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How Emoji and Explanations Influence Adherence to AI Recommendations

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ABSTRACT

Emoji have become an essential part of modern communication, helping to convey emotions and tone quickly and concisely. Emoji used by humans and Intelligent Agents (IA) have been shown to affect people's decision making intentions, suggesting they could be used to manipulate users to follow their advice. We present a mixed-methods crowdsourcing study (N = 194) that shows that adherence to an IA's recommendation and user experience are not affected by emoji when used in a positive, collaborative way. However, we demonstrate that explanations provided by an IA do increase adherence to its recommendation.

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1 INTRODUCTION

Emoticons and emoji are non-verbal information exchange forms that have become increasingly popular in modern communication methods such as text messages, emails, and social media. Originating in the 19th century and digitalized in 1982 by Scott Fahlman, Emoticons, short for "emotion icons," are a group of characters that use punctuation marks and letters to convey a facial expression or emotion [1, 5, 29], while emoji are small graphic images that represent an emotion, concept, or object. Both are used to add non-verbal cues to written communication and can help communicate tone, emotion, and semantic meanings [1, 6]. For the sake of brevity, we will use the term emoji as an umbrella term. Considering the growing number of situations in which Intelligent Agents (IAs) advise humans, it is vital to understand how emoji affect human decision making. Existing research on the topic has focused primarily on human-human interaction. Previous studies have shown that the use of emoji by humans can influence the perceptions of messages and intention to make a decision based on the message [8, 17, 18, 20]. We present a user study that explores the impact of emoji and explanations on decisions making.

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2 RELATED WORK

In various sectors, such as customer service, education, and healthcare, IAs are frequently enriched with emoji for more human-like interactions [9, 13]. IAs that use emoji can influence human-AI interactions, though this influence varies across different communication contexts and topics [3, 9, 13].

The presence of emoji in communications can significantly influence the way the receivers perceive the intention behind the messages, and this can ultimately impact and guide people's decision-making processes [8, 17, 18, 20]. Duan et al. [8] delved into the effect of emoticons on decision-making and found that the intention to use advice increases upon including emoticons. The study noticed a stronger impact of emoticons on the decision making processes of participants who displayed a lower need for cognition. A study by McHaney and George [18] evaluated the role of emoticons in detecting deception. Their findings suggested that written messages embedded with emoticons were more likely to be perceived as manipulative or deceptive in contrast to plain text, impacting the trust and decision-making processes of the receivers. Manganari and Dimara [17] examined the relationship between hotel review valence and emoji usage. Their results showed that the appearance of emoji in negative reviews increases the review's perceived authenticity and affects the user's booking intentions. A study exploring emoji use by a virtual agent showed that they could influence factors such as perceived expertise and skin color, negatively affecting a virtual agent's persuasiveness and competence [31]. In summary, using emojis in text communication can profoundly influence the receivers' perception of the messages and indirectly affect their decision making processes.

AI-driven recommender systems offer recommendations using content-based, collaborative filtering, or hybrid methods [2, 24, 27]. The understanding of the rationale behind these recommendations can improve user-system trust, effectiveness, and satisfaction [4, 10, 21, 28, 30, 33]. Recent advancements focus on interactive, conversational explanations [16, 19] and conversational recommender systems (CRS), which engage users interactively and improve recommendation accuracy [12, 14]. The influence of emoji,

with and without accompanying AI explanations, on users' adherence to recommendations is the focus of this study.

3 STUDY

We used a mixed-methods crowdsourcing study to measure the impact of emoji and explanations used by an IA on human decision making. The following research questions inform the design of our experiment.

3.1 Research questions

RQ1 *How do emoji used by an IA affect human decision making?* We think that people will be more likely to follow an IA's advice when IAs use (appropriate) emoji, as previous research has shown that the presence of emoji increases people's intention to use the advice [8, 17]. This could be attributed to a higher engagement [34, 35] and familiarity with the advice-giver that emoji could afford.

