An Exploratory Study of Reactions to Bot Comments on GitHub

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ABSTRACT

The widespread use of bots to support software development makes social coding platforms such as GitHub a particularly rich source of data for the study of human-bot interaction. Software development bots are used to automate repetitive tasks, interacting with their human counterparts via comments posted on the various discussion interfaces available on such platforms. One type of interaction supported by GitHub involves reacting to comments using predefined emoji. To investigate how users react to bot comments, we conducted an observational study comprising 54 million GitHub comments, with a particular focus on comments that elicited the laugh reaction. The results from our analysis suggest that some reaction types are not equally distributed across human and bot comments and that a bot's design and purpose influence the types of reactions it receives. Furthermore, while the laugh reaction is not exclusively used to express laughter, it can be used to convey humor when a bot behaves unexpectedly. These insights could inform the way bots are designed and help developers equip them with the ability to recognize and recover from unanticipated situations. In turn, bots could better support the communication, collaboration, and productivity of teams using social coding platforms.

KEYWORDS

bots, humor, laugh, emoji, reactions, social coding platforms, GitHub

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1 INTRODUCTION

The popularity of social coding platforms for software development has been steadily rising over the last decade. These platforms support several tasks related to the software development process, such as flagging issues, proposing changes to address those issues, and reviewing the proposed changes. For some tasks, users can interact using discussion threads, which are associated with a given issue or proposed change. Bots that support developers with these tasks have become popular and their participation in discussions is increasingly commonplace [30]. Those bots—also referred to as chatbots—interact using natural language via comments. Users can then respond to these comments and—in some platforms (e.g., GitHub)—react to them using predefined emoji (see Fig. 1).

Although researchers have separately studied the use of bots on GitHub [30, 33] and the role of reactions in discussion threads [4, 26], only a few studies have addressed how users interact with bots via the reaction interface, and these have focused on specific bots [5] or on providing general design principles [15]. Furthermore—to the best of our knowledge—no study has investigated how users interact with bot comments using the `laugh` reaction. As humor has been proposed to make interactions with chatbots more enjoyable [7, 13] (including in task-oriented settings [18, 22]) and as a way for chatbots to recover from errors [21], a better understanding of what makes GitHub users "laugh" at (or with) bots could help improve chatbot user experiences on social coding platforms.

To address this gap, we conducted an exploratory observational study that examined user reactions to comments on GitHub. We retrieved over 54 million comments made on issue threads throughout 2020 and guided our analysis by focusing on three aspects. First, we looked at the overall differences between how users react to human comments versus how they react to bot comments. Second, we selected ten popular bots and investigated how different bots elicit different reactions from users. For these two aspects, we first considered all reactions and then focused on the `laugh` reaction. A third aspect consisted of a qualitative analysis of randomly selected bot comments with `laugh` reactions and was aimed at understanding the individual characteristics of those comments. The results from our study could help inform the design of task-oriented bots that can better interpret how users react to their comments, detect whether these comments have unintentionally elicited humor, and possibly harness this humor to recover from such situations.

Name	+1	-1	laugh	confused	heart	hooray	rocket	eyes
Emoji	👍	👎	😄	😕	❤️	🎉	🚀	👀

Figure 1: There are eight emoji reactions available on GitHub.

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2 BACKGROUND AND MOTIVATION

One of the motivations behind the widespread adoption of bots on GitHub is the support that these bots provide with respect to repetitive tasks [30]. Multiple studies have found that the adoption of bots reduces manual labor, enhances code quality, and increases productivity [1, 24, 31, 32]. Although these bots are principally designed for supporting development tasks, they are nonetheless interactive, communicating with human users via the various discussion interfaces available on GitHub. These bots can be therefore studied using the Computers Are Social Actors (CASA) framework, which posits that user interactions with computers are fundamentally social in nature [20] and that many social conventions that guide interpersonal behavior are also evident in human-computer interaction (HCI) [19]. One such convention is the use of humor.

