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CREATING AN ADAPTIVE VOICE AND LANGUAGE MODEL CAPABLE OF EMOTIONAL RESPONSE AND SELF-PROFILING TO EMULATE USER PERSONALITY

CREACIÓN DE UN MODELO DE VOZ Y LENGUAJE ADAPTATIVO CAPAZ DE RESPUESTA EMOCIONAL Y AUTOPROFILIADO PARA EMULAR LA PERSONALIDAD DEL USUARIO

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Creating an Adaptive Voice and Language Model Capable of Emotional Response and Self-Profiling to Emulate User Personality

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ABSTRACT

This work aims to show a cheap alternative of implementing an adaptive voice and language model, which has the opportunity not only react to the interlocutors' emotions but also adapt the personality of the bot to the personality of the user. Through moderated Framework and a feedback loop process the author explores the possibility of a system model. The conversational agent of this framework uses Natural Language Process (NLP) technique for the psychological profiling in order to be self-directed and self-aware. Moreover, this system can be kept current with successive activity sequences with gradual enhancement in the identification of the user personality, which determines the manner in which the model interacts with the user. The author also presents a plan on how to design such a model supported by theory, method, and feasibility and possible uses

Keywords: adaptive voice model, psychological profiling, natural language processing (nlp), emotionally intelligent systems

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Creación de un Modelo de Voz y Lenguaje Adaptativo Capaz de Respuesta Emocional y Autoprofiliado para Emular la Personalidad del Usuario

RESUMEN

Esta autoría tiene como objetivo mostrar una alternativa económica para implementar un modelo de voz y lenguaje adaptativo, que no solo tenga la capacidad de reaccionar a las emociones de los interlocutores, sino también de adaptar la personalidad del bot a la personalidad del usuario. A través de un marco moderado y un proceso de bucle de retroalimentación, el autor explora la posibilidad de un modelo de sistema. El agente conversacional de este marco utiliza técnicas de Procesamiento del Lenguaje Natural (PLN) para el perfilado psicológico con el fin de ser autodirigido y autoconsciente. Además, este sistema puede mantenerse actualizado mediante secuencias sucesivas de actividad, logrando una mejora gradual en la identificación de la personalidad del usuario, lo que determina la forma en que el modelo interactúa con él. El autor también presenta un plan sobre cómo diseñar dicho modelo, respaldado por teoría, método, viabilidad y posibles usos.

Palabras clave: modelo de voz adaptativo, perfilado psicológico, procesamiento del lenguaje natural (pln), sistemas emocionalmente inteligentes

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INTRODUCTION

The integration of two modalities of emotional intelligence and personality flexibility into conversational agents is a promising subfield in artificial intelligence research. The recent achievements in the domains of large language models reached levels of excellence for natural language comprehension and production (Flores and Luna, 2024) (Ocana et al., 2023a) (Pellert et al., 2024), but these systems currently lack sincere emotional intelligence and matched personality personalities as those. Thus, to achieve this the author proposes a framework how to create an ‘’emotional’’ dialogue system building from already existing cost-efficient language models such to provide an effective and affordable cost.

The improvement of conversation has taken the place of the worry that these conversational agents only generate automatic responses (Poggi and Pelachaud, 2000) and that it integrated key psychological models. In Saha´s et al. (2024), research it was identified that current dialog systems even have the ability to comprehend and apperceive affective information, while Matsumoto et al., (2022) regard the emotion to a system such that a change coincides with other studies, and recognising that interacting with an artificial intelligence system is not only a linguistic activity, but also affects and interacting with a stable personality (Dolgikh, 2024)(Flores and Luna, 2024)(Flores, 2023)(Sonlu et al., 2021).

Thus, personality adaptation has become a factor in which is very important for developing more realistic interfaces for AI systems. Müller et al., (2019) reveals that users are accepting of systems that have personalities that are manmade and can alter preference as the user would wish. The same was also seen by Guo et al., (2024) who state that, as compared to other dialogue systems, the personality-oriented methods offer considerably improved engagement levels and user satisfaction rates. There is a strong interaction effect between personality modeling and the added element of emotional intelligence according to recent studies conducted by Ma et al., (2024), Flores (2024), and Wen et al. (2024).

