The Effect of Emojis when interacting with Conversational Interface Assisted Health Coaching System

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ABSTRACT

The recent rise of conversational interfaces have made it possible to integrate this technology into various domains, among which is health. Dialogue systems and conversational agents can bring a lot into healthcare to reduce cost, increase efficiency and provide continuing care, albeit its infancy and complexity about building natural dialogues. However, the design guidelines to design dialogues for conversational agents are usually based on common knowledge, and less frequently on empirical evidence. For example, the use of emojis in conversational agent dialogues is still a debated issue, and the added value of adding such graphical elements is mainly anecdotal. In this work, we present an empirical study comparing users feedback when interacting with chatbot applications that use different dialogue styles, i.e., plain text or text with emoji, when asking different health related questions. The analysis found that when participants had to score an interaction with a chatbot that asks personal questions on their mental wellbeing, they rated the interaction with higher scores with respect to enjoyment, attitude and confidence. Differently, participants rated with lower scores a chatbot that uses emojis when asking information on their physical wellbeing compared to a dialogue with plain text. We believe this work can contribute to the research on integrating conversational agents in the health and wellbeing context and can serve as a guidance in the design and development of interfaces for text-based dialogue systems.

CCS CONCEPTS

• **Human-centered computing → Visualization design and evaluation methods**;

KEYWORDS

Conversational agents, health and wellbeing, chatbots, emojis, dialogue systems, information tracking.

1 INTRODUCTION

The renaissance in conversational user interfaces is evident in many domains to help handle tasks, support users and accomplish goals. Personal assistants, known as virtual personal assistants (VPAs), intelligent personal assistants, mobile assistants or voice assistants, have become mainstream. In this paper, we use the term conversational interface to refer to the technology that supports conversational interaction with virtual agents by means of speech, text and other modalities. Examples include, Apple's Siri[1], Google Now[2], Microsoft Cortana[3] and Amazon Alexa[4]. The rise in conversational agents strongly benefited from the advances in computational power and neural network models, specifically deep learning models [8, 22]. That said, users can either text or speak to their conversational agents in a natural way to obtain information, access services or issue commands.

There is a need to cover the user interaction and experience with VPAs. This is crucial to reveal weak interaction points of the virtual assistant and to inform the design of better dialogue systems. With all the approaches used to develop conversational interfaces, including template based [12], pattern matching [23], retrieval-based [16], knowledge-based [1], and using advanced machine learning approaches [24], there remains the point of user experience with the technology. Even if a system is technologically advanced, it will not succeed unless it is accepted and adopted by users. Until recently, evidences showed that users stopped using their virtual personal assistants after an initial stage of experimentation [22]. In some cases, they might encounter issues and barriers in the interaction, such as speech recognition errors, and so reverted to more accustomed and accurate modes of input. Many conversational agents provide specialised functions and are context specific, such as fitness monitoring, health tracking and food recipes planning [4–6]. Adopting a conversational agent per domain requires also picking the conversational style the bot should follow, which could be speech, text, or graphical elements, such as buttons or emojis.

[1]https://www.apple.com/ios/siri/
[2]https://www.google.com/intl/it/landing/now/
[3]https://www.microsoft.com/en-us/windows/cortana
[4]https://developer.amazon.com/alexa

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In this paper, we discuss the effect of communication style of a conversational health coaching system in the context of health and wellness. We particularly focus on the role of emojis in textual conversational agents for physical activity and mental wellness health tracking. For that, we will describe our system and the result of a study with 58 participants. The study consisted of two chatbot versions, one emoji based dialogue and one plain text dialogue to converse with users about their physical activity and mental wellbeing. We hypothesised that using emojis will benefit the most to conversational dialogues where user emotion and empathy are relevant, such as mental wellness. Whereas, it's less relevant to conversation dialogues intended for physical activity data tracking. Regardless, emojis could make the generated replies more anthropomorphic and interesting, which might enhance user experiences with the dialogue systems [13].