Early attempts to develop chatbots that explicitly incorporated humor were started by Loehr [16], who developed a system that used natural language and could embed puns in conversations. Morkes et al. [18] introduced humor through a conversational agent during a task-oriented interaction and found that the presence of humor enhanced the agent's likability in the eyes of human participants. More recently, research has addressed how chatbots harness human traits like humor on social media platforms such as Facebook [13, 25] and Twitter [11], while a survey of humor in HCI highlighted its role in improving user experience [23]. Humor can therefore shape a significant part of a bot's personality, improving its interactions with users. To guide our study of the humor that could possibly arise in bot comments on GitHub, we frame our qualitative analysis using incongruity theories of humor. These theories claim that "humor arises from the perception of an incongruity between a set of expectations and what is actually perceived" [3] and have been applied in computational humor to recognize humorous intent [27], proposed for the study of human-chatbot interaction [17], and used to equip task-oriented chatbots with humor [8].

3 METHODOLOGY

We build on our review of the literature to motivate the design of an observational study to address the three aforementioned aspects.

3.1 Data Acquisition

Our study used data acquired between February and May 2021 from the 2020 GitHub event timeline, which we extracted using GH Archive [10]. We focused on comments made on issues, extracting events of type `IssueCommentEvent`. This provided us with 54,394,463 events. To retrieve the reactions to these events, we used GitHub's REST API. This yielded 3,476,282 comments with at least one reaction and a total of 5,427,039 reactions. Note that some comments were unavailable at the time of access via the API, possibly due to deletion. We then used GitHub users' `type` attribute to partition these comments into those that were made by a human (3,457,495) and those that were made by a bot (18,787).

3.2 Data Analysis

To analyze our dataset, we followed a mixed methods approach. We used descriptive statistics across all three aspects of our analysis. Specifically, we report counts as well as sample means ($\bar{x}$), medians ($\tilde{x}$), and standard deviations (s). We also used sentiment analysis and inferential statistics to probe whether bot comments that elicited a `laugh` reaction were different from their counterparts made by humans. For our sentiment analysis, we first filtered the comments to include only those in English and exclude those longer than or equal to 50,000 characters and shorter than or equal to 50 characters. We then applied VADER [12], which assigned a sentiment score ranging from -1 to $+1$ to each comment, and SentiCR [2], which classified comments as either *non-negative* or *negative*. We report the results of both methods. Finally, we manually inspected the issue discussion threads for 100 randomly-selected bot comments with `laugh` reactions, performing a qualitative analysis consisting of the following questions: (i) *Was the reason for the* `laugh` *reaction evident?* (ii) *Was the explanation for the* `laugh` *reaction dependent on the comment's context or was it standalone (i.e., only dependent on the comment itself)?* (iii) *Was the* `laugh` *reaction explicitly sought by the bot comment (i.e., directed at eliciting the* `laugh` *reaction)?* (iv) *Was the* `laugh` *reaction caused by an incongruity (i.e., an inconsistency between what users might expect from the comment and what was actually presented in it)?* To identify common themes across the different issue discussion threads, we coded each comment, following a strategy similar to paragraph-by-paragraph coding [29], and proposed an explanation for the presence of the `laugh` reaction.

4 RESULTS

We report our results with respect to the three aspects of our study.

4.1 Human versus Bot

Bot comments with at least one reaction were made by 311 distinct bots over 16,370 issues in 6057 repositories. Human comments with at least one reaction were made by 691,361 distinct users, over 2,221,510 issues in 322,390 repositories.

4.1.1 All Reactions. We identified 5,397,646 reactions (from 955,515 unique users) to comments made by humans and 29,393 reactions (from 14,264 unique users) to comments made by bots. These reactions were distributed over 3,457,495 human comments and 18,787 bot comments, from a total of 38,744,040 human and 10,322,745 bot comments that were available at the time of access. This means that 8.92% of human comments elicited reactions, while only 0.182% of bot comments elicited reactions.

The proportion of the total number of reactions by reaction type for both comments by human and bot users is shown in Fig. 2. Most reactions have approximately the same proportion for both types of users. However, while for humans 71.6% of reactions were a `+1`, `+1` only accounted for 48.1% of reactions to bot comments. On the other end of the spectrum, the proportion of the `-1` reaction was higher for bots (14.5%) than for humans (2.19%).

