The Impact of Empathy in Conversational AI: A Controlled Experiment with a Legal Chatbot

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Abstract

The rise of ChatGPT has revealed the potential of chatbots and other conversational AI tools to assist humans in fields such as law and healthcare, where the best human experts can engage in empathetic conversations. The belief is that if chatbots can connect with humans on a social and emotional level, they can reduce the cognitive effort required by humans to solve their problems, while increasing user satisfaction and trust. Although existing research has shown that empathy is crucial for designing human-AI conversations and their outcomes (effort, helpfulness, trust), it fails to separate the impact of empathy in language display from the AI's underlying "cognitive" abilities, like logical reasoning. To address this gap, this research aims to develop and empirically test a theory of empathy in the language displayed by conversational AI, explaining the relational outcomes of human-AI conversations in terms of cognitive effort, helpfulness, and trustworthiness. Using this theory, a chatbot is designed using syntactic and rhetorical linguistic elements that evoke empathy when providing legal services to tenants renting property. Through a randomized controlled experiment with a 2 by 3 factorial design, the effects of this empathetic chatbot on three relational outcomes in human-AI conversations are examined and compared to a non-empathetic chatbot that maintains the same logic. A baseline model utilizing non-conversational access to legal services via frequently asked questions ("FAQs") is also implemented, and the subjects' emotional state (anger) is manipulated as a moderating factor. The study involves 277 participants randomly assigned to one of six groups. The findings demonstrate the significance of both main and interaction effects on trustworthiness, usefulness, and cognitive effort. The results indicate that subtle changes in language syntax and style can have substantial implications for the outcomes of human-AI conversations. These findings contribute to the growing literature on conversational AI and have practical implications for the design of conversational and generative AI.

Keywords:
Conversational AI, Social Intelligence, Empathy in Dialogue, Linguistics, human-AI teaming

1. Introduction

Conversational artificial intelligence ("AI"), colloquially also referred to as a chatbot, plays an increasing role in everyday life, both in a commercial and a personal setting (Nicolescu and Tudorache, 2022; Pamungkas, 2019; Pelau et al., 2021). Such conversational agents use natural language and dialogue in order to address a human need. Today, chatbots are not only used to help humans engage in mundane tasks like online shopping, but they are also used to rendering more demanding services that in the past typically required very interpersonal communication and interaction with a human expert. For example, they are increasingly used in service settings like healthcare or law, where in the past the personal experience with a human expert with deep tacit knowledge, a doctor or a lawyer, have been assumed to be the major success factor for delivering high-quality services. (Magrabi et al., 2019; Seitz and Bekmeier-Feuerhahn, 2021). In the context of legal services, conversational AI may even broaden access to legal services and justice (King, 2020; Queudot et al., 2020). While some generic conversational AI agents such as Alexa and Siri utilize spoken and audio-based interactions, most domain-specific chatbots used for such interpersonal service settings rely only on text-based communication via a webpage or mobile application that humans access

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via their personal devices (e.g., phone, tablet, laptop, etc.) (Pamungkas, 2019).

Chatbots can be realized with different AI solutions, ranging from rule-based, deterministic systems to more advanced *generative* models, that rely on the advancement in statistical machine learning, and in particular deep learning, and enable the conversational agent to engage in more self-directed, independent conversations. Many domain-specific chatbots for services like healthcare or legal services rely on some form of rule-based systems to account for domain-specific knowledge. Research and practice increasingly tries to complement such rule-based system with generative AI models for natural language processing (”NLP”) to realize more ”human-like”, or in scientific jargon more *anthropomorphic*, chatbots that are able to engage in more complex conversations with a human agent (Pamungkas, 2019). The rise of open-source solutions for ’generative’ natural language models using deep neural networks, in particular, has manifested this trend. The goal is to design chatbots with a greater ability to establish some sort of social relationship with its human counterparts (Stokel-Walker and Van Noorden, 2023).

Such efforts are in line with insights in research related to human-human interaction and service relationships prior to the advent of conversational AI, which highlighted that interpersonal service experiences and outcomes strongly dependent upon the human experts’ ability to take the client’s perspective: The greater the ”social” skills of the expert, the greater the service experience and customer satisfaction. In law, for example, the lawyer’s ability to ask the right questions in the ”interview” phase of the consultation, their ability to take the client’s perspective, while also showing empathy is argued to impact service outcomes, both in terms of the client’s satisfaction but also the clients overall understanding of their legal rights (Howieson and Rogers, 2019). Indeed, recent research on AI, human-computer-interaction (”HCI”), as well as domain-specific studies in healthcare (e.g., healthcare informatics), argues that not only the ”cognitive” ability of the conversational AI agent but also the ”social” intelligence has a significant impact on the outcome of the ”social human-AI relationship” (Casas et al., 2021; Pamungkas, 2019; Pelau et al., 2021). Thus, prior research has made an effort to design conversational AI that is able to infuse emotions, and in particular *empathy* during conversations. Empathy, a term adapted from the German word ”Einfuehlung”, to describe an agent’s ability to understand and share feelings of another (Merriam-Webster, 2023) as is argued to be a major factor of user satisfaction (Pelau et al., 2021). Empirical studies evaluating chatbots with ”social skills” suggest causal evidence for that (Pelau et al., 2021). However, there are several limitations to existing work.

First, such research does not disentangle the ”cognitive” and social intelligence of conversational AI, twisting the effects of the empathy of the chatbot on relational outcomes. Second, non-deterministic generative AI models designed to inject emotions and empathy into the dialogue are often trained on data collected in very different conversational settings (e.g. Twitter, Facebook, etc.), labeled by heterogeneous groups of non-expert Mechanical Turks guided by very different definitions of empathy, causing biases in how the conversational AI generates and uses empathy in conversation. Third, and most importantly existing work does not sufficiently disentangle empathy as it is displayed in the language during a conversation from underlying more complex effective and cognitive processes of empathy (Alam et al., 2018; Cuff et al., 2016; Herlin and Visapää, 2016; Otterbacher et al., 2017). Existing design and modeling efforts fail to capture the linguistic foundations of empathy as it is displayed through syntax and rhetoric in language. Even though theory in linguistics developed prior to the emergence of conversational AI (Kuno and Kaburaki, 1977; Kuroshima and Iwata, 2016) has highlighted that simple changes to the language in terms of basic (e.g. tense) and rhetoric (e.g. use of certain phrases) syntax structure - without any changes to the underlying logic of the sentence - have a significant impact on perceived empathy in dialogue, existing research does not yet sufficiently explain whether and how empathy in language syntax of a conversational AI agent can impact perceived trustworthiness, helpfulness, and usefulness of the solutions shared during human-AI conversations. Thus, the research question to be answered remains: *How does empathy in language display of a conversational AI agent impact relational outcomes of human-AI conversations?* To answer this question we performed an experimental study performed online involving 277 Chicago residents seeking advise from a legal chatbot for a particular renting scenario to examine the effect of empathy in language display on two relational outcomes - trustworthiness, helpfulness - and also the perceived cognitive effort. We use a between-subject factorial research design with six different treatment groups comparing two different chatbots using different rules for empathy in language display - an empathy chatbot drawing upon syntactic and rhetoric rules of empathy in language display, and a non-empathic chatbot - and also FAQ page as another baseline treatment. In addition, we also induced some of our participants with ”anger”, to examine the moderating effect of emotions. Our experiment revealed three major findings. First, we find that empathy in language display has a main positive effect on helpfulness irrespective of the emotions - meaning anger. Second, we find a non-linear effect for trustworthiness: If there is no anger, empathy display has a very strong positive effect on trustworthiness, while the inducement of anger, reverses this effect: When angry, the trustworthiness of the empathy is much lower. Further, we find that use of a chatbot significantly reduces the cognitive effort compared to an FAQ page, with anger having a strong moderating effect.