RQ2 *How do AI explanations by an emoji-using IA affect human decision making?* We think that AI explanations will increase the likelihood that people will follow the advice of an IA. In recent years, several studies have shown that AI explanations increase the possibility that people will accept AI recommendations [11, 25, 26]. We expect that by explaining, people will feel that recommendations are well supported by evidence. Therefore, we think we will observe similar effects for an emoji-using IA.

RQ3 *How do emoji used by an IA affect user experience?* We think emoji will positively affect the user experience, especially about perspicuity. We believe that the emoji will make the intentions of the IA clearer to the user, thus improving the clarity of its message. There are indications that emoji used by an IA can positively affect user satisfaction [32].

RQ4 *What reasons and underlying factors influence users' decisions to agree or disagree with an IA's recommendation, particularly in the presence of explanations or emoji communication?* We conducted a content analysis to see the underlying influence of participants' decision to adhere to the IA's recommendation.

3.2 Study Design

We conducted a between-subject crowdsourcing study ($N = 194$) using a task-oriented IA in four scenarios. The IA presents a scenario where it needs to provide a recommendation to one of its users (see Appendix A.1). The participant is asked to help the IA choose the best of two options. In addition to indicating their recommendation, the participant is asked to optionally explain their decision (to investigate RQ4).

We include the following four conditions: (1) control; (2) emoji; (3) explanation (XAI); and (4) emoji and XAI. In the emoji conditions (3 and 4), the IA uses emojis in its messages that mimic how a friendly and thoughtful human colleague might use them. Furthermore, the IA explains its recommendation in the conditions with explanations (3 and 4).

To improve ecological validity, we designed tasks that a crowd worker could realistically provide feedback on, namely, making everyday decisions. Furthermore, to improve generalizability, we performed the study across four contexts: machine repair, home energy optimization, vacations, and restaurants (see Appendix A.2). To allow for influence by the independent variables, the scenarios do not have an obviously correct answer. As such, a pre-study was performed without emoji and explanations to confirm that the scenario options were not heavily skewed.

All conditions follow the same template as shown in Appendix A.1, and the order of the scenarios is randomized. The choice of emoji was based on a pre-study in which we presented a dialogue between the IA and a human worker without emoji. We asked participants to indicate which emoji would be appropriate if they wanted to come across as a competent and trustworthy team player. Furthermore, we considered the interpretability of emoji and chose emoji with clear meanings as reported by Cherbonnier and Michinov [5]. To make the study as realistic as possible, we built a fully functional IA using TickTalkTurk [23], a tool developed to implement crowd-sourcing work through a conversational interface.

3.3 Measures

Our study utilized an Embedded Design approach (Creswell and Clark [7]) in which we prioritized the quantitative data as the primary source and supplemented it with a qualitative analysis as a secondary source. The primary dependent variable is whether or not the participant adhered to the IA's recommendation, otherwise referred to as *agreement* (RQ1 and RQ2). Secondly, we measured the user experience (UX) using the User Experience Questionnaire (UEQ) [15] (RQ3). Lastly, we conducted a content analysis of the comments to explore why users adhere to the IA's recommendation (to investigate RQ4).

4 RESULTS

Here, we investigate how our participants' decision making and UX were influenced by the four different combinations of emoji and XAI. To decide on our statistical methods, we first performed all the necessary pre-tests, such as Shapiro-Wilk normality tests and Levene's homogeneity of variance. We omit the pre-tests for the sake of brevity.

