perceive emoji ambiguity in context. I found that conscientiousness increases the time it takes a person to resolve an emoji ambiguity. On the contrary, people with a high level of neuroticism make decisions about the interpretation of emojis faster. The context turned out to be a significant interaction effect. Thus, it can be concluded that personality traits have a relationship with how users perceive and interpret emojis. These findings can be used in the design of responsive, interactive systems, make their use more personalized and reduce miscommunication in text messaging.

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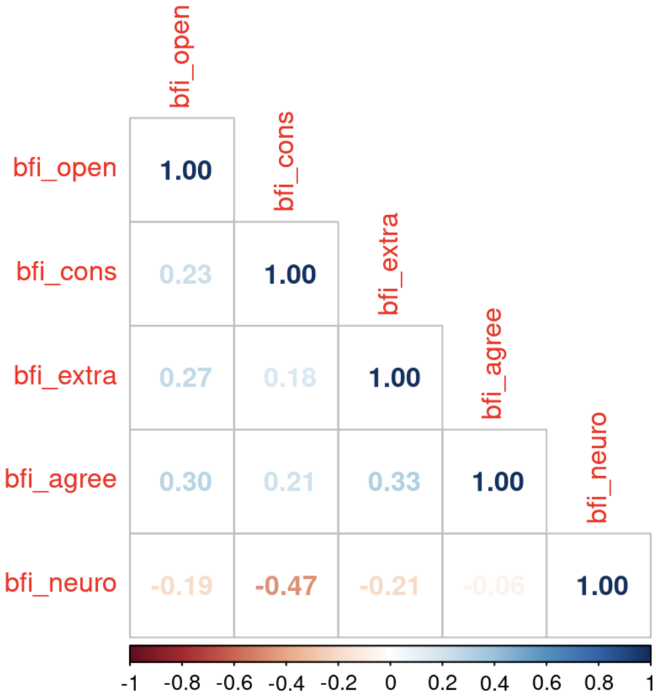
A Appendix

A.1 Appendix 1: Final set of emoji with context

Context 1	Context 2
Please get well soon 🙏	We won this round 🙏
Huge discounts on friday 😱	Couldn’t sleep after the movie 😱
Cant even think about exam 😬	I spilled coffee near professor 😬
Let’s pretend we didn’t see it 🙈	She gave me such a nice gift 🙈
This kitten is so cute 🥺	That’s such sad news 🥺
Some sharks live to 500 years 😳	Sent her a selfie instead of docs 😳
They have no tickets left 🤷‍♂️	No idea what gift to buy 🤷‍♂️
I’m tired and ready for bed 🥱	Falling asleep in class 🥱
I am really exhausted 😪	Kitten is back at the shelter 😪
Dont know what do you mean 👀	Look at that woman over there 👀
I don’t know as I was not there 👐	I miss and can’t wait to see you 👐
I heard about your exam! 👏	Everything is closed again 👏
His arrogance must be stopped 👊	You did a very brave thing 👊
Nice to meet you ✋	Very good thought ✋
I dont care actually 💁‍♀️	That’s what it means 💁‍♀️
Its extremely hot today 😩	I am so tired of all this work 😩
So tired of my allergies 🤧	I’ve just watched Hatiko 🤧
I cannot believe it is true 😵	Looks like I drank too much 😵
Thats mind-blowing 💥	What a great news 💥
I finally received my degree 😎	What a good weather today 😎
No idea on what do you mean 🙄	Need some help to carry the sofa 🙄
She yelled at her husband 🤭	This dirt is disgusting 🤭

A.2 Appendix 2: Correlation plot for BFI scores



A.3 Appendix 3: Regression models' outputs

Conscientiousness and context

	Model 1
(Intercept)	7.99^{***}
	(0.18)
bfi_cons	0.01^{**}
	(0.00)
group2	0.78^{**}
	(0.26)
bfi_cons:group2	-0.01^{**}
	(0.01)
R^2	0.08
Adj. R^2	0.06
Num. obs.	139

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 2: Conscientiousness and context

Neuroticism and context

	Model 1
(Intercept)	8.89^{***}
	(0.15)
bfi_neuro	-0.01^{**}
	(0.00)
group2	-0.36
	(0.22)
bfi_neuro:group2	0.01^{*}
	(0.00)
R^2	0.08
Adj. R^2	0.06
Num. obs.	139

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 3: Neuroticism and context

Extraversion and context

	Model 1
(Intercept)	8.48^{***}
	(0.15)
bfi_extra	0.00
	(0.00)
group2	0.25
	(0.22)
bfi_extra:group2	-0.00
	(0.00)
R^2	0.03
Adj. R^2	0.00
Num. obs.	139

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4: Extraversion and context

Agreeableness and context

	Model 1
(Intercept)	8.57^{***}
	(0.28)
bfi_agree	-0.00
	(0.01)
group2	0.21
	(0.39)
bfi_agree:group2	-0.00
	(0.01)
R^2	0.03
Adj. R^2	0.00
Num. obs.	139

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 5: Agreeableness and context

Openness and context

	Model 1
(Intercept)	8.45^{***}
	(0.26)
bfi_open	0.00
	(0.00)
group2	-0.19
	(0.39)
bfi_open:group2	0.01
	(0.01)
R^2	0.03
Adj. R^2	0.01
Num. obs.	139

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 6: Statistical models

All BFI traits scores and context

	Model 1
(Intercept)	8.73^{***}
	(0.41)
bfi_open	0.00
	(0.01)
bfi_cons	0.01
	(0.00)
bfi_neuro	-0.01
	(0.00)
bfi_agree	-0.01
	(0.01)
bfi_extra	-0.00
	(0.00)
group2	-0.12
	(0.63)
bfi_open:group2	0.01
	(0.01)
bfi_cons:group2	-0.01^{*}
	(0.01)
bfi_neuro:group2	0.01
	(0.01)
bfi_agree:group2	0.00
	(0.01)
R^2	0.14
Adj. R^2	0.07
Num. obs.	139

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 7: All BFI traits scores and context