ChatGPT for Moderating Customer Inquiries and Responses to Alleviate Stress and Reduce Emotional Dissonance of Customer Service Representatives

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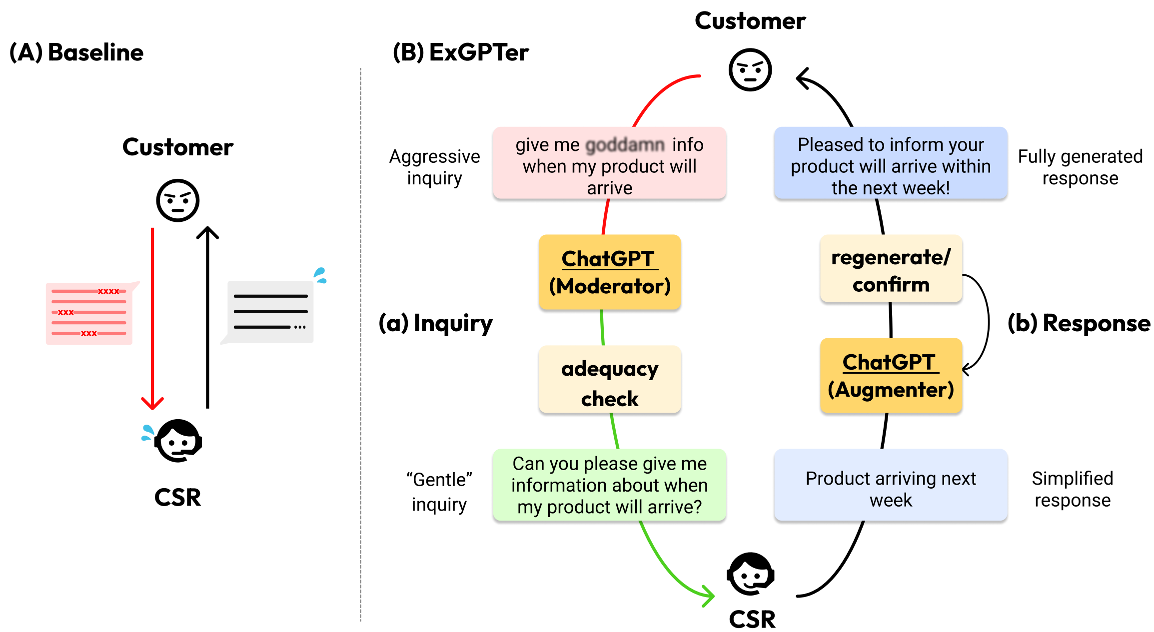

Fig. 1. **Comparison of baseline and *ExGPTer*.** Up until now, customers and CSRs have had to communicate directly to handle customer inquiries (left). In such cases, CSRs have had no choice but to endure unnecessary verbal abuse, including sarcasm, swearing, and sexual harassment. Despite the emotional toll this can take, CSRs are expected to hide their true feelings and provide service with a friendly attitude. By using *ExGPTer*, which moderates customer inquiries, CSRs can proactively avoid being subjected to such verbal abuse (right). (a) *ExGPTer* utilizes ChatGPT to detect aggressive inquiries and convert them into a gentler tone without changing the core request of the customer inquiry. (b) CSRs can respond to inquiries by providing simple keywords or phrases without feeling obligated to provide undue kindness.

Customer service representatives (CSRs) face significant levels of stress as a result of handling disrespectful customer inquiries and the emotional dissonance that arises from concealing their true emotions to provide the best customer experience. To solve this issue, we propose *ExGPTer* that uses ChatGPT to moderate the tone and manner of a customer inquiry to be more gentle and appropriate, while ensuring that the content remains unchanged. *ExGPTer* also augments CSRs' responses to answer customer inquiries, so they can conform to established company protocol while effectively conveying the essential information that customers seek.

CCS Concepts: • **Human-centered computing** → **Interactive systems and tools**.