These adaptive systems therefore use advanced machine learning architectures and are fully reliant on the model structures. As seen in Rathi et al., (2022) through Psychometric profiling via natural language processing, and in Flores (2023) on frameworks of deep learning-based personality assessment, the work in the discipline was initiated. As Flores (2023) discusses, these technological advancements have been accompanied on one side by research in reinforcement learning approaches where these systems have been introduced in continuing interaction and proved to learn and improve their own emotional reactions.

However, one has been as equally challenging the other as has been an attempt to develop genuinely adaptable and emotionally intelligent systems. As Flores, Luna (2024) and Llanes et al., (2024) noted this is so because for human emotion and personality modeling, there are wide differences of margin between the human response patterns and behaviors machine expectations. Moreover, maintaining similar emotional consistency across such different interaction contexts is not obvious as perceived by the system erratic behaviour– this was also addressed in the recent work of Flores (2023). AI advancement integrates all of these components of emotional intelligence, personality adaptation and machine learning in a single work. Despite the encouragement of mastery of the components of Fan et al., (2017) within artificial agents, noted that emotional AI is quite desirable for an effective interaction between people and AI. Kossack and Unger., (2023) also agree with this point by showing that emotion-aware chatbots are ideal for enhancing user interaction and satisfaction.

This proposed framework builds from previous stablished foundations by building a robust system and incorporating real time personality adaptation and emotional intelligence through the addition of the mirroring approach in the feedback loop (Flores, 2023). With the latest advances in natural language processing is possible to create a complete system for more human centred (Lee et aL, 2023) (Flores and Luna, 2024) and personality assessment techniques according to Sikström et al., (2024). Flores, (2023) proposed how such systems can learn and adapt their emotional responses through continued interaction.

Although, it’s difficult to create emotional and adaptive systems, but it is possible. Compared to other modelling approaches, such as (Llanes et al. 2024), which are simpler and less capable of handling the small differences in user behavior and patterns of their responses to content, human emotion and personality demand sophisticated modeling methods, as Flores and Luna (2024) and Llanes et al. (2024) point out. Building upon these foundations, the proposed framework is derived as a robust approach to real time personality adaptation in combination with emotional intelligence based on feedback incorporating mirroring features (Flores 2023) (Lee et al. 2023). Thus, the use of personality assessment techniques (Flores and Luna 2024) (Sikström et al. 2024), will serve to build robust system previous research on how frameworks are extended is complicated by the fact that the system needs also to keep consistency between different interaction contexts, an issue that has been pointed out in recent work by Flores (2023).

By integrating emotional intelligence and personality adaptation with machine learning into a holistic design, is meant to take a significant challenge but also progress in AI. Fan et al., (2017) suggest that emotional intelligence in artificial agents no longer amounts to just a desirable trait but is a requirement required for true and productive human AI interaction supported by Kossack and Unger (2023)

METHODOLOGY

The methodology of this work is base system capable to update the model continuously and, after the analysis of the information, the result should be saved, processed and distinguished to complete. This, as Flores (2023), Sikström et al., (2024) and Saha et al., (2024) have demonstrated in interactive-user-feedback-adaptive systems are much more engaging and reliable. This makes it possible for the language model to change its response dependant on the user feedback data as proposed by Guo et al., (2024) and Wen et al., (2024) on personality-based conversation.

The system consists of four major components:

User Profiling

The foundation of this research work is based on the reliance of the deep learning model Chat GPT that uses inputs from the users in synch with time to build a psychological and behavioural profile. Prior work of Flores (2023), Müller et al., 2017, and Rathi et al., (2022), shows that applied artificial intelligence to utilisation of personality detection and analysis is feasible and advisable. Furthermore, advanced strategies presented by Flores and Luna (2024) and Ocaña, et al., (2023b) points out, the personality styles can be estimated accurately and reliably with the help of NLP methods.