4.1.2 Laugh Reaction. A total of 125,442 comments made by humans included a `laugh` reaction, while 1073 bot comments included a `laugh` reaction. Of these comments, 83,406 human and 974 bot comments were included in our sentiment analysis. Using VADER, human comments received a mean score of $\bar{x} = 0.291$ ($\tilde{x} = 0.368, s = 0.470$), while bot comments received a mean score of $\bar{x} = 0.290$ ($\tilde{x} = 0.250, s = 0.433$). As the distributions of sentiment scores were nonparametric, we performed a Mann-Whitney

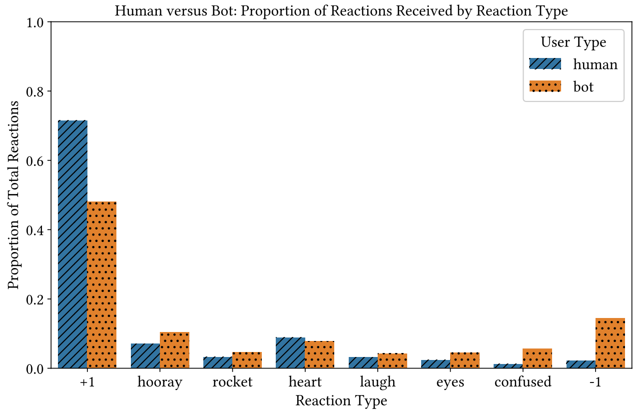

Figure 2: Proportion of reactions received—by reaction type—for both human and bot comments.

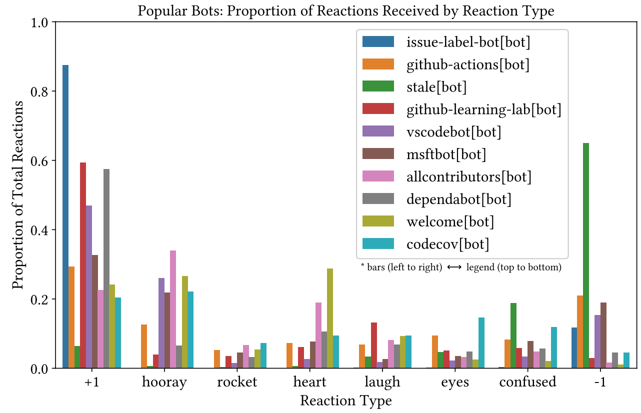

Figure 3: Proportion of reactions received—by reaction type—for a selection of popular bots.

U test to probe for differences between the scores of human and bot comments, observing no significant differences between them ($U = 40047367.0, p = 0.224$). Using SentiCR, 83.4% (69,596) of human comments were classified as *non-negative* while 16.6% (13,810) were classified as *negative*. For bot comments, 89.6% (873) were classified as *non-negative* while 10.4% (101) were classified as *negative*.

4.2 Popular Bots

We selected 10 bots for further analysis based on the number of unique users that reacted to comments posted (see Table 1).

4.2.1 All Reactions. The proportion of the total number of reactions by reaction type for our selection of popular bots is shown in Fig. 3. For certain reaction types, a few bots stand out. A total of 65.0% of reactions to comments by `stale[bot]`, for example, are a `-1`, while the group mean is $\bar{x} = 14.7\%$ ($\tilde{x} = 13.2\%, s = 18.2\%$). This is also the case for the `heart` reaction ($\bar{x} = 9.23\%, \tilde{x} = 8.03\%, s = 8.35\%$), which is more prominent on comments by `welcome[bot]` (28.8%) and `allcontributors[bot]` (19.0%). For the `+1` reaction—which has a wide distribution of proportions ($\bar{x} = 38.7\%, \tilde{x} = 31.0\%, s = 22.8\%$)—`issue-label-bot[bot]` stands out, with `+1` representing 87.5% of reactions to its comments. Other reaction types, such as `rocket` ($\bar{x} = 3.77\%, \tilde{x} = 3.62\%, s = 2.38\%$), have narrower distributions.

4.2.2 Laugh Reaction. For the `laugh` reaction, the distribution among these bots had a mean of $\bar{x} = 6.17\%$ ($\tilde{x} = 6.50\%, s = 3.86\%$). The bot with the highest proportion of `laugh` reactions was `github-learning-lab[bot]` (13.2%), while the bot with the most `laugh` reactions was `github-actions[bot]`, with a total of 398 reactions over 315 comments. Finally, the bot with the highest average `laugh` reactions per comment (including only comments with `laugh` reactions) was `vscodebot[bot]` ($\bar{x} = 2.33, \tilde{x} = 2, s = 1.66, N = 9$).