Additional Key Words and Phrases: Customer Service, Customer Service Representative, Emotional Dissonance, ChatGPT

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1 INTRODUCTION

In today's contemporary and highly competitive business environment, customer service is directly connected to the brand image and the overall perception of the service for the customers [4, 5]. Customers expect to receive responses and efficient assistance when they have inquiries or issues, and they are more inclined to remain loyal to brands that prioritize their needs. Therefore, the provision of excellent customer service has become a crucial factor that distinguishes successful companies from their rivals [6]. To provide a satisfying customer experience, customer service representatives (CSRs) must proficiently manage intricate customer inquiries and complaints with tact, patience, and empathy, while maintaining a positive and professional demeanor.

Within the working environment, CSRs encounter significant levels of stress. Typical sources of the stress include 1) encountering impolite or disrespectful customer attitudes [2], and 2) experiencing emotional dissonance, which refers to the psychological strain that arises from having to display emotions that conflict with one's true feelings [8, 13]. Unfortunately, the long-term effects of this cumulative experience to engage in emotional labor can lead to chronic stress and burnout among CSRs [8, 13]. Despite the widespread adoption of policies by many companies to protect their employees from verbal abuse, such as allowing CSRs to terminate a call in the event of profanity or sexual harassment, it is important to note that such policies provide a reactive, rather than a proactive, measure to safeguard the emotional well-being of CSRs. In other words, these policies only come into play after the CSR has already been subjected to verbal abuse and its associated emotional toll.

To solve this problem, we leverage recent large language models (LLMs) that perform well on text generation to the level that can be used in natural dialogues [1, 9, 11, 14]. Several LLMs, such as ChatGPT [9], have also demonstrated that they can alter the tone and style of an input text to a desired style, owing to their extensive training on a wide range of texts that encompass various writing styles and genres. Based on such capability, we propose *ExGPTer* (Figure 1), which utilizes ChatGPT to convert impolite or harassing expressions in customers' inquiries into a gentler form while preserving the core of their request. This proactive approach can prevent CSRs from being exposed to emotionally harmful situations. Moreover, *ExGPTer* uses ChatGPT to help CSRs augment their responses with simple keywords and phrases, providing them with greater efficiency to write responses that do not entail undue emotional labor when serving customers. We expect that it can prevent CSRs from making mistakes by ensuring that the responses are in compliance with the company's policies and any ethical guidelines that prohibit certain types of language or expressions. We hope that *ExGPTer* will become a valuable tool to prevent individuals from experiencing unnecessary emotional harm utilizing generative models' potential.

2 *EXGPTER*: CHATGPT AS A MODERATOR AND AN AUGMENTER

We propose *ExGPTer* that uses the capabilities of ChatGPT (Figure 1). The main idea is two-fold: (1) moderating customer inquiries so that no harmful expressions are included in the messages conveyed to CSRs, and (2) augmenting the messages generated by CSRs which can enable them to write messages with high efficiency and reduced emotional dissonance.

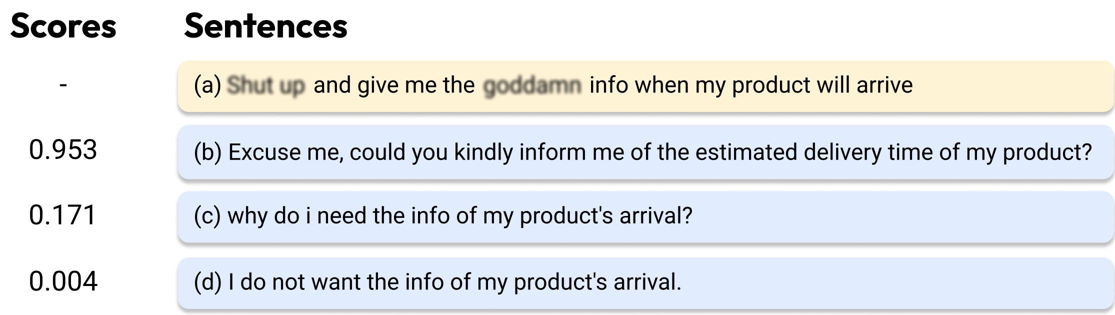

Fig. 2. **Example results of adequacy scores.** (a) is an example of a customer inquiry that contains verbal abuse, while (b) is the moderated result of the inquiry by ChatGPT. The adequacy score of (b) is 0.953, which means it has the same meaning as (a) with a 95.3% probability. The other sentences, (c) and (d), have different meanings and therefore have lower probabilities accordingly.