Emotional Intelligence

Based on the study by Dolgikh, (2024) and Wang et al., (2024) the frameworks of affective computing in conversational systems should be applied to create or emulate emotional intelligence. This is done such as to complement the enhanced sentiment analysis methods Flores (2023), Matsumoto etal:2022, and Ma et al.,2024 suggested that systems that emulates such emotions can gather deeper insight of user emotions. The ability to perform the accurate sentiment analysis is enabled through use of advance techniques endorsed by Flores (2023), Matsumoto et al., (2022),, and Ma et al., (2024). Also, the earlier work done by Kossack and Unger, 2023, Fan et al., 2017, and Bilquise et al., 2022 depicted these same aspects enhancing the mechanism of trust and overall user engagement significantly.

Personality Emulation

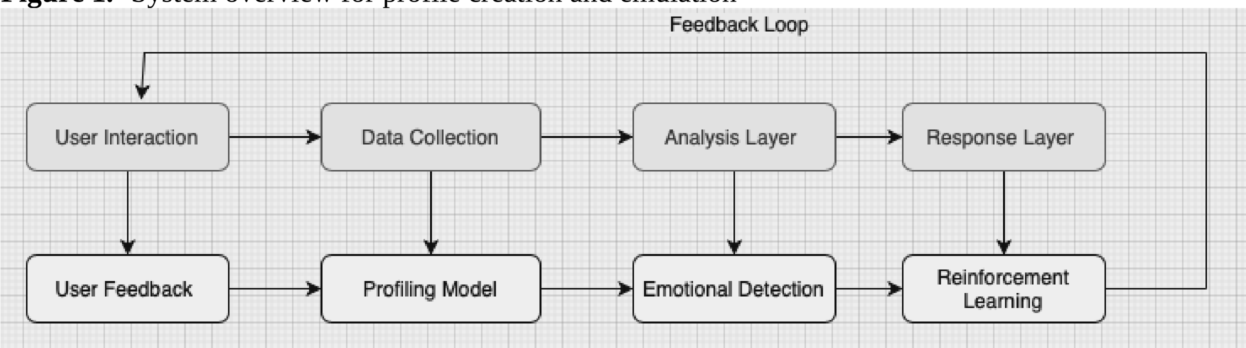
Based on the study by Dolgikh, et al., (2024) and Wang et al., (2024), this introduced the frameworks of affective computing in conversational systems. To complement the enhanced sentiment analysis methods of Flores (2023), Matsumoto et al., (2022), and Ma et al., (2024) this provides a deeper insight of user emotions. The ability to perform the accurate sentiment analysis is enabled through use of advance techniques endorsed by Flores (2023), Matsumoto et al., (2022), and Ma et al., (2024). Also, the earlier work done by Kossack and Unger, 2023, Fan et al., 2017, and Bilquise et al., 2022 depicted herein revealed that Responses enhance the mechanism of trust and overall user engagement significantly.

Feedback Loop and Iteration

Based on the study by Dolgikh, (2024) and Wang et al., (2024), this introduced the frameworks of affective computing in conversational systems. To complement the enhanced sentiment analysis methods of Flores (2023), Matsumoto et al., (2022), and Ma et al., (2024) this provides a deeper insight of user emotions. The ability to perform the accurate sentiment analysis is enabled through use of advance techniques endorsed by Flores (2023), Matsumoto et al., (2022),, and Ma et al., (2024). Also, the earlier work done by Kossack and Unger, (2023), Fan et al., (2017), and Bilquise et al., (2022) depicted herein revealed that Responses enhance the mechanism of trust and overall user engagement significantly.

Basing this component the initial process flow of these components are presented as follows in **Figure 1.**

Figure 1.- System overview for profile creation and emulation



RESULTS

Following stipulated stablished framework this study found that the proposed system must be built upon with the component below:

User Interaction

1.-Text Inputs: Linguistic analysis of user-generated content to detect sentiment, emotions, and underlying personality traits.