2. Theory and Hypotheses

2.1. Theoretical Foundations

In this work, we draw upon the linguistic theory of empathy in language structure to explain how empathy displayed in the language chosen by a text-based conversational AI agent impacts relational outcomes related to human- AI conversations (Kuno and Kaburaki, 1977; Kuroshima and Iwata, 2016). Our theoretical assumption is that empathy can be displayed through basic and rhetorical syntax structure: subtle changes in syntax structure have a significant impact on empathy display; even if the underlying logic of the sentence remains the same. Our theoretical foundations goes back to earlier work on linguistics in the Japanese language, which later on have been continued and detailed in the context of English language (Kuno and Kaburaki, 1977; Kuroshima and Iwata, 2016) with a focus on linguistic style through mimicry and linguistic alignment Otterbacher et al., 2017. For example, structuring a sentence in active tense rather then passive tense ("John hit Mary" versus "Mary was hit by John") changes the perspective of the receiver because it shifts the "camera angle" (Kuno and Kaburaki, 1977, page 627). The active tense conveys objectivity, while the passive tense put the camera closer to the object, in this case "Mary". Following this argument, syntactic elements create empathy since changes to the "camera angle" change the speakers' identification with "varying degrees" with the person addressed in the direct conversation of the AI agent (Kuno and Kaburaki, 1977, page 628). Rhetoric syntax elements can create similar mechanisms of the AI's identification with its conversational partner, the human, through language. Language syntax can be viewed as a form of anthropomorphism rendered through language display in conversation having positive effects on relational outcomes. Further, the impact of empathy displayed through language may even be stronger if the conversational partner is in a negative emotional state (e.g. anger) as empathy may counteract the negative implications of anger on a human's attentions. Figure 1 visualizes our theoretical model of empathy in language display.

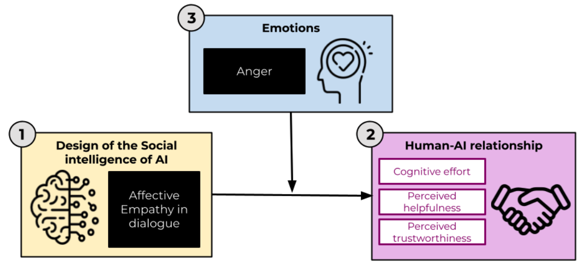


Figure 1: Theoretical Model

One of the key theoretical elements that will allow for empathy to be displayed is to have the writing style align with the linguistic elements with pronouns and person form, verb tense, and punctuation (Otterbacher et al., 2017). For example, those who were using singular third-person pronouns (e.g., she, her, he, him, their, theirs, etc.,) were more likely to be scoring low in empathy, but it is important to note that prior research showed that this was not a focus on themselves nor their conversational partners. One other key item to highlight from Otterbacher is that those who tend to score low on empathy used the past tense of the verb as well. Additionally, Otterbacher's work showed that exclamations led to lower perceptions of empathy, while using punctuation in a more formal writing style along with using more colloquial language style. Finally, this work details the concept of mimicry where (i) the content will be mimicked as it is influenced, (ii) it is generally positive, and (iii) there is no pattern on how the empathy profile mitigates this process - where this writing style is casual and more likely to elicit a response.

2.2. The Effect of Empathy in Language Display on Human-AI Teaming Outcomes

Our theory of empathy in language display considers ten (10) theory factors that capture key linguistic elements in dialogue style and syntax (see Table 1). As previously discussed, the proper utilization of the person form and pronouns may lead to whether or not there is a perception of empathy. Similarly, the person form of first person plural (e.g., we, us, our, ourselves) and second person (e.g., you, your, yourselves) lends to a perspective of empathy and feeling together by changing the "camera angle" and creating a symmetry between both parties (Herlin and Visapää, 2016). This idea of symmetry between the two parties will give the opportunity for the user to feel that the service that they are using will offer a greater affective perspective, which is a grounding element in linguistic expressions that serves to specify the relation between the expression and speech situation (Langacker, 1999). Additionally, prior studies have also shown that utilizing personal pronouns will lead to similar relational perceptions (Packard et al., 2018). Verb tense is also key for the conversational agent to employ when trying to convey a feeling of empathy to the user as the use of present tense of the verb is not commenting on the telling of the events, but, rather assessing the referent in a general sentence (Kuroshima and Iwata, 2016). This aspect not only provides a differentiating strategy of separating the user's experience from the chatbot's by partitioning itself from the situation entirely; however, by acknowledging the user's situation, the chatbot can sound empathetic without having the first hand experience of the user's situation. Additionally, the use of interactive phrasing and subsequent punctuation (Liebrecht et al., 2021) may create similar effects due the reliance of invitational rhetoric using phrasing such as ”may”, ”would”, ”should”, and ”please” creating an appearance of empathy in language display by putting focus on the conversational partner. This may lead to another item featured in Table 1 where linguistic elements that stimulate dialogue will lead respondents to share their thoughts and experiences as the language display will use phrasing such as ”Could you please share” and ”Shall we” (Alam et al., 2018; Cox and Ooi, 2022; Liebrecht et al., 2021).