2 DIALOG SYSTEMS AND EMOJIS

Recent years have witnessed the widespread usage of emojis on messaging platforms and communication mediums. Emojis were originally created as a compact expression of emotions in text-based online communications [18]. Emojis are a set of pictographic Unicode characters, broadly utilised on almost all social platforms and in different media. One of the main advantages of using emojis is that they could better express user emotions beyond plain texts, making communication more livelier [27]. Kelly et al., [14] speculated that the presence of emojis might influence selecting a communication channel for types of mediated conversation. Whereas, a study by Zhou et al., [28] focused on emoji proliferation and stickers and the lessening dependence on text. The study interviewed and observed data from 30 participants to investigate how rural and urban Chinese adults creatively use emoji, stickers, and text in their mobile communication practices. The paper highlights how participants use emojis to convey different meanings and non-verbal cues that might be poorly conveyed by text. Moreover, emojis are also used in combination with text and other media (such as stickers, photos and GIFs) to further expand their expressive message and complementing text. Research on emojis have categorised different patterns of use [20]:

- *Decorative use.* One or more emojis are used to decorate and accompany text. Yet, they are not an integral part of the message.
- *Emotional use.* Emojis are used to communicate feelings and emotions. They can be used to change the tone of a message (using sarcasm or irony).
- *Stand-in use.* The emoji is used to replace an actual word.
- *Reaction use.* The emoji is used to communicate a direct reaction.
- *Stand-alone use.* Several emojis are used to communicate a complex message. This is an extension of the use of emojis as reactions.

Herring et al., [9] analysed the frequency and pragmatic functions of graphical elements in threads sampled from public Facebook groups. Six main functions of these elements emerged from the data, namely mention, reaction, tone modification, riffing, action, and narrative sequence. The study suggested improvements for the design of conversational graphical elements in social media systems [9]. The use of emoji has been also implemented in modern conversational agents, including chat-based dialogue systems [10]. Communication with chatbots has evolved beyond simple text adding rich content to our conversations, including not only emojis, but also photos, GIFs, location, web-links and voice messages to enrich communication.

When considering chatbot applications, many differences exists between using plain-text versus emoticon enriched dialogues. This is often related to the dialogue domain, the user interest and demographics, and the conversation flow. As people increasingly use emoticons to express, stress or disambiguate their sentiment; it's crucial for automated sentiment analysis tools to account for such graphical cues for sentiment. Hogenboom et al., [11] analysed how emoticons typically convey sentiment and how to exploit this with manually created emoticon sentiment lexicon to improve a lexicon based sentiment classification method. The study evaluated the approach on 2,080 Dutch tweets and forum messages, containing emoticons. The findings concluded that using emoticons significantly improved sentiment classification accuracy. Other attempts have been made to combine emoji classification and sentiment analysis. For example, a work by Xie et al., [27] focused on automatic emoji recommendation given the context information in multi-turn dialogue systems. The study proposed a hierarchical long-short term memory model (HLSTM) to construct dialogue representations, followed by a softmax classifier for emoji classification.

The way users interact with a dialogue system with or without emoticons can play a role in their interest and engagement with the dialogue system. A study by Hill et al., [10] analysed how communication changes when people communicate with an intelligent agent as opposed to a human. The study compared instant human messaging conversations to exchange with a chatbot along seven dimensions, i.e. words per message, words per conversation, messages per conversation, word uniqueness, use of profanity, shorthand and emoticons. Conversational interfaces have been studied in their many facets, including natural language processing, artificial intelligence, human computer interaction, and usability [15]. Botplication uses context, history and structured conversation elements for input and output to provide a conversational user experience while overcoming the limitations of text-only interfaces [15]. When carefully designed, dialogue conversational agents can offer a convenient, engaging way of getting support at any time. This could be extremely useful in health context. Fitzpatrick et al., [7] determined the feasibility, acceptability, and preliminary efficacy of a fully automated conversational agent to deliver a self-help program for college students who self-identified as having symptoms of anxiety and depression. Emojis can be used to simplify emotional expression and to provide more expressive communication. Adding an emoji sometimes completely changes the context of the conversation and provides completely different meaning. Unlike plain text that are informational and carry the meaning of a message within the text, emojis are richer in terms of the meaning they carry and can present stronger emotional tendencies. That said, the same text can be written with plain text and emojis, however, it can deliver more emotional weights with emojis added. For example, the text "Are you kidding me?" and "Are you kidding me? 😄" convey different meanings. The first sentence sounds serious whereas the second one looks humorous and ironic. Emoji meaning