2.-Interaction Patterns: How the user responds to specific conversational prompts, how they engage with certain topics, and the pacing of their responses.

3.-Psychological Models: Adding primary psychological models including the Five F actor Personality Model or the Myers Briggs Type Indicator to arrive at a theoretical personality profile.

As stipulated before language models including unsupervised clustering are used to analyse the user's response and activities to recognise patterns (Dolgikh, 2024), Fan et al. (2017), Flores, Luna (2024) and Ocaña (2023b). These patterns then can be related to a set of psychological characteristics in which further behaviour will affect the model response (Lee et al., 2024).

Emotional Intelligence Integration - EMI

The developed model of EMI is itself an example of a high level of creative advancement in human-computer interaction based on several levels of affective computing (Dolgikh, 2024) (Flores, 2023). According to Ocaña et al. (2023a), AI systems aimed for emotional detection can be used in situations where emotional responses are significant, for example in diagnosis of autism spectrum disorder. The identification of the sentiment of the inputs shows that the system incorporates specialised sentiment analysis procedures which Flores and Lunda (2024), Kossack and Unger (2023), Ocaña et al. (2023b) has been useful in studying users' behaviour or affective feedback in computerised contexts. assessments, especially in specific domains including autism spectrum disorder (ASD) where emotions are particularly important.

The detection of minor emotions from user inputs is a complex feature of the system which uses sentiment analysis to determine emotions; techniques embraced by Flores and Luna (2024), Kossack and Unger (2023), Ocaña et al. (2023b) while analysing users' interactions and feelings in digital platforms. This emotional awareness is further boosted through the incorporation of social emotional development theories as noted in Fan et al. (2017), Le, et al. (2024) & Ocaña et al. (2021) autism spectrum disorder assessment, where emotional recognition plays a crucial role. The system's ability to detect emotional undertones in user inputs leverages advanced sentiment analysis techniques, which Flores and Lunda

(2024), Kossack and Unger (2023), Ocaña et al. (2023b) have shown to be effective in analysing user interactions and emotional expressions in digital environments.

This emotional awareness is further enhanced through the integration of social-emotional development frameworks, as highlighted in Fan et al. (2017), Le, et al. (2024) Ocaña et al. (2021a) in which the system retrieves what was described as indicator of emotion involvement by Guo et al. (2024), Ma et al. (2024), Llanes et al. (2024), Velagaleti, et al., (2024).

Moreover, Flores and Luna (2024), Kossack and Unger (2023), and Ocaña et al. (2023b) have effectively described the methodologies used in the system for conducting adaptive sentiment analysis. At their core, these methodologies allow for the perceiving of user emotions in the context of number-based digital interactions thus serving as a basis in this research work. To enrich this perception of user emotions, the system has also been endowed with the capability for socially and emotionally intelligent interactions, in line with the approaches of Fan et al. (2017), Le et al. (2024), and Ocaña et al. (2021a). This endowment allows for a level of engagement with users that goes beyond responding to them at the level of basic emotions. Finally, Guo et al. (2024), Ma et al. (2024), Llanes et al. (2024), Ocaña et al. (2021b), and Wen et al. (2024) have described the system design as one that understands emotional engagement signals. These are "signals" that indicate the user is expressing specific traits of emotions like sadness, happiness, anger, or fear.

Emotional response is noticed more in cyberspace, which Le et al. (2024) and Ocaña et al. (2023c) found to be a place with positive pathways for interaction when it comes to emotional appeals. To do this, the response generator built upon these emotional insights to create a shift in conversation tenor. Transformation, from less empathetic interactions to more empathetic ones. Timing was essential to sustain the empathically relevant part of the interaction (the human bridge part of the conversation). This was something that Ocaña et al. (2021c) gave high marks when interacting in user experience on cyberspace. It was also something that Le et al. (2024) said was especially crucial for "learning moments¨ and implemented also by Yu et al., (2024) and Yadav et al., (2020).