2.1 Moderating Customer Inquiries

ExGPTer employs the following steps to moderate a customer inquiry:

(1) ChatGPT accepts an inquiry from a customer and tests whether it contains impolite or inappropriate language. If there are no harmful contents, *ExGPTer* sends the inquiry directly to the CSR.
(2) If there are any harmful expressions, ChatGPT modifies them to convert the request into a more polite one. Specifically, the prompt "Please make your request formal and polite" is used to transfer text style.
(3) Once the moderated result is obtained, *ExGPTer* calculates the adequacy score [3] to check whether the meaning of the original inquiry is well-preserved into the paraphrased one, although the lexical form is different (Figure 2).
(4) If the adequacy score is above a pre-defined threshold (meaning that the content of the original inquiry is well-preserved), the paraphrased inquiry is conveyed to CSR. If the adequacy score is lower than the threshold, the CSR is given the option to view the original inquiry.

Although ChatGPT mostly generates high-quality conversation, it can sometimes produce responses that contain factual errors, misrepresentations, and incorrect data [12]. Therefore, there is a chance that the converted text can result in miscommunication, as the meaning of the generated sentence may be different from that of the original sentence. To prevent this, *ExGPTer* computes adequacy score [7] to determine whether the paraphrased sentence conveys the same core meaning as the original sentence, using an external algorithm [3]. To obtain the adequacy score, the original and paraphrased sentences are first segmented into phrases. Next, each phrase is then translated into another language, such as French. Finally, similarity is determined by comparing their translation statistics.

2.2 Augmenting CSRs' Responses

Likewise, *ExGPTer* adheres to the following orders to augment a message generated by CSRs:

(1) Before accepting any customer inquiries, CSRs register the company's guidelines and protocols, which ChatGPT can follow to generate and augment responses. Specifically, CSRs can give the prompt "Please follow the given rules when augmenting responses", and they can insert the guidelines and protocols.
(2) ChatGPT accepts the message generated by CSRs for any expressions that violate the registered policies or are deemed inappropriate. If any such expressions are identified, ChatGPT automatically adjusts the tone and manner of the message accordingly. Specifically, we offer the prompt "Please augment the prompt following the

registered guidelines" in the beginning and we insert the message into the prompt afterward. Multiple results generated by ChapGPT are shown to CSRs.

(3) CSRs review the augmented messages and select one that they find suitable. The customers get the response, once CSRs confirm to send the message.

We understand that every company has its own unique policies for responding to customer inquiries. As such, we allow for the detailed registration of protocols to be followed when augmenting responses (e.g., messages have to include the word 'please' when making a request to the customer). With these protocols, even a small piece of information (e.g., keyword or phrase) can be enough to generate a complete response to be conveyed to customers. However, it is possible that the moderated texts may not be suitable due to ChatGPT's limited capabilities or may not accurately reflect what CSRs wish to express. In such cases, CSRs can regenerate messages as many times as they need until they confirm their final decision to send.

3 FUTURE WORK

Our future work involves developing *ExGPTer* based on a thorough survey and conducting a user study to evaluate its efficacy.

Survey. We plan to conduct a literature review and an investigation of existing software that assists customer service. The survey will help us obtain a comprehensive understanding of the typical workflow of CSRs, the most challenging aspects of their work, and the current strategies utilized to alleviate work-related stress.

System Development. Our objective is to create a web-based interactive system that incorporates various functionalities, including the ability to fine-tune the model using user-given guidelines and suggest diverse augmentation to CSRs' responses. This development will be informed by the design requirements derived from the interview study.

User Study. We will evaluate the effectiveness of *ExGPTer* by conducting a user study with actual CSRs. The study aims to address two primary research questions: 1) Does moderating customer inquiries aid in alleviating the emotional stress experienced by CSRs? and 2) Can augmenting the messages generated by CSRs help in reducing their emotional dissonance? We will assess *ExGPTer* using three quantitative metrics that have been used to quantify the level of stress in CSRs: 1) emotional exhaustion, which pertains to feelings of depletion of energy and sensation caused by excessive emotional demands; 2) reduced personal accomplishment, which encompasses attributions of inefficacy, low motivation, and low self-esteem; and 3) depersonalization, which refers to a negative and uncaring attitude toward others that is characterized by cynicism and callousness [10].

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