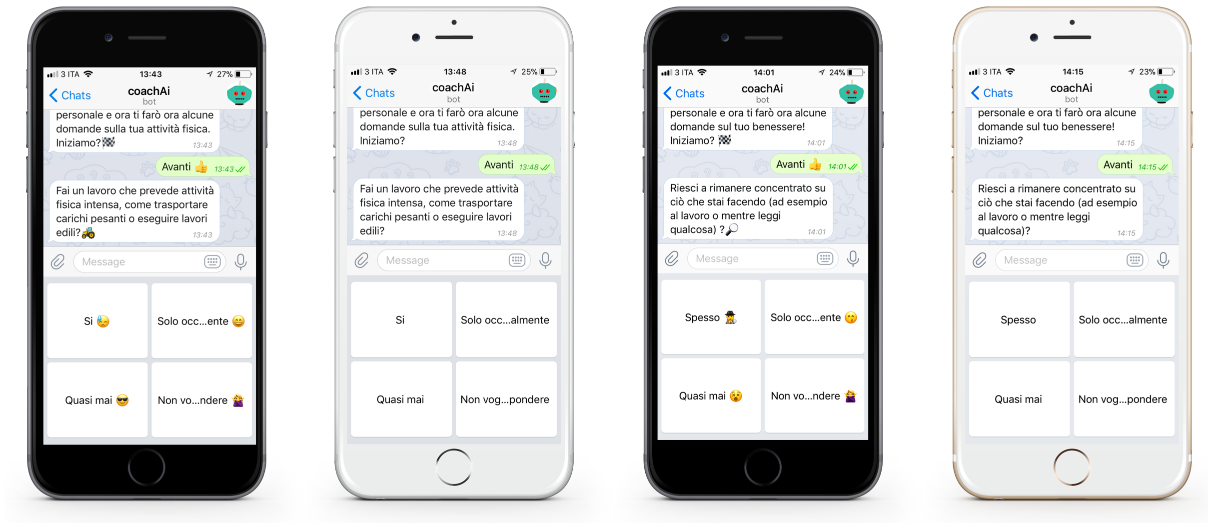

Figure 1: An interface view of the four bot versions.

is also subject to contextual and cultural interpretation. A work by Lu et al., [18] presented an analysis on how users use emojis around the world. The study demonstrated that the categories and frequencies of emojis used by people with different cultural background provide rich signals for the identification and the understanding of cultural differences among smartphone users. In this work, we seek to address this gap by focusing on a specific type of conversational agent: chatbot for tracking personal health information. We focus on two types of personal information related to the health domain: physical and mental wellbeing. Chatbots for physical wellbeing usually ask questions about user's overall exercise activity [17]. This type of chatbots ask users for objective information about their amount of exercise, set of questions about their overall exercise and activity lifestyle. On the other side, chatbot for mental wellbeing collect more sensitive and personal information. Bots for mental wellness approach the dialogue structure from a conversational standing point [3]. The dialogue usually covers user habits and feelings, asking information on sensitive topics, such as an individual's mental state, and how they perceive their lifestyle. The empirical evidence on the effect of the use of emoji is still scarce in the literature. To fill this gap, we designed a study to test the effect of communication style of a conversational system architecture in the context of collecting information on user's physical and mental wellness.