4.3 Qualitative Analysis

The comments selected for our qualitative analysis were made by 26 different bots. For 91 of the 100 comments in the sample, the presence of the `laugh` reaction was evident after going through the issue discussion thread, while for the other 9, this was not the case. For 41 comments, the explanation for the `laugh` reaction depended on the context, while 57 were standalone and for 2, this was unclear. Only 2 comments explicitly sought the `laugh` reaction. Of these 2, one was a joke and the other contained a funny image. Finally, for 29 comments, the `laugh` reaction could have been caused by an incongruity, while for 61 comments this was not apparently the case, and for 10 comments, this was unclear. Fig. 4 depicts an example of such incongruity.

The most prominent themes were *tutorial* (32 comments), *report* (16 comments), and *closing issue* (16 comments). The *tutorial* theme was only present in comments by `github-learning-lab[bot]`, while *report* was present in comments by 10 different bots, and *closing issue* in comments by 4 different bots. Of these three themes, *tutorial* comments were mostly not incongruent (Yes = 1, No = 31, Maybe = 1), while incongruity appeared more in *report* (Yes = 10, No = 5, Maybe = 1) and *closing issue* comments (Yes = 8, No = 3, Maybe = 5). Finally, some noteworthy explanations for the presence of a `laugh` reaction due to incongruity included the following: (i) reaction to a bot closing an issue that had recently been reported

Figure 4: Example of the `laugh` reaction to a bot comment being caused by an incongruity. While the issue depicted is clearly spam, `vscodebot[bot]` suggests that it could be a duplicate of something completely unrelated.

Table 1: GitHub Bots that Received Reactions from the Highest Number of Distinct Users

Bot	Description	Distinct Users
`issue-label-bot[bot]`	Automatically labels issues as either a feature request, bug, or question.	3564
`github-actions[bot]`	Performs automated workflows supported by GitHub actions.	2138
`stale[bot]`	Closes abandoned issues after a period of inactivity.	1789
`github-learning-lab[bot]`	Helps users learn how to use GitHub.	1595
`vscodebot[bot]`	Bot used by the VSCode repository.	966
`msftbot[bot]`	Microsoft's GitHub bot.	454
`allcontributors[bot]`	Automatically adds contributor acknowledgments.	415
`welcome[bot]`	Welcomes new users to a repository.	388
`dependabot[bot]`	Detects and updates vulnerable dependencies.	388
`codecov[bot]`	Provides coverage reports and helps with the code review workflow.	302

as still present, (ii) reaction to a bot thanking another bot for its contribution, and (iii) reaction from a user to being welcomed by a bot that the user himself created.

5 DISCUSSION

Overall, our results show that while a far smaller percentage of bot comments receive reactions when compared to human comments, the proportions of the types of reactions received are mostly similar across both groups. One notable exception is the proportion of `-1` reactions. The fact that bots receive more `-1` reactions than humans could be attributed to users being more willing to give negative feedback to bots and to the fact that some bots perform tasks that are regarded as friction points in the software development process (e.g., closing an issue, requesting a review) [14]. For `stale[bot]`, for example, its role in closing issues results in it getting a disproportionate share of `-1` reactions. On the other hand, bots that perform tasks that are regarded as positive, such as `welcome[bot]` and `allcontributors[bot]`, naturally get a higher proportion of `heart` reactions than the average. Receiving an unusually high (or low) proportion of a given type of reaction can also be due to the design of the bot. A closer inspection of `issue-label-bot[bot]`'s comments, for instance, shows that it explicitly asks for a `-1` or `+1` to refine the way it labels issues, as was noted by Liu et al. [15].