Guo et al. (2024), Ma et al. (2024), Llanes et al. (2024), Ocaña et al. (2021b), Wen et al. (2024) describe emotional involvement indicators that the system uses to categorise and respond to essential emotions such as happiness, sadness, anger, fear. For instance, in virtual environments, Le, et al. (2024) and Ocaña et al. (2023c) showed that emotionally engaging interface interactions are effective in increasing users engagement and learning outcomes. For example Le et al. (2024), Ocaña et al. (2021c) have shown that emotional resonance in which model's communication can vary to an empathetic style when user faces frustration, and maintaining an intention to convey the emotion as intended during entire the interaction time, are key success factors for user experience and learning effectiveness supported by Le, et al. (2024) and Ocaña et al. (2023c) as had demonstrated the effectiveness of emotionally engaging interactions in improving user engagement and learning outcomes. The model's response generator utilizes these emotional insights to adjust its communication style, showing empathy during moments of user frustration and maintaining appropriate emotional resonance throughout the interaction, a capability that Le et al. (2024), Ocaña et al. (2021c) had shown to significantly impact user experience and learning effectiveness.

Personality Emulation

After the creation of the user profile, the next goal for the system is to replicate the user personality characteristics. This is done by manipulation of the language model’s response patterns in a dynamic nature (Flores, 2023)(Kubjana, 2024)(Velagaleti et al., 2024). For example, if the system recognizes that the user is an open and extrovert personality, then the system interacts with the user in an energetic way or uses more energetic intonation to express the messages.

This paper proposes that the component leverages a personality modulation where:

1.- The model adjusts its communication style (formal, casual, direct, nuanced).

2.- The model tries to tailor its emotion delivery (more upbeat, reserved,supportive).

3.- The model could simulate cognitive patterns such as decision-making, preferences, or certain habitual language patterns based on the user’s psychological profile.

4-Emotion Detection: Using natural language process tools like sentiment lexicons and deep learning models (e.g., BERT, OPEN AI) to detect underlying emotions in the text.

5.-Emotion Response Generation: Selecting from a range of pre-trained emotional response templates that match the detected emotional state.

3.4 Feedback Loop and Iteration

Interactions become progressive with the system updating and modifying the user profile. Thus, it can be called adaptive (Flores, 2023)(Đula et al., 2024), due to such learning helps the model to develop the ability to recognise the user's personality and psychological state (Döring et al., 2024). At each interaction, the model evaluates:

- Has the user become more positive, negative, or remain the same?