3 STUDY DESIGN

This study compares interactions with chatbot agents used to collect information on two different types of personal data: mental and physical wellbeing. While mental wellbeing is usually evaluated with questions on the person emotional, affective and cognitive status (e.g. "How are you feeling now?"), physical activity is assessed through objective and information (e.g. "How many times do you exercise a day?"). To recreate these two conditions in the experimental study, we developed two different dialogues based on two widely used questionnaires created to assess wellbeing in general population: the General Health Questionnaire - GHQ [21] and the Global Physical Activity Questionnaire - GPAQ [2]. The GHQ is a screening questionnaire for identifying minor psychiatric disorders in the general population, including non-clinical population [21]. The GHQ comprises 12 items with a four-point Likert response scale. The GPAQ is a questionnaire developed by the World Health Organisation for monitoring physical activity measuring sedentary and active behaviour in different contexts (daily routine, work and leisure time) [2]. GPAQ originally includes 16 items, but only 12 of them were used in this study to match the length of the two dialogues. Both questionnaires were used as bases for creating two comparable chatbot dialogues, and for each dialogue an emoji and a plain text version were created (see Figure-1 for a visual view of the different chatbot interfaces and Table 1 for excerpts from the different dialogues). Emojis were inserted at the end of each sentence as decorations, and they did not replace any text.

3.1 Participants and Experimental Design

The study involved 58 participants randomly assigned to one of the two conditions. The two conditions are consistent with the 2x2 design, with topic of the dialogue domain (physical vs. mental wellbeing) and style of communication (with emoji vs. text only) as independent variables. All participants interacted with both dialogue systems (physical and mental information), one was characterised using the emoji in the dialogue and one with plain text. The order of presentation was counterbalanced across participants.

The overall sample consisted of 28 male and 30 female participants. Their age ranged from 18 to 60 years old (M= 29.9, SD= 11.9). Half of the participants responded to the mental wellbeing dialogue enriched with emojis and the physical wellbeing dialogue in plain text *(Group A)*, while for the other half the combination of type of dialogue and style of communication was inverted *(Group B)*. The two groups did not differ in terms of age, level of self-confidence, trust

Table 1: Examples from the two dialogues used in the study.

Source	Emoji example	Plain text example
Mental Wellbeing - GHQ	Have you recently lost much sleep over worry? 🛌 • More than usual 😵 • As usual 😓 • Less than usual 😴 • I prefer not to answer 🙅	Have you recently felt constantly under strain? • More than usual • As usual • Less than usual • I prefer not to answer
Physical Wellbeing - GPAQ	Do you walk or use a bicycle to get to and from places? 🚲 • Very often 🚵 • Sometimes 🚴 • Rarely 🚳 • I prefer not to answer 🚫	Does your work involve vigorous-intensity activity that causes large increases in breathing or heart rate? • Very often • Sometimes • Rarely • I prefer not to answer

Table 2: Characteristics and descriptive statistics for the experimental groups. The Mann-Whitney test was used to test for differences between the two groups.

	Group A	Group B	Comparison
Emoji enriched dialogue	*Mental wellbeing (GHQ)*	*Physical wellbeing (GPAQ)*	
Plain text dialogue	*Physical wellbeing (GPAQ)*	*Mental wellbeing (GHQ)*	
Gender	F=15, M=14	F=15, M=14	
Age	29.9 (12.8)	29.8 (11.1)	Z= -0.6; p=.55
Self-confidence	3.9 (0.8)	3.9 (0.9)	Z= -0.01; p=.93
Trust propensity	3.7 (0.9)	3.4 (0.7)	Z= -0.9; p=.33
Familiarity with emojis	4.3 (1.3)	4.2 (1.5)	Z= -1.2; p=.90

propensity and emoji familiarity (all tested with the Mann-Whitney nonparametric test) (see Table-2).

3.2 Procedure

After the welcoming and the instructions on how to perform the testing, participants were asked to respond to the questionnaire for measuring individual self-confidence and trust. After completing the questionnaire, participants started the first dialogue with the chatbot using the Telegram desktop application. Although the availability of the chatbot on major devices, such as smartphone and web, we chose the desktop version of Telegram to make using the chatbot as easy as possible and display it on a computer screen rather than a small smartphone screen. At the end of each interaction participants completed a questionnaire for estimating engagement, attitude and confidence in the conversational agent. After the last interaction, participants were asked to answer the questions comparing the experience with the two dialogues. The whole procedure took about 20 min, with an average time of 4 minutes of interaction per dialogue.

Table 3: Scales and items used in the questionnaire. Items followed by an asterisk were inverted for the analysis. Cronbach's alphas are reported for each scale.