Focusing on results for the `laugh` reaction specifically, we observe that there are no significant differences between how this reaction is used to react to human versus bot comments. Similarly, none of the bots in our selection stood out in terms of the proportion of `laugh` reactions received. Although the proportion of `laugh` reactions to `github-learning-lab[bot]` was the highest across the selection, our qualitative analysis showed that most of these reactions were not due to any type of humor being evoked by the bot. In fact, the `laugh` reaction seems to be used not only to express laughter—or as a reaction to an interaction that could be considered humorous—but also to show that a user is pleased. This could be due to the choice of emoji used to represent the `laugh` reaction on GitHub, which is described as *Grinning Face with Smiling Eyes* in Unicode's Common Locale Data Repository [28], and might not be explicitly associated with humor. Indeed, Borges et al. describe the `laugh` reaction as being used to express a "fun situation *or* [emphasis added] happiness" [4]. Nevertheless, our qualitative results also show that the `laugh` reaction *can* be used to express humor. In these cases, humor is usually not explicitly sought. Instead, it arises from an incongruity, most commonly related to an unexpected report or a bot trying to close an issue. These findings are once more aligned with work by Borges et al., who also noted that `laugh` can be used to "express sarcasm or irony in negative situations" [4]. In these cases, the presence of the unanticipated `laugh` reaction could serve as a signal that the bot's behavior was not aligned with user expectations. Bots could then follow `issue-label-bot[bot]`'s strategy and refine their behavior accordingly, potentially even harnessing the underlying humor to recover from such situations.

This study also has some limitations worth discussing. First, we do not take into account bot users that are not labeled as bots. To address this, we could incorporate methods proposed for identifying bots into our data acquisition pipeline [6, 9]. Second, our dataset consists only of comments made on issue threads, even though bots also comment on pull requests [33]. Including those comments would broaden the scope of our analysis. Third, some bots follow predefined behaviors that bias the reactions they receive. These behaviors should be taken into consideration to avoid arriving at misleading conclusions. Finally, our qualitative analysis only included a sample of 100 bot comments. Annotating a larger sample would provide a more solid base for our findings.

6 CONCLUSION

In this paper, we presented results from an observational study analyzing how users react to comments on GitHub. Our findings suggest that while some reaction types are used differently when reacting to human versus bot comments or across comments made by different bots, this is not the case for the `laugh` reaction. Furthermore, while the `laugh` reaction is not exclusively used to express humor, it *can* be used to express humor arising from an incongruity when a bot behaves unexpectedly. These insights could inform the design of bots that can take into account how users react to their comments in order to align their behavior with user expectations. While this study explicitly considered the `laugh` reaction, extensions to other reactions can be envisioned. Our aim is to build on this study to explore this line of research and address the aforementioned limitations in future work.

REFERENCES

[1] Ahmad Abdellatif, Khaled Badran, and Emad Shihab. 2020. MSRBot: Using Bots to Answer Questions from Software Repositories. *Empirical Software Engineering* 25, 3 (2020), 1834–1863. https://doi.org/10.1007/s10664-019-09788-5

[2] Toufique Ahmed, Amiangshu Bosu, Anindya Iqbal, and Shahram Rahimi. 2017. SentiCR: A Customized Sentiment Analysis Tool for Code Review Interactions. In *2017 32nd IEEE/ACM International Conference on Automated Software Engineering (ASE)* (Urbana, IL, USA). IEEE, New York, NY, USA, 106–111. https://doi.org/10.1109/ASE.2017.8115623

[3] Salvatore Attardo. 2008. A Primer for the Linguistics of Humor. In *The Primer of Humor Research*, Victor Raskin (Ed.). Mouton de Gruyter, Berlin, Germany, 101–155.

[4] Hudson Borges, Rodrigo Brito, and Marco Tulio Valente. 2019. Beyond Textual Issues: Understanding the Usage and Impact of GitHub Reactions. In *Proceedings of the XXXIII Brazilian Symposium on Software Engineering* (Salvador, Brazil). ACM, New York, NY, USA, 397–406. https://doi.org/10.1145/3350768.3350788

[5] Chris Brown and Chris Parnin. 2019. Sorry to Bother You: Designing Bots for Effective Recommendations. In *2019 IEEE/ACM 1st International Workshop on Bots in Software Engineering (BotSE)* (Montreal, QC, Canada). IEEE, New York, NY, USA, 54–58. https://doi.org/10.1109/BotSE.2019.00021

[6] Tapajit Dey, Sara Mousavi, Eduardo Ponce, Tanner Fry, Bogdan Vasilescu, Anna Filippova, and Audris Mockus. 2020. Detecting and Characterizing Bots That Commit Code. In *Proceedings of the 17th International Conference on Mining Software Repositories* (Seoul, Republic of Korea). ACM, New York, NY, USA, 209–219. https://doi.org/10.1145/3379597.3387478

[7] Pawel Dybala, Michal Ptaszynski, Rafal Rzepka, and Kenji Araki. 2009. Humoroids: Conversational Agents that Induce Positive Emotions with Humor. In *Proceedings of the 8th International Conference on Autonomous Agents and Multiagent Systems* (Budapest, Hungary) *(AAMAS '09, Vol. 2)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, USA, 1171–1172.