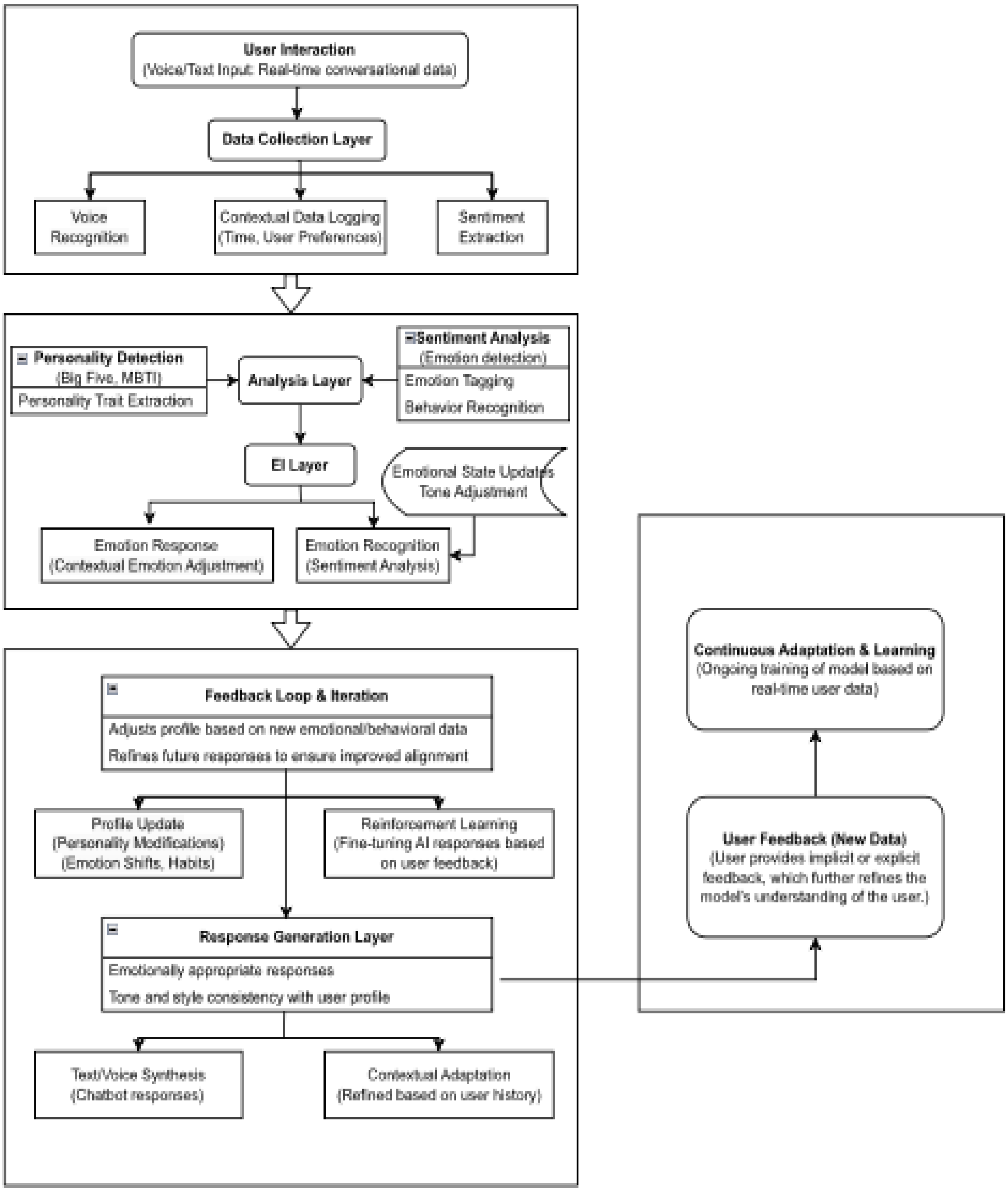
There are emerging personality traits that were not seen before and they have been into existence for some time now.

- What types of behaviours including topics of conversation, style of speaking have become more or less common?

The behaviour modification used in this process is known as reinforcement learning to fine tune the model response to the changes in the profile. model becomes increasingly adept at understanding the nuances of the user's personality and emotional state. At each interaction, the model evaluates:

- Has the user's emotional state shifted significantly?
- Are there emerging personality traits that were previously underrepresented?
- What patterns of behaviour (e.g., topic preferences, language style) have become more prominent

Figure 2.- Resultant Diagram Flow for the Interactive Implemented System Module



DISCUSSION

System Implementation

Having shown the efficacy of the AI industry on creating programs for conversing with people in natural language such as ChatGPT from Open AI, and well known and studied models therefore this served as a foundation for the proposed model implementation as previously stablished in HCI literature for the basis of system models (Chakriswaran, et al., 2019)(Yadav, et al., 2020)(Yu et al., 2024) and specially of

Flores, (2023) due to the establishment of a model in creating ai proliferation of human traits and in his subsequent research (Luna and Flores, 2024).

Thus, the system implementation will be a specific description for this proposed implementation and is as follows:

User Interface**:** The user can either give commands vocally or type them out for system interaction. The user interacts with the system at two levels, above and below the system layer. The system layer receives the input coming from the user layer. Input and express output are stored in the memory of the system for nearly instantaneous processing.