Scale	Item
Enjoyment $\alpha = .91$	I enjoyed chatting with the conversational agent during the interaction I felt comfortable answering the questions The more I interacted with the agent, the more I liked the experience I would like to chat again with this conversational agent in the future
Attitude $\alpha = .87$	I found a kind of "emotional connection" between myself and the conversational agent I found the dialog with the conversational agent to be realistic I noticed a negative emotional change in myself during the interaction * I found the dialog to be coherent. In other words, the sequence of responses of the conversational partner made sense
Confidence $\alpha = .77$	The agent asked very personal questions * I trust the conversational agent I found the questions to be very intrusive * I answered the questions with honesty

3.3 Measures

The measures consisted in a questionnaire for assessing individual self-confidence and trust, and for estimating engagement, attitude and confidence in the chatbot. Finally, participants were asked to answer few questions comparing the experience with the two dialogues.

Individual self-confidence and trust propensity. Self-disclosure was measured using three dimensions of the Wheeless's scale [26].

Specifically, the three dimensions of self-disclosure were measured using a 6-point scale for each, namely: (i) amount of disclosure, (ii) positive/negative nature of disclosure, and (iii) honesty of disclosure. Moreover, four items from the Mayer and Davis's Trust Propensity Scale [19] were used to measure dispositional trust. For both self-confidence and trust propensity, scale values were calculated as the average of the items. These measures were collected to control for differences between the two experimental groups.

Familiarity with emojis. Three items, rated on a 6-point scale, were used to assess participants' familiarity with the use of emojis. The items were: i) I like to read/text with emojis; ii) I use emoji in chatting apps such as Telegram and Whatsapp; iii) I think emojis enrich the communication. Also, these items were used to control for differences between the groups.

Interaction experience: enjoyment, attitude and confidence. The interaction was evaluated using three scales, i.e. engagement, attitude and confidence, each composed of four items with a 6-point Likert rating scale (from "strongly agree" to "strongly disagree"). The items used in the scales were adapted from [25]. The enjoyment scale comprises items related to the enjoyment and entertainment in the interaction. The attitude scale measures user's attitude toward the dialogue and the interaction with the agent. Lastly, the confidence scale evaluates user perception of the privacy and intrusiveness of the questions in the dialogue. The items are reported in Table 3.

Dialogue comparison. Three items, rated on a 6-point scale (from "strongly agree" to "strongly disagree"), were asked immediately following the last questionnaire for comparing participants' experience with the two dialogues. The sentences were: i) The two dialogues were identical; ii) I liked more the dialogue with the emojis; iii) The dialogue without emojis was easier to read.

3.4 Results

Data was analysed through a mixed-design ANOVA model, with "communication style" (emoji vs. plain-text) as within-subject factor and "experimental group" (group A vs. group B) as between-subject factor. The difference between the two groups was that in the former participants saw the mental wellbeing dialogue with the emoji and the physical wellbeing dialogue in plain text, while in the latter the conditions were inverted. Regarding the interaction experience, descriptive measures from the three scales are reported in Table-4:

Table 4: Questionnaire results for the interaction experience. Average values (SDs in parentheses)

Dimension	*Mental wellbeing*		*Physical wellbeing*	
	Emoji	Text	Emoji	Text
Enjoyment	4.7 (1.1)	4.1 (1.4)	4.2 (1.3)	4.8 (1.0)
Attitude	4.0 (0.9)	3.4 (1.3)	3.5 (1.2)	4.0 (0.7)
Confidence	4.6 (0.8)	4.2 (1.0)	4.7 (0.8)	5.0 (0.8)

The ANOVA found a significant effect of the between subject factor for all the three scales. When participants had to score the mental wellbeing dialogue with emoji and the physical wellbeing dialogue with plain text, they assigned higher scores for both enjoyment ($F(1,56)= 4.4$; $p<.05$), attitude ($F(1,56)= 4.2$; $p<.05$) and confidence ($F(1,56)= 8.9$; $p<.01$). Moreover, a significant interaction