[8] Juan Carlos Farah, Vandit Sharma, Sandy Ingram, and Denis Gillet. 2021. Conveying the Perception of Humor Arising from Ambiguous Grammatical Constructs in Human-Chatbot Interaction. In *Proceedings of the 9th International Conference on Human-Agent Interaction (HAI '21)* (Virtual Event, Japan). ACM, New York, NY, USA, 257–262. https://doi.org/10.1145/3472307.3484677

[9] Mehdi Golzadeh, Damien Legay, Alexandre Decan, and Tom Mens. 2020. Bot or Not? Detecting Bots in GitHub Pull Request Activity Based on Comment Similarity. In *Proceedings of the IEEE/ACM 42nd International Conference on Software Engineering Workshops* (Seoul, Republic of Korea). ACM, New York, NY, USA, 31–35. https://doi.org/10.1145/3387940.3391503

[10] Ilya Grigorik. 2012. *GH Archive*. GH Archive. gharchive.org

[11] Christian Grimme, Mike Preuss, Lena Adam, and Heike Trautmann. 2017. Social Bots: Human-Like by Means of Human Control? *Big Data* 5, 4 (2017), 279–293. https://doi.org/10.1089/big.2017.0044

[12] C J Hutto and Eric Gilbert. 2014. VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. In *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media* (Ann Arbor, MI, USA). AAAI, Palo Alto, CA, USA, 216–225.

[13] Mohit Jain, Pratyush Kumar, Ramachandra Kota, and Shwetak N Patel. 2018. Evaluating and Informing the Design of Chatbots. In *Proceedings of the 2018 Designing Interactive Systems Conference* (Hong Kong, China). ACM, New York, NY, USA, 895–906. https://doi.org/10.1145/3196709.3196735

[14] Carlene Lebeuf, Margaret-Anne Storey, and Alexey Zagalsky. 2017. How Software Developers Mitigate Collaboration Friction with Chatbots. In *Procedings of the Talking with Conversational Agents in Collaborative Action Workshop at the 20th ACM Conference on Computer-Supported Cooperative Work and Social Computing (CSCW '17)*. ACM, New York, NY, USA, 6 pages. arXiv:1702.07011

[15] Dongyu Liu, Micah J Smith, and Kalyan Veeramachaneni. 2020. Understanding User-Bot Interactions for Small-Scale Automation in Open-Source Development. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA). ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3334480.3382998

[16] Dan Loehr. 1996. An Integration of a Pun Generator with a Natural Language Robot. In *Proceedings of the International Workshop on Computational Humor* (Enschede, The Netherlands), Jan Hendrik Hulstijn and Anton Nijholt (Eds.). University of Twente, Enschede, The Netherlands, 161–172.

[17] Michael M Meany and Tom Clark. 2010. Humour Theory and Conversational Agents: An Application in the Development of Computer-Based Agents. *International Journal of the Humanities* 8, 5 (2010), 129–140.

[18] John Morkes, Hadyn K Kernal, and Clifford Nass. 1999. Effects of Humor in Task-Oriented Human-Computer Interaction and Computer-Mediated Communication: A Direct Test of SRCT Theory. *Human-Computer Interaction* 14, 4 (1999), 395–435. https://doi.org/10.1207/S15327051HCI1404_2

[19] Clifford Nass, Youngme Moon, and Nancy Green. 1997. Are Machines Gender Neutral? Gender-Stereotypic Responses to Computers with Voices. *Journal of Applied Social Psychology* 27, 10 (1997), 864–876.

[20] Clifford Nass, Jonathan Steuer, and Ellen R Tauber. 1994. Computers Are Social Actors. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems Celebrating Interdependence - CHI '94* (Boston, MA, USA). ACM, New York, NY, USA, 72–78. https://doi.org/10.1145/191666.191703

[21] Andreea I Niculescu and Rafael E Banchs. 2015. Strategies to Cope with Errors in Human-Machine Spoken Interactions: Using Chatbots as Back-Off Mechanism for Task-Oriented Dialogues. In *Proceedings of the Errors by Humans and Machines in Multimedia, Multimodal and Multilingual Data Processing Workshop (ERRARE 2015)* (Sinaia, Romania). Romanian Academy, Bucharest, Romania, 6 pages.