4.1 Effects on Decision Making (RQ1 and RQ2)

We use the Kruskal Wallis H-test to compare the level of agreement between the four conditions, *control, XAI, emoji, emoji-XAI.* The level of agreement ranges from 0 to 4, depending on the number of scenarios for which the participants adhered to IA's advice. The test summary revealed a significant effect ($\chi^2(3) = 17.446, p < .001$). More specifically, the following pairs exhibited significant differences: emoji ($M = 2.708, SD = .824$) vs XAI ($M = 3.223, SD = .823, 2(3) = -33.080, p < .05$), emoji vs emoji-xai ($M = 3.271, SD = .707, \chi^2(3) = -35.021, p < .05$) and control ($M = 2.816, SD = .782$) vs emoji-XAI ($\chi^2(3) = -29.451, p < .05$). Conversely, the following pairs did not reveal significant differences: emoji vs control ($\chi^2(3) = 5.570, p = 1.000$), control vs XAI ($\chi^2(3) = -27.510, p = .057$), and XAI vs emoji-XAI ($\chi^2(3) = 1.941, p = 1.000$) (see Figure 1). This finding indicates that **emojis and explanations do not affect adherence to IA advice** when compared to the control condition.

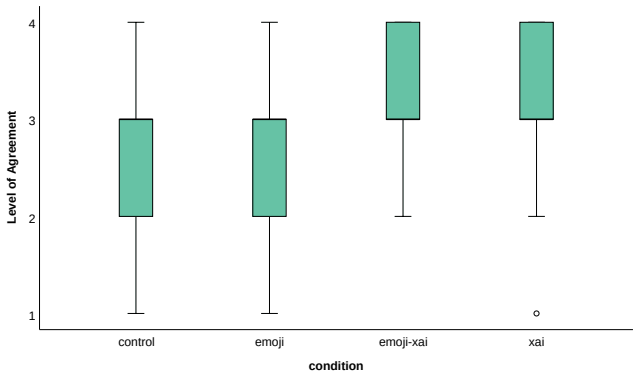

Figure 1: Level of agreement score in all conditions. The explainable AI (XAI)-emoji and XAI conditions have higher agreement scores than the emoji and control (no intervention) conditions.

However, in the presence of emoji, XAI has a significant effect (emoji vs emoji-XAI).

4.2 Effects on User Experience (UX) (RQ3)

A one-way Brown-Forsythe ANOVA with participants' overall UEQ scores as the dependent variable across all scenarios, and condition as the independent variable, displayed no significant main effect ($F(3, 190) = 1.128, p = .339, \eta_p^2 = .018$). These results showcase that IAs explaining, with or without emoji, did not significantly impact UX across all study scenarios compared to the control condition (RQ3).

4.3 Qualitative

To answer RQ4, we explored the explanations that participants were asked to optionally provide for their decision. We identified *seven* themes (T) that could explain the underlying factors that influence participants' decisions, namely T1: Utilizing their common knowledge; T2: Learned from the past experience; T3: Strategically lowest cost; T4: Personal preferences; T5: Cannot make a decision; T6: Needs professional opinion; and T7: Trust the IA's underlying model. We also found that participants' rationale behind their decision varied across different scenarios, leading to some themes not showing in certain scenarios.

5 DISCUSSION

Our findings did not show a significant impact of emoji-using IAs on human decision making or user experience (RQ1 & RQ3). As such, designers of IAs can use emoji without considering the implications on human decision making - at least when used in a positive way that adheres to collaborative practices. Interestingly, this contradicts previous research that showed that emoji affect human's intention to adhere to advice from humans and IAs. Perhaps, this could be explained by the strength of the (negative) emotions conveyed in the scenarios used by previous research, for example, for poor hotel reviews [17]. As such, future work could explore how different emotions conveyed by emotion impact adherence to an IA's recommendation.

Furthermore, **our findings indicate that AI explanations provided by an emoji-using IA increased adherence to the IA's recommendation (RQ2).** This aligns with previous studies showing AI explanations can enhance the acceptance of AI recommendations [11, 25, 26]. Ultimately, designers of IA should be mindful when using explanations as humans are more likely to adhere to its advice. This can be problematic if this results in humans blindly trusting the IA, which may be wrong.

Finally, our content analysis revealed seven key factors that could explain the underlying factors influencing participants' adherence to the IA's recommendations. These factors include being unable to make a decision, needing a professional opinion, and trusting the IA's underlying model. **This indicates that people were more likely to adhere to the IA when they felt less confident in their knowledge (RQ4).** Designers should consider that the effect of explanations might be stronger when humans are less knowledgeable on the topic.