Table 1 features additional syntactical and rhetorical theoretical elements that are necessary to mimic an empathetic response in language display that form the basis of our chatbot development. Rhetorical based elements, such as acknowledgement of the user's dialogue interactions and collective reasoning, may lead to a greater appreciation of feedback from the respondent as it acknowledges the dialogue between the two parties as well leading towards a collective consciousness rather than individual cognitive effort by creating the perception of anthropomorphism through language display. (Liebrecht et al., 2021). In order for the respondent to perceive the chatbot as more empathetic, phrasing such as ”Let us think this through” leads the user to believe that they are thinking through the problem together and utilizing joint reasoning that will eventually allow them to disclose more sensitive information. Further, using stylistic elements of empathetic imperative by combining ”do + verb (infinitive tense)” that chatbots kindly puts the ”camera” onto the human partner during dialogue (Alam et al., 2018; Cox and Ooi, 2022; Pelau et al., 2021). The use of interim questioning about the emotional state of the respondent shows an understanding of the situation and expresses an understanding of the person and the problem itself which in it itself appears empathetic in the language display (Feng et al., 2004). Through the ”injection” of affective statements of care during the conversation, the chatbot can display affective empathy that may have significant implications for creating a stronger social bond between the AI and the human (Campbell and Miller, 2023; Keen, 2006).

Following our theory logic, it is these theoretical elements that would convey empathy in the conversation which ultimately bond the human and the AI together, and thus, impact the human's perceived trustworthiness and helpfulness of the AI while also lowering their cognitive effort for solving their individual problem: *Hypothesis 1: Empathy in language display has a positive effect on relational outcomes of human-AI conversations (trustworthiness, cognitive effort, satisfaction)*

2.3. The Moderating Effect of Anger

Our theory also captures the moderating effect of anger and how empathy impacts the language display in the chatbot. Anger, as a negative emotional state, is viewed as a coping mechanism to remove an obstacle (Sassenrath et al., 2017), and can influence cognitive processes, like social decision-making, which usually leads to less perspective-taking; however, the inducement of anger does not lead to less perspective-taking, empathy, compassion, or sharing of affect (Weiblen et al., 2021). This could be explained that prior research explored trait anger and empathy rather than the emotional state of anger, which could lead into the development of mutual empathy and the concept of self-empathy, a term that has been explored by Judith V. Jordan (Jordan, 1997). Self-empathy develops as people become aware of the feelings of others and this awareness will lead to an enhanced level of trust between the two parties which is a sense of understanding the other person along with being understood increases the interaction. This connection with the self as the object as well as the experiencing self places ones self emotionally in the place of each figure and allows the understanding of the actions and feelings, including the relational of ones self and the other, to grow and change in a direction that allows for greater empathy. This idea that empathy is a two way process - the ability to empathize with others and to be empathize with - is affecting both parties in their interactions (Jordan, 1997).

Similarly to the concept of self empathy, the moderating effect of anger can lead to a phenomenon called imagined empathy, which is where (i) the person who went through an anger-inducing event imagines the emotions of the other person, (ii) the person has higher imagined reactive empathy (others sympathized with them), and (iii) the person has imagined parallel empathy (others felt the same way they did) with close

Theoretical element	No Empathy	Empathy
Person form (Herlin and Visapää, 2016)	Third person singular. (*"This problem can be solved"*).	First person plural; second person if necessary. Example: "We can solve this together"
Pronouns (Packard et al., 2018)	No personal pronouns (no reflexivity or transitivity of words), e.g. *The deposit*.	Personal pronouns (combined with active tense & transitivity and reflexivity of verbs) e.g. *Your deposit*.
Tense (Kuroshima and Iwata, 2016)	Past tense	Present tense
Exclamations (Liebrecht et al., 2021)	No "please", "may", "would", "should"	No exclamations!
Stimulating Dialogue (Alam et al., 2018; Cox and Ooi, 2022; Liebrecht et al., 2021)	Direct, neutral statements for instruction (*Click Button with "Continue"*).	Stimulating Dialogue (*"Let us see" or "Let us check" or "Shall we", "how about"? "Could you please share"*)
Acknowledging (Liebrecht et al., 2021)	No acknowledgment.	Bot acknowledges dialogue interactions: Example 1: "Thank you for telling me that", Example 2: "This is helpful. Thanks."
Collective Reasoning (Alam et al., 2018; Cox and Ooi, 2022; Pelau et al., 2021)	Present facts, results, or legal conclusion in a fact base way, e.g. *"based on case law etc. . . "*.	Language that focuses on "thinking together" and "joint reasoning", e.g. *when presenting the legal rule, bot says: "Let us think this through". "The way I understand our situation is that "*..
Imperative statement: Empathetic Imperative (Do + Infinitive) (Alam et al., 2018; Cox and Ooi, 2022; Pelau et al., 2021)	Direct neutral statements for instruction., e.g. *Click 'Proceed' [Verb]*.	Empathetic Imperative (Do + Infinitive)., e.g. *"Please do [verb]..."*.
Interim "questioning" about emotional state (showing understanding) (Feng et al., 2004)	No interim questioning	Ask interim questions that express understanding of the person
"Caring statements" (used sometimes but not always) (Campbell and Miller, 2023; Keen, 2006)	No affective statements	Affective statement of care. (*"We truly care about you and your experiences. We know how challenging and stressful it can be when you have a problem with a landlord."*)

Table 1: Theoretical Elements

others compared to distant others (Vorauer and Petsnik, 2022). Much like self empathy, imagined empathy may lead to increased perspective taking as the individual will have increased empathetic concern for others in need and a willingness to assist (Sassenrath et al., 2017). This empathetic perspective taking consist of two key components: (i) adopting the psychological point of view of others, which is the cognitive component, and (ii) empathetic concern: feelings of sympathy or concern for unfortunate others, which is the affective component (Richardson et al., 1994). What this means is that in order for the chatbot to adopt a successful point of view in the perspective of the user, the chatbot must understand what the circumstances are for the user to be seeking out its services; additionally, the chatbot must show genuine feelings of concern to the user.

When clients seek out professional services, especially when they are in the emotional state of anger, the appropriate response from the service provide that would be expected would be an affective empathetic response as (i) the professional mirrors their emotion via mimicry and (ii) takes on the client's perspective during the information gathering process. These appropriate responses would foster greater trust, increase self-disclosure, and help the client understand their predicament better (Howieson and Rogers, 2019). Similarly, when chatbot users are also in the emotional state of anger, they have a level of expectation for these chatbots based on their prior experience with these professionals. In this study, the user is given additional details within the scenario in an effort to induce anger such as *"the heat not working during a harsh Chicago winter"* and *"an unresponsive landlord not returning a deposit after many weeks in a substantial dollar amount"*. From this descriptive passage, we hope could lead the user to assume the role of the tenant who was taken advantage of to study how the chatbot would empathize with the user, when compared to another user who is only given the basic facts of the case. This increased perspective taking through self empathy and imagined empathy will lead to better results from the empathetic chatbot for those users given the scenario with the moderating effect of anger. Therefore, the second hypothesis is proposing that: *Hypothesis 2: Anger positively moderates the effect of empathy in language display of conversational AI.*