User Input Layer: This layer is concerned with the user commands about speech and sentiment. Also, any contextual information that might be necessary to work with the command is included, just in case it's needed to understand the command better. For the most part, everything is collected and processed in real-time so that the system can be responsive to the user without any noticeable delay.

Analysis Layer: The layer for understanding what the commands mean and working out a plan for executing them. Machine learning tools and emotionally competent electronics strapped to the system do the work of interpreting sentiment and working out the commands' meaning.

User Engagement: The system is a "not-a-human" based on the past interactions with the current user and with other users. These interactions refine and update the user profile, which makes it almost lifelike. The system "thinks" using past interactions, helping it with cognitive and communication-style analysis. And yet, it’s a profile in personality, which makes it almost humanistic in nature.

Emotional Intelligence. The system notices emotional changes in the input from the user. Based on this analysis, the system always tries to "stay with the user," meaning it aligns its tone and content with the user’s emotional state. Six: Deciding What to "Say" and What Not to "Say". The system has to be good at both aspects—saying the right things and not saying the wrong things.

Feedback Loop and Iteration: The system keeps on gathering feedback from every interaction it has with the user, which it then uses to continuously refine the user profile. **-** Continuous interaction between the system and user provides a good base of data from which the user profile can be enhanced. In a system as complex and adaptive as this, poor starting data can quickly be turned around into a profile that's decent and usable. There are two layers of the system that come into play when we're talking about the profile.

Response Generation: The system uses the data it gathers from the layers before this one to create an output that is personalized and therefore more likely to elicit the kind of response that we need to engage the user. **-** The system can render the response in either text or voice, depending on which sort of input the user provided to the system to initiate the interaction.

User Feedback: After the system's output has been rendered and the interaction is, in theory, complete, the user provides the system with fresh data—be it verbal or non-verbal—that is going to have a subsequent impact on the next interaction.

Continuous Adjustment and Learning: The model continuously learns and adjusts its user profile based on the most recent interactions—reverberations of which can be heard in the next command issued by the user. Using reinforcement learning, the system becomes increasingly more responsive and anticipatory concerning user needs whilst imitating what the user is feeling.

CONCLUSION

This paper has primarily been a mapping of the HCI basis, elements and proposed theories, detailing the potential use cases for adaptive conversational agents—in the author's view, mostly promising ones. The efficient, smarts applications of adaptive conversational agents do not amount to a revolution. What this paper really wants to strive is to give foundation to the implementation of given system and how these technologies might, through their use in entirely novel capacities, turn that efficiency dial down for the greater good of humanity. This could lead to the secret, of self-aware AI, if these technologies are to have a transformative adaptive conversational agent which currently they do not possess.

Adaptive conversational agents represent the new foundational world of AI, theres still questions to ask such as Why are they "social"? Because they interact with us in a way that only humans have up until now. At least, that's the ideal. Chen and Xiao (2024) assert that the pairing of these agents with large language models is changing the landscape of AI. But true socialise sues might require extensive experimentation in the language's models. This means that if humanity takes statement at face value, then the main significance of these agents doing something that a LLM (Large Language Model) by itself doesn't do is "acting human." Or, to put it another hand, "interacting socially" (i.e., in a human-like manner and without the necessity of a human on the other end). However, a chatty agent that works with a LLM is still just a powerful agent on various task even without the emotional capabilities. Why? Because the LLM is essentially an enormous statistical machine that finds, with varying levels of success, the "next best word" to produce, given the "previous words" and "context" it's been cued into seeing as a result of being trained on an unfathomable amount of "relationship data.

The ethical issues that might arise not only in the part from the user data collection but also over the emotionality of AI as Flores and Luna (2024) described extensively, however, this is a novel proposal, that overlies the fields of Human Computer Interaction with behavioural and perhaps even political science as to the ¨humanization¨ of AI will bring even harder existential challenges for humanity. The changes on the adjustment of AI modelling might come over as potential invasion to autonomous AI. For now, this paper encourages future research for the proposed testing to first achieve an accurate perhaps not accurate but definitely emotional AI such that of humans.

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