5.1 Ethical Considerations and Limitations

The use of emoji raises ethical considerations, such as the potential for misinterpretation or miscommunication due to cultural and individual differences in understanding and interpretation. Furthermore, there is a potential for misuse, for example, by using emoji to drive people to make more emotional decisions.

The participants did not have to make decisions that affected themselves directly as we simulated several scenarios where an IA provided advice to a user. Therefore, we defined tasks that most people would have a fundamental understanding of and opinion on. As such, the participants would be more likely to be able to identify with the user in the scenarios.

As crowd workers, the participants may not fully engage with the tasks. Therefore, we used attention checks to filter out participants that were not paying attention and kept the study under ten minutes. Furthermore, previous work has shown that using an interactive conversational user interface is more engaging than other forms of crowd work [22].

6 CONCLUSION

Emoji have become essential to communication and help convey emotions and tone quickly and concisely. Although they can positively impact communication, there is also potential for misuse. As AI systems become more prevalent, the scenarios in which people receive advice from AI agents increase. Interestingly, emoji can impact the intention to follow the advice given by humans and Intelligent Agents (IAs). However, our study reveals that by themselves, emoji used to convey positive and collaborative emotions do not substantially affect whether humans adhere to an IA's advice. Conversely, explanations provided by an IA increased adherence.

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A APPENDIX

A.1 Conversation template

(1) Bot: Hi! I'm an intelligent assistant that helps people make decisions related to their home, work, and life 👋.
(2) Bot: I could use some feedback from you to improve the accuracy of my recommendations ☺️.
(3) Bot: I will present five different scenarios and ask you to indicate what you would do.
(4) Bot: Are you on board? 💪
(5) User: [affirm]
(6) *The following section repeats for all five scenarios*
(7) Bot: [Explains the scenario]
(8) Bot: [Explains the available options (A and B)]
(9) Bot: [Provides recommendation and **optionally an explanation**] 🤔
(10) Bot: What do you think I should recommend for the users? 🧐
(11) User: [A or B]
(12) Bot: Thank you. Do you have any additional comments to support your decision? 👍
(13) User: [affirm or deny]
(14) Bot: (*if affirm*) Okay, please provide your comments in one sentence.
(15) User: [User provides feedback]
(16) Bot: Okay, thanks for the information! 🙂
(17) Bot: Alright, next scenario... ➡️

(18) *The following closing message will be displayed after all five scenarios are completed*
(19) Bot: You have completed the task! Now, please click the link below to complete this research 🙂.
(20) Bot: survey

A.2 Scenarios

(1) *Machine repair* A technician is trying to fix a 4-year-old washing machine that is taking longer than normal to run a regular wash cycle. We provide the following options: clean the water inlet filter or run a high-temperature wash with bleach. The assistant recommends running an empty wash with bleach **as the piping will likely have accumulated mold and debris over a few years that can affect the quality of the washing.**
(2) *Home energy optimization* A user has a very high energy bill and wants to reduce their usage without reducing comfort too much. We provide the following options: (A) reduce the target room temperature on their electric heater by 1℃ (1.8°F), or (B) reduce it by 2℃ (3.6°F). I recommend option B **as this will give the most savings.**
(3) *Vacation* The user wants a wintertime vacation recommendation. We have the following two options: option A is a 3-hour flight, is sunny, and has lots of outdoor activities, or option B which is a 1-hour flight, has decent weather, and has lots of cultural activities. We recommend option A **as a sunny destination during winter is highly recommended.**
(4) *Restaurant* Two students want a restaurant recommendation for two. We have the following options: (A) an Italian restaurant, 20 km (12.4 miles) away, and rated 4.8/5 by users, or (B) a Thai restaurant that is 10 km (6.2 miles) away and rated 4.6/5 by users. I recommend option A **as the rating is higher**.