3. Research Method

3.1. Experiment Setup

3.1.1. Setting and Task

Rentervention is a joint project by The Law Center for Better Housing's, a non-profit organization, the Lawyers Trust Fund of Illinois, and other advocates in the Chicago area. Rentervention's goal is to provide free and confidential advice for those who are facing eviction and/or having problems with their landlords. Additionally, Rentervention offers information to tenants that allows them to help themselves through common housing issues and learning more about their rights through the utilization of chatbots. With assistance from Rentervention, we developed a website and constructed a scenario as detailed in Figure 2 in order to guide the chatbot in assisting the user with a legal task of medium complexity as we knew the answers to the legal questions because there is a correct solution. Our scenario had other varying levels of complexity from easy to highly complex based on the following parameters for our chatbot to consider: (i) type of unit such as single family detached, six units or less, or seven units or more, (ii) the location of the unit, for example, whether the unit was in City of Chicago, Cook County, or elsewhere, (iii) the occupancy of the building (i.e., landlord occupied or offsite), (iv) the terms of the lease, such as the amount of the security deposit, amount of rent, and whether or not if there was a written lease, (v) events that occurred such as normal wear and tear, (vi) end of lease actions by the tenant such as informing the landlord of the new mailing address or using the deposit to pay the last month rent, and (vii) end of lease actions by the landlord such at sending communications to the tenant, sending evidence supporting repair amounts, and if or when money was sent back to the tenant.

After the participant reviewed the scenario, we invited the users to participate in one of three exercises: (i) the empathetic chatbot, (ii) the non-empathetic chatbot, and (iii) the static information source. The participants interacted with the chatbots based on the parameters on either a computer/laptop, tablet, or mobile device, and were able to draft a ”*letter*” at the end of the exercise. At the end of the exercise, the participants were tasked to take a comprehension quiz on what they learned through the series of tasks on the subject of landlord-tenant law in Chicago. When completed with the quiz, the participant was then tasked to complete a survey asking questions as detailed in Table 4 and others such as ”*Please evaluate to what extent you feel the following.*” for other measurements such as Anger (*post-experiment survey question confirming anger and the construct*), Psychological Safety, Technological Self Efficacy, and preference for online interactions which were not used for this study. The constructs detailed in Table 4 were chosen by us to be used to quantify the measurements of the effect of the empathetic chatbot and the moderating effect of anger had on the chatbot.

You rented an apartment at **233 South Wacker, Chicago, IL 60606** from Larry Landlord. It is a large building with more than 40 units. You moved in on **August 25, 2021,** and moved out completely on **August 24, 2022**. No rent is owed; you paid it all on time. You provided your landlord your new address.

You had a written lease with your landlord for $2,250 per month and a security deposit of $2,000. You still have a copy of the lease.

On **October 1, 2022**, your former landlord in writing (by email) said that the kitchen floor had been damaged and needed to be repaired. He says the damage was beyond normal wear and tear, but you do not agree. He gave you a rough estimate of $3,000 to replace the kitchen floor, and said that he would keep the full amount of your security deposit. Your former landlord did not send receipts.

Getting back as much of the security deposit as possible would be very helpful for you.

First, you want to know if you can get all or some of your security deposit back from your landlord.

Second, if you are entitled to the return of all or some of your security deposit, you want to know what you need to do to get your security deposit back.

Figure 2: General Scenario

3.1.2. Treatment Groups/Constructs and Measures

The independent variables is the treatment of the group, especially in two forms: the choice of information including FAQ, non-empathetic chatbot and empathetic chatbot and the inducement of anger including with anger inducement and without it. The independent variables are treated as dummies in analysis of results. The anger inducement is confirmed with a post-experiment survey for weighting the level of ”mad”, ”anger”, and ”furious” in a level of 10. The t-test is done with the hypothesis that the with-anger and without-anger treatment does not affect reported anger level. The hypothesis is rejected with The statistic of -33.95 and the p-value of 2.93E-137.

The confounding variable is the number of comprehension questions answered correctly representing the comprehension level of the individual. There are three dependent variables, including perceived helpfulness, perceived trustworthiness, and cognitive effort needed.

The way the anger was introduced into the experiment was that there were two separate scenarios given: (i) the anger inducing scenario and (ii) the non-anger inducing scenario. The anger inducement text asks the participants to envision themselves in the scenario as much as they can. Considering the anger inducement was through text, it was necessary to not only provide a narrative that would make a reasonable person angry, but we had to capitalize words and phrases, mark them in bold, or even use more than one exclamation point as well to express anger as if it were a textual exchange.

3.1.3. Experimental Workflow

We created a website-based experiment with LandBot (the Chatbot dialogue engine which pulled the empathetic and non-empathetic responses based on the respondent's answers pursuant to the scenario, https://landbot.io) and Qualtrics (group assignment based on pre-survey, https://www.qualtrics.com) embedded and hosted at Firebase. The data collected are stored in Firebase database. The framework is written in Flask and the website front-end in React; both of which are Python based libraries.

Question No.	Pre-Screening Question
Question No. 1	Are you 18 years or older?
Question No. 2	Are you a student?
Question No. 3	What is your zip code?
Question No. 4	Do you consent to participating in this research?
Question No. 5	How old are you?
Question No. 6	How many times have you had a legal problem with your landlord in the past five years?

Table 2: Pre-Screening Questions

During the experimental phase, participants accessed the study using a unique ID (their SonaID) after undergoing a pre-screening process. The pre-screening involved a series of questions such as their age group, zip code, and total number of times they had legal problems with a landlord as detailed in Table 2. Based on participants' responses, treatment groups were assigned to address potential confounding factors and ensure equal distributions across the groups in terms of age and prior experience with lessor-lessee law. The assignment results for the groupings can be seen in Table 3.

Bot/Information Source	Emotional State of Human	
	No Anger	Anger
Chatbot with Empathy	Group A (47)	Group B (47)
Chatbot without Empathy	Group C (47)	Group D (45)
FAQ as control group	Group E (46)	Group F (46)

Table 3: Factorial Treatment Design

The survey process involves different groupings that determine whether participants receive anger inducement text or not. Specifically, groups A, C, and E receive anger inducement, while groups B, D, and F do not. Subsequently, participants are assigned to one of three conditions based on their group assignment: Group C and D receive the Empathetic Bot, Group A and B receive the Nonempathetic Bot, and Group E and F receive the FAQ . As suggested by the screenshots of the chatbot interactions - several phrases changed from the nonempathetic bot to empathetic bot. For example, ”the tenant” was changed to ”you”, ”let us” was used as a means of collective reasoning, ”the information provided” was changed to ”what we know”, ”the landlord” was changed to ”your landlord”, ”to have received” was changed to ”you should have received”. The phrases were changed to express more empathy and this is not the only case in the text.