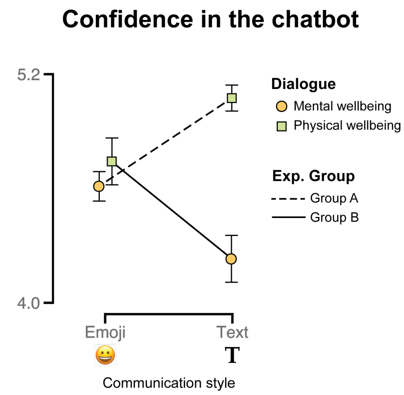

Figure 2: Scores for the "confidence" scale.

between factors has been observed specifically for the confidence scales ($F(1,56)= 21.44$; $p<.01$). This effect indicates that the profile of confidence ratings when the dialogue had emojis or plain text where different depending on the type of dialogue. Post-hoc analysis revealed that the confidence for the dialogue with emojis were similar between physical and mental wellbeing, however, compared with the plain text version, the scores raised for the physical wellbeing dialogue and decreased for the mental wellbeing one (see Figure-2). Regarding the items comparing the two dialogues, the ANOVA found a difference only on the third item of the scale. Both groups noticed a difference in the two dialogues and tended to prefer the dialogue with emojis. However, group A found the dialogue without emojis easier to read compared to group B ($F(1,56)= 4.36$, $p<.05$).

Interaction time analysis: To assess possible differences in the time taken to interact with the dialogue systems, we ran a mixed-design ANOVA on interaction time (time taken to complete the two dialogues measured in seconds, see Table 5). The analysis suggested no statistically significant differences in interaction time between the two communication styles ($F(1,56)= 1.68$; $p> .05$). There was a significant effect of the between subject factor ($F(1,56)= 13.57$; $p< .01$), showing that group A required more time (M= 365 sec, SD=105) to complete the two dialogues with respect to group B (M=206 sec, SD=102). A possible explanation is that when users are engaged in the conversation, and have a positive attitude and high confidence toward the chatbot, as in the group A, they spent more time interacting with the agent.

Table 5: Average time taken to complete the dialogues (in seconds)

	Mental wellbeing		*Physical wellbeing*	
	Emoji	Text	Emoji	Text
Time	383 (217)	190 (71)	223 (134)	346 (134)

4 DISCUSSION & LIMITATIONS

The results point out that emojis can benefit enjoyment, attitude and confidence with the conversational agent. This effect is clearly noticeable for the confidence scale: participants were confident in sharing information with the bot about their mental wellbeing when the dialogue included emojis, while they were less confident when the dialogue was in plain text only. The effect was inverted for the dialogue about physical wellbeing, with a decrease in confidence when the emojis were used. The dialogue with the conversational agents was mainly based on questions and answers. We can hypothesise that different effects of the use of emojis might emerge with different types of interactions. This work focused on a specific application context, the health domain, that covers personal and private aspects of a person's life. We expect emojis to vary in their effect with respect to different contexts and settings. Moreover, this work explored the decorative use of emojis in both mental and physical wellbeing dialogs, while different patterns of use might provide different results. While there were no significant differences regarding the age of the two experimental groups, participants were mainly young adults - most of the participants (76%) had less than 30 years old, and this limits the generalisation of the results. Our findings highlighted the values of having emojis in different domains and its effect on user confidence in the conversational agent. Chatbot services might benefit from having a nuanced understanding of emotional content in text represented by emojis and it would be interesting to replicate this research to test a chatbot integrating an AI-based emoji generator. Another interesting aspect for future research is to improve the personalisation within chatbots by creating a user model, before the user actually interacts with the chatbot (e.g. the user could fill in a personality questionnaire, such that the chatbot adapts to the user). This includes analysing how users will perceive the use of self-prepared sets of emojis that resembles their emotion.

5 CONCLUSION

Using conversational agents in various domains is increasing in popularity. One complexity with conversation systems is building the dialogue itself. This study investigated the effect of a chatbot application that uses different dialogue styles when tracking users' health data. The results of the user study show that a simple task with question/answer might require using emojis to engage users when the conversation covers private and personal aspects, such as mental wellness. When the dialogue focuses on physical activity and information, the use of plain text would be preferable. We believe that these findings can support the research on integrating conversational agents in the context of health and wellbeing, and provide an initial guidance in the design and development of conversational interfaces that use emojis in their dialogue model.

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