[22] Andreea I Niculescu, Betsy van Dijk, Anton Nijholt, Haizhou Li, and Swee Lan See. 2013. Making Social Robots More Attractive: The Effects of Voice Pitch, Humor and Empathy. *International Journal of Social Robotics* 5, 2 (2013), 171–191. https://doi.org/10.1007/s12369-012-0171-x

[23] Anton Nijholt, Andreea I Niculescu, Alessandro Valitutti, and Rafael E Banchs. 2017. Humor in Human-Computer Interaction: A Short Survey. In *Adjunct Proceedings of the 16th IFIP TC 13 International Conference on Human Computer Interaction (INTERACT)* (Mumbai, India). Indian Institute of Technology Bombay, Mumbai, India, 192–214.

[24] Zhenhui Peng and Xiaojuan Ma. 2019. Exploring How Software Developers Work with Mention Bot in GitHub. *CCF Transactions on Pervasive Computing and Interaction* 1, 3 (2019), 190–203. https://doi.org/10.1007/s42486-019-00013-2

[25] Scott Schanke, Gordon Burtch, and Gautam Ray. 2021. Estimating the Impact of 'Humanizing' Customer Service Chatbots. *Information Systems Research* 32, 3 (2021), 736–751. https://doi.org/10.1287/isre.2021.1015

[26] Teyon Son, Tao Xiao, Dong Wang, Raula Gaikovina Kula, Takashi Ishio, and Kenichi Matsumoto. 2021. *More Than React: Investigating The Role of EmojiReaction in GitHub Pull Requests.* Technical Report. Nara Institute of Science and Technology. arXiv:2108.08094 http://arxiv.org/abs/2108.08094

[27] Julia Taylor and Lawrence Mazlack. 2005. Toward Computational Recognition of Humorous Intent. In *Proceedings of the 27th Annual Conference of the Cognitive Science Society* (Stresa, Italy), Bruno G Bara, Lawrence Barsalou, and Monica Bucciarelli (Eds.). Lawrence Erlbaum Associates, Inc., Mahwah, NJ, USA, 2166–2171.

[28] Unicode. 2021. *Unicode CLDR Project*. Unicode. cldr.unicode.org/

[29] Cathy Urquhart. 2012. *Grounded Theory for Qualitative Research: A Practical Guide*. Sage, London, UK.

[30] Mairieli Wessel, Bruno Mendes de Souza, Igor Steinmacher, Igor S Wiese, Ivanilton Polato, Ana Paula Chaves, and Marco A Gerosa. 2018. The Power of Bots: Characterizing and Understanding Bots in OSS Projects. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 19 pages. Issue CSCW. https://doi.org/10.1145/3274451

[31] Mairieli Wessel, Alexander Serebrenik, Igor Wiese, Igor Steinmacher, and Marco A Gerosa. 2020. Effects of Adopting Code Review Bots on Pull Requests to OSS Projects. In *Proceedings of the 2020 IEEE International Conference on Software Maintenance and Evolution (ICSME)* (Adelaide, Australia). IEEE, New York, NY, USA, 11 pages. https://doi.org/10.1109/ICSME46990.2020.00011

[32] Mairieli Wessel, Alexander Serebrenik, Igor Wiese, Igor Steinmacher, and Marco A Gerosa. 2020. What to Expect from Code Review Bots on GitHub?: A Survey with OSS Maintainers. In *Proceedings of the 34th Brazilian Symposium on Software Engineering* (Natal, Brazil). ACM, New York, NY, USA, 457–462. https://doi.org/10.1145/3422392.3422459

[33] Marvin Wyrich, Raoul Ghit, Tobias Haller, and Christian Müller. 2021. Bots Don't Mind Waiting, Do They? Comparing the Interaction With Automatically and Manually Created Pull Requests. In *Proceedings of the 2021 IEEE/ACM Third International Workshop on Bots in Software Engineering (BotSE)*. IEEE, New York, NY, USA, 6–10. arXiv:2103.03591 http://arxiv.org/abs/2103.03591