After completing the chatbot experiences, participants proceed to a post-survey where they respond to multiple-choice questions based on the legal rules applicable to their problem from the chatbot interaction or from viewing the FAQ pages. They are also asked to provide ratings on a 7-point Likert scale (Joshi et al., 2015) for the following metrics of interest, divided into three parts: 1. Cognitive Effort; 2. Usefulness; 3. Trustworthiness. The specific items used for assessment can be found in Table 4.

Label	Item
Helpfulness	
Question/Item	**Using the scale, how would you describe the online help?**
Helpfulness	Not at all helpful:Very helpful
Usefulness	Not at all useful:Very useful
Informative	Not at all informative:Very informative
Trustworthiness	
Question/Item	**Please evaluate the online help’s credibility.**
Trustworthy	I believe that this online help is trustworthy.
Honesty	I do not doubt the honesty of information provided by this online help.
Ability	I feel assured that this online help has the ability to protect me.
Overall	Overall, I trust in this online help.
Cognitive Effort	
Question/Item	**Please evaluate your effort while using the online help.**
Thinking	I needed a lot of thinking when using the online help.
Contemplated	I often contemplated when using the online help.
Demanding	Generally speaking, using the online help was cognitively demanding.
Effort	When using the online help, I invested high mental effort.

Table 4: Final Selection of Items

3.2. Statistical Approach

Following data collection from 277 participants from Chicago gathered in the SONA (psychology participant) pool of Northwestern University, a series of statistical analyses were conducted to explore the relationships and effects within the collected data. A classical factorial design analysis using two-way Analysis of Variance (”ANOVA”) was performed, adhering to recommended frameworks proposed by Poirier et al., 2021 and Youhasan et al., 2020. This analysis allowed for the examination of main effects and interaction effects among the variables.

To further investigate the relationships and effects, Generalized Linear Models (GLM) were utilized for regression analysis. Both simple effects and interaction effects were explored, following the guidelines provided by Arnold et al., 2021.

4. Results

4.1. ANOVA Analysis

This study employs ANOVA to examine the influence of different treatments or conditions on our dependent variables and draw conclusions on the hypotheses. ANOVA analyses were conducted on three distinct models for each dependent variable to investigate the main effects (Dubé et al., 2022, Kakii et al., 2022, Yim et al., 2023). A sensitivity power analysis in F-test of ANOVA with a=.05, 80%power showed that with our sample size 277, the ANOVA has the power to detect small to median-sized interaction (f=0.17). All models in ANOVA analysis uses dummy coding to analyze the main effect more clearly (“Coding Systems for Categorical Variables in Regression Analysis”, n.d. and “Contrast Coding with Three-level Variables — Page Piccinini”, n.d.) and effect size is estimated using partial eta squared (“FAQ: How do I interpret the coefficients of an effect-coded variable involved in an interaction in a regression model?”, n.d.) - small effect from 0.01, median effect from 0.06 and large effect from 0.14 (“FAQ/effectSize - CBU statistics Wiki”, n.d.).

Model 1 utilizes a two-by-two design, dividing the data based on factors of ChatBot vs FAQ and With-Anger-Inducement vs Without. The baseline for model 1 are Bot and WithAnger.

Model 2 examines differences between the Empathetic Chatbot and the nonEmpathetic Chatbot, as well as their interaction with anger inducement, using a two-by-two design. The sample included in model2 only covers the experiments that uses chatbot - therefore, model 2 excludes the FAQ group. The baseline for model 2 are EmpathyBot and WithAnger.

Finally, Model 3 employs a three-by-two design to explore the impact of three equally treated information gain conditions on anger inducement. The baseline for model 3 are EmpathyBot and WithAnger.

4.1.1. Helpfulness

The perceived helpfulness of the participants is analyzed across the treatment groups. Table 5 shows the ANOVA analysis results for helpfulness in all three models and Figure 3 shows the interaction plot of helpfulness in all three models.

#		SS	df	F	PR(>F)	η_p^2
1	Intercept	23723.69	1.0	3165.34	3.36E-152***	0.921***
	NoBot	3.591	1.0	0.479	4.894e-01	0.002
	WithoutAnger	0.771	1.0	0.102	7.487E-01	0.000
	NoBot:WithoutAnger	0.127	1.0	0.017	8.965E-01	0.000
2	Intercept	12709.86	1.0	1620.40	3.04E-92***	0.900***
	NonEmpathy	14.340	1.0	1.828	1.780E-01	0.010*
	WithoutAnger	1.204	1.0	0.153	6.957E-01	0.001
	NonEmpathy:WithoutAnger	0.408	1.0	0.052	8.199E-01	0.000
3	Intercept	12709.86	1.0	1714.02	3.44E-119***	0.863***
	NonEmpathyBot	12.339	1.0	1.664	1.982E-01	0.006
	FAQ	14.340	1.0	1.934	1.655E-01	0.007
	WithoutAnger	1.204	1.0	0.162	6.873E-01	0.001
	NonEmpathyBot:WithAnger	0.412	1.0	0.055	8.139E-01	0.000
	FAQ:WithoutAnger	0.408	1.0	0.055	8.148E-01	0.000

Table 5: ANOVA results for Helpfulness

In model 1, from the interaction plot (Figure 3a), the use of chatbot increases perceived helpfulness, disrespect of the presence of anger inducement (from 15.754 to 16.187 and from 15.716 to 16.058). Anger inducement generally lowers the perceived helpfulness when viewing from the mean values but the difference is small (from 16.187 to 16.058 and from 15.754 to 15.716). In ANOVA analysis results (Table 5), only the intercept term is significant(F=3165.34, p¡0.001, η_p^2=0.92), which absorbs both the constant and the treatment effect of both using chatbot and anger induced. Because only the intercept term is significant, no significant evidence shows the use of chatbot and anger inducement affect the mean of helpfulness, despite the trend we see in the interaction plot.

In model 2, from the interaction plot (Figure 3b), the use of empathy in chatbot increases perceived helpfulness, disrespect of anger inducement (from 15.654 to 15.693 and from 16.445 to 16.671). Anger inducement lowers the perceived helpfulness in both conditions (from 16.672 to 16.445 and from 15.693 to 15.654). In ANOVA analysis results (Table 5), the intercept is significant (F=1620.40, p¡0.001, η_p^2=0.90), suggesting the combined effect of constant and the group EmpathyBot with anger inducement. Additionally, non-empathetic chatbot (F=1.83, p=0.18, η_p^2=0.01) has a small effect size on perceived helpfulness, meaning it explains a small part of variance, even though the treatment is not significant.

In model 3, from the interaction plot (Figure 3c), the use of empathy shows a larger improve on perceived helpfulness, as perceived helpfulness in both FAQ and non-empathetic chatbot groups stay close to each other (15.754 and 15.693 when compared to 16.671). The inducement of anger lowers the perceived helpfulness in a small degree in all levels of communication means (from 16.671 to 16.445). In ANOVA analysis results (Table 5), only the intercept term is significant [F=1714.02, p¡0.01, η_p^2=0.86], suggesting the combined effect of both the constant and the baseline treatment group empathybot and with anger.

Linking back to the hypotheses, the results in the interaction plot support hypothesis 1 that the use of empathetic language increased the perceived helpfulness but not hypothesis 2 that anger is affecting the effect. However, the ANOVA analysis results do not provide significant evidence to support hypothesis 1, which will be explained better in regression analysis.

4.1.2. Trustworthiness

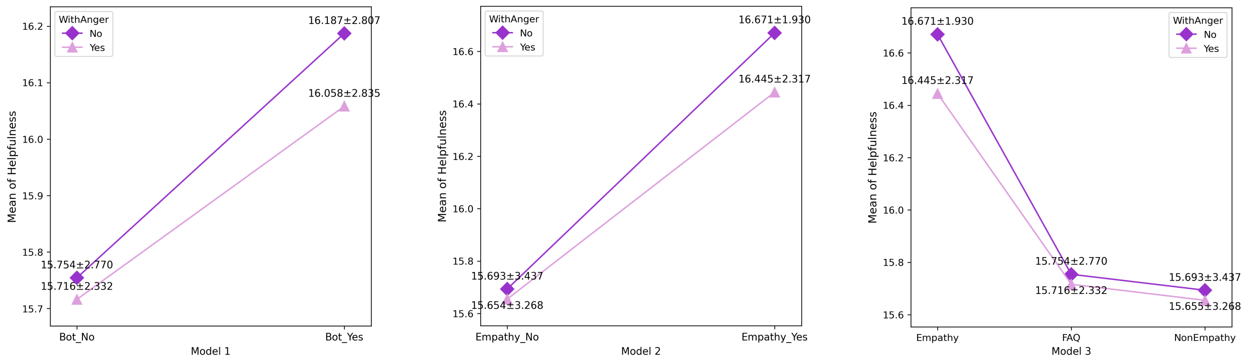
The perceived trustworthiness of the communication method is analyzed through ANOVA analysis (Figure 6) and the interaction plot (Figure 4) shows the relationship of the mean values across the treatments in all three models.

#		SS	df	F	PR(>F)	η_p^2
1	Intercept	21994.07	1.0	1583.93	1.16E-115***	0.853***
	NoBot	52.338	1.0	3.769	5.323E-02*	0.014*
	WithoutAnger	58.161	1.0	4.189	4.165E-02**	0.015*
	NoBot:WithoutAnger	38.998	1.0	2.809	9.491E-02*	0.010*
2	Intercept	10904.76	1.0	795.04	3.89E-68***	0.815***
	NonEmpathy	5.069	1.0	0.370	5.440E-01	0.002
	WithoutAnger	129.096	1.0	9.412	2.487E-03***	0.049*
	NonEmpathy:WithoutAnger	70.894	1.0	5.169	2.417E-02**	0.028*
3	Intercept	10904.76	1.0	800.41	7.18E-83***	0.747***
	FAQ	54.853	1.0	4.026	4.579E-02**	0.015*
	NonEmpathyBot	5.069	1.0	0.372	5.424E-01	0.001
	WithoutAnger	129.096	1.0	9.476	2.296E-03***	0.034*
	FAQ:WithoutAnger	92.158	1.0	6.764	9.810E-03***	0.024*
	NonEmpathyBot:WithoutAnger	70.894	1.0	5.204	2.332E-02**	0.019*

Table 6: ANOVA results for Trustworthiness

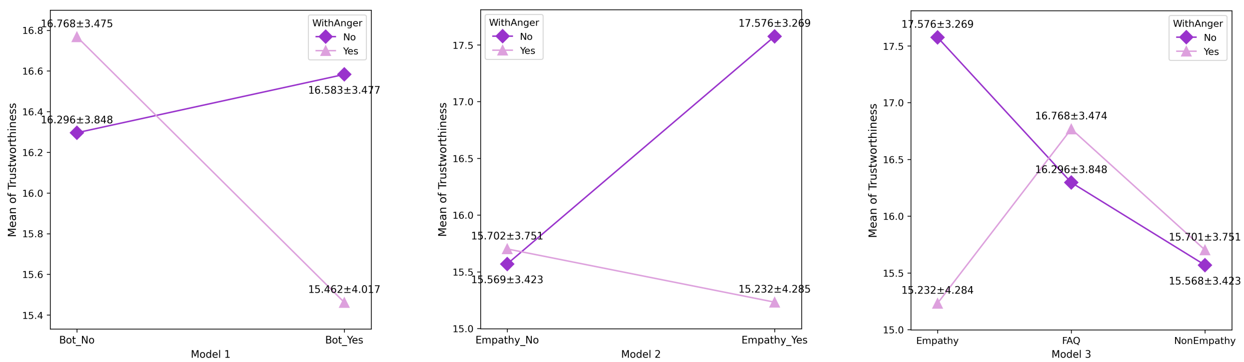
For Model 1, from the interaction plot (Figure 4a), we see that anger inducement has strong effect on trustworthiness. While without anger inducement, using the chatbot increases the perceived trustworthiness by a little bit (from 16.396 to 16.583). After the treatment with anger, the use of chatbot strongly decreases the perceived trustworthiness (from 16.768 to 15.462). The difference indicates that anger inducement affects perceived trustworthiness strongly. In the ANOVA table (6), all the terms are significant. The intercept (F=1583.93, p¡0.001, η_p^2=0.85) shows the combination of constant and baseline (chatbot with anger) effect. The NoBot term (F=3.77, p¡0.1, η_p^2=0.014) shows the significant small effect of the chatbot and no chatbot treatment on perceived trustworthiness. The anger inducement treatment term (F=4.19, p¡0.05, η_p^2=0.015) shows the significant small effect of anger inducement on perceived trustworthiness. The interaction term between chatbot and anger inducement (F=2.81, p¡0.1, η_p^2=0.01) shows significant small effect of the interaction term on trustworthiness.

In Model 2, from the interaction plot (Figure 4b), we see that when there's no anger induced, the perceived trustworthiness increases with using empathetic language in chatbot (from 15.569 to 17.576)



(a) (b) (c)

Figure 3: Interaction Plot for Helpfulness. (a) Model1; (b)Model2; (c) Model3



(a) (b) (c)

Figure 4: Interaction Plot for Trustworthiness. (a) Model1; (b)Model2; (c) Model3

while with anger induced, the perceived trustworthiness drops a little (from 15.702 to 15.232). In ANOVA analysis, the intercept term is significant (F-795.04, p¡0.001, η_p^2=0.81) shows the significant big effect of both constant and baseline combined. The WithoutAnger term (F-9.42, p¡0.01, η_p^2=0.05) shows significant small to medium effect of anger inducement on perceived trustworthiness. The interaction term (F=5.27, p¡0.01, $\eta_p^2 = 0.02$) is also significant, showing a small effect of the interaction between the use of empathetic language and anger inducement on trustworthiness.

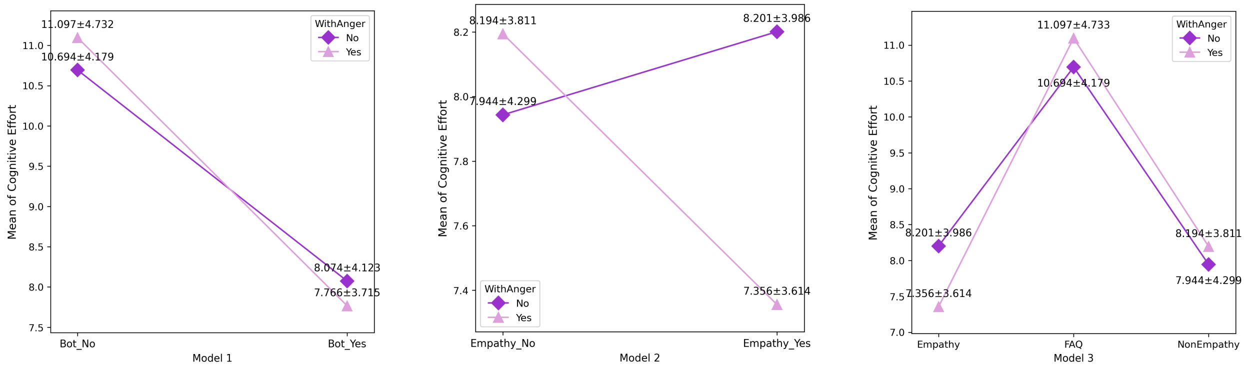
In case of model 3, the interaction plot (Figure 4c) shows a decreasing trend of trustworthiness from empathetic chatbot to FAQ and then to non-empathetic chatbot (from 17.576 to 16.296 to 15.568). With anger induced, FAQ treatment has the highest perceived trustworthiness (16.768), while both the empathetic and non-empathetic chatbot lowers the perceived trustworthiness (15.232 and 15.701). In ANOVA analysis results, the intercept term (F=800.41, p¡0.001, η_p^2=0.75) suggests significant big effect of both constant and baseline (empathetic bot with anger induced). The FAQ term (F=4.03, p¡0.05, η_p^2=0.01) shows significant small effect of the FAQ term on perceived trustworthiness. The WithoutAnger term (F=9.48, p¡0.01, $\eta_p^2 = 0.03$) shows significant small to median effect of anger inducement treatment on perceived trustworthiness. In case of the interaction terms, the interaction between anger treatment and FAQ (F=6.76, p¡0.01, $\eta_p^2 = 0.02$) has small significant effect while the interaction between anger treatment and non-empathetic bot (F=5.20, p¡0.01, η_p^2=0.02) has small significant effect on perceived trustworthiness.

The results from the interaction plot support both hypotheses while the ANOVA analysis results support only the second hypothesis. The difference lies in the strong interaction the interaction between anger and the use of empathetic language, which is supported in the regression analysis section.

4.1.3. Cognitive Effort

The cognitive effort needed for specific communication method is analyzed using both the interaction plot (Figure 5)and ANOVA analysis(Table 7).

In Model 1, as suggested in the interaction plot (Figure 5a), the use of chatbot comes with a decrease in the cognitive effort needed by the audiences in both with anger and without anger groups (from 11.097 to 7.766 and from 10.694 to 8.074). The inducement of



(a) (b) (c)

Figure 5: Interaction Plot for Cognitive Effort. (a) Model1; (b)Model2; (c) Model3

Models		SS	df	F	PR(>F)	η_p^2
1	Intercept	5548.34	1.0	328.27	1.015e-48***	0.546***
	NoBot	340.303	1.0	20.134	1.065E-05***	0.069**
	WithoutAnger	4.381	1.0	0.259	6.111E-01	0.001
	NoBot:WithoutAnger	7.754	1.0	0.459	4.988E-01	0.002
2	Intercept	2543.18	1.0	164.25	3.552E-27***	0.476***
	NonEmpathy	16.142	1.0	1.042	3.086E-01	0.006
	WithoutAnger	16.779	1.0	1.084	2.993E-01	0.006
	NonEmpathy:WithoutAnger	13.868	1.0	0.896	3.452E-01	0.005
3	Intercept	2543.18	1.0	149.94	9.811E-28***	0.356***
	FAQ	325.357	1.0	19.182	1.699E-05***	0.066**
	NonEmpathyBot	16.142	1.0	0.952	3.302E-01	0.003
	WithoutAnger	16.779	1.0	0.989	3.208E-01	0.004
	FAQ:WithoutAnger	18.094	1.0	1.067	3.026E-01	0.004
	NonEmpathyBot:WithoutAnger	13.868	1.0	0.818	3.667E-01	0.003

Table 7: ANOVA results for Cognitive Effort

anger treatment has some different effect when chatbot is used and when it's FAQ, as the cognitive effort needed is higher for groups with anger in FAQ group (11.097 ¿ 10.694) while lower in chatbot groups (7.766 ¡8.074). In the ANOVA results, the intercept term (F=328.27, p¡0.001, η_p^2=0.55) demonstrates significant big effect of both the constant and baseline (FAQ with anger) in cognitive effort needed. The NoBot or FAQ term (F=20.13, p¡0.01, $\eta_p^2 = 0.07$) shows significant median effect of FAQ, or the use of chatbot in cognitive effort needed.

In Model 2, the interaction plot (Figure 5b) shows when there's anger, the use of empathetic language decreases the cognitive effort needed (from 8.194 to 7.356) while when there's no anger, the use of empathetic language increases the cognitive effort needed in a smaller degree (from 7.944 to 8.201). In ANOVA results, only the interaction term is significant (F=164.25, p¡0.01, $\eta_p^2 = 0.48$), showing big effect of both the constant and baseline (chatbot with anger) combined.

For Model 3, the interaction plot (Figure 5c) suggests that the FAQ group has the highest cognitive effort needed (11.097 and 10.684) while both empathetic chatbot and non-empathetic chatbot groups have smaller cognitive effort needed. In ANOVA results, the intercept (F=149.94, p¡0.01, η_p^2=0.36) shows significant big effect of both the constant and baseline (empathetic bot with anger) combined. The FAQ term (F=19.18, p¡0.01, η_p^2=0.07) demonstrates significant medium effect of the use of FAQ on cognitive effort needed.

The results from the interaction plot support both hypotheses, which is really evident in model 2. Results from the ANOVA analysis, however, cannot support hypothesis 1 or 2. The lack of significance in the results is the major cause. On the other hand, it's clear that the use of chatbot lowers the the cognitive effort needed from both the interaction plot and ANOVA analysis.

4.2. Regression Analysis

We conducted regression analysis to examine the more detailed effects of independent variables. We only report the most interesting one: on perceived trustworthiness. Similar to the ANOVA analysis, we analyzed three groups of models: 1. Two-by-two comparison of Bot/FAQ vs. AngerInducement; 2. Two-by-two comparison of Empathy/NonEmpathy Bot vs. AngerInducement; 3. Three-by-two comparison of EmpathyBot Treatment vs. AngerInducement. In each model, two regressions are analyzed: the first one with all the direct effects from independent variables and the second with the interaction term added. Aside from the two regressions within each group, we began with baseline model that contains only a control variable: comprehension count, which is the number of interpretation questions answered correctly with contents related to the information provided in the chatbot/FAQ experience.

In model 0, we see that comprehension count has a significant positive correlation (coefficient=1.04) with helpfulness, which is true for all regressions in all models, suggesting a strong correlation between perceived helpfulness and comprehension level. In model 1, we see that there's no significant term, indicating no significant correlation between the use of chatbot and helpfulness. In model 2 regression (4), we see that not using empathetic language (NonEmpathy term) has significant negative correlation with helpfulness, demonstrating a positive correlation between the use of empathetic language and perceived helpfulness. This significance disappears with the introduction of the interaction term. In model 3, we see that both non-empathetic chatbot and FAQ has negative correlation (coefficient=-0.91 and -0.84) with helpfulness. As well as model 2, the significance also disappears with the introduction of the interaction term, suggesting that empathetic language in chatbot has significant effeect on helpfulness while the introduction of anger does not affect it.

As a result, the regression results suggest that hypothesis 1: Empathy in language display has a positive effect on cognitive effort is supported but needs to consider the interaction effect. A more detailed analysis on the main effect and interaction effect of the empathetic language shows that the main effect is hidden with the introduction of the interaction term, which explains the disappearance of significance of the empathy term in ANOVA analysis. Considering adjusted R2 (highest value of 0.15) and AIC (lowest value of 1301.98), regression (6): Helpfulness $\sim$ ComprehensionCount + WithoutAnger + NonEmpathyBot + FAQ is the best model to describe helpfulness.

From model 0, we see that the intercept has significant positive correlation (coefficient=0.929) with trustworthiness. This correlation lasts for all three models. From model 1, we only see significance after the introduction of the interaction term between chatbot and anger inducement. One thing to note is that without anger inducement is positive correlated with trustworthiness (coefficient=1.161), therefore the inducement of anger hinders trustworthiness in participants. In Model 2, the hindering effect of anger inducement is clearer as the significant positive coefficient (1.17 and 2.46) in without anger term. Also, the interaction effect between non-empathetic language and without anger has significant negative (coefficient=-2.61) correlation with trustworthiness, indicating that non-empathetic language without anger inducement lowers trustworthiness as well as empathetic language with anger. In model 3, similar thing happens that both the levels in chatbot and the anger inducement term becomes significant with the inclusion of the interaction term, suggesting its significance in explanation power. In regression (7), without anger shows positive correlation with trustworthiness (coefficient=2.445), showing the hindering effect of anger inducement. FAQ has positive correlation with trustworthiness (coefficient=1.536), while interaction terms between without anger and both non-empathetic chatbot and FAQ are negatively correlated to trustworthiness (coefficient=-2.60 and -2.86), suggesting that the effect of anger inducement and empathetic chatbot are offsetting each other.

Referring back to hypotheses, the results from the regression analysis on trustworthiness suggest strong support for both hypotheses 1 and 2. The use of empathetic language generally improves trustworthiness, but with the introduction of anger, a negative emotion, the empathetic language works in the opposite direction, which also explains the ANOVA results that the use The best regression model considering adjusted R2(highest value of 0.087) and AIC(lowest value of 1499.09) is regression (7). Its formula is Trustworthiness $\sim$ ComprehensionCount + NonEmpathyBot + WithoutAnger + FAQ + NonEmpathyBot:WithoutAnger + FAQ:WithoutAnger.

4.2.1. Cognitive Effort

In model 0, we see that there's no significant correlation between cognitive effort and comprehension count, meaning that there's no evidence that the perceived cognitive effort needed is correlated with the measured comprehension results. In model 1, not using chatbot has significant positive correlation with cognitive effort (coefficient=2.9 and 3.3), meaning that the use of chatbot would decrease the cognitive effort needed. In model 2, while empathetic language does not have significant correlation with cognitive effort, comprehension count has significant negative correlation with cognitive effort (coefficient=-0.79 and -0.78). It suggests that when only using chatbot (the population in model2 is limited to the respondents that are only using chatbot), comprehension level is negatively correlated with the cognitive effort needed. In model 3, when all levels of the chatbot are involved in the model, the only term that is significant is FAQ treatment. FAQ is positively correlated with cognitive effort (coefficient=3.13 and 3.74), which is also corroborated by the results of model 1, suggesting that not using the chatbot (FAQ) significantly increases cognitive effort needed.

Therefore, referring back to the hypotheses, in case of hypothesis 1: Empathy in language display has a positive effect on cognitive effort is not supported as none of the empathy language related term is significant. Hypothesis 2 that Anger positively moderates the effect of empathy is not supported either as none of the terms related to anger inducement is significant. However, it's supported that the use of chatbot strongly lowers the coginitive effort needed by people.

Considering adjusted R2 (the highest value 0.105), AIC (the lowest value 1570.93), and BIC (the lowest value 1585.43), regression (2) is the best model to describe cognitive effort with the formula that

Cognitive Effort $\sim$ ComprehensionCount + NoBot + WithoutAnger.

5. Discussion

5.1. Research on AI empathy in human-AI relationships

This study yielded several interesting findings. When reviewing the results of our experiment and analyses, we investigated the impact that empathy in language display had on relational outcomes of human-AI conversations (trustworthiness, cognitive effort, and satisfaction). Within the chatbot, we used two linguistic elements to create empathy: syntactical, by changing the the ”camera angle” which changes the speakers' identification with ”varying degrees” with the person addressed in the direct conversation of the AI agent (Kuno and Kaburaki, 1977), and rhetorical syntax, which creates similar mechanisms of the AI's identification with its conversational partner, the human, through language. As such, we provide a new perspective towards empathy through syntax and rhetoric and distinguish it from work using empathy labeling or anthromorphism (Crolic et al., 2022; Kuno and Kaburaki, 1977; Kuroshima and Iwata, 2016; Mohr et al., 2007; Pamungkas, 2019; Pelau et al., 2021). First, the results support that the use of empathetic language increased the perceived helpfulness (irrespective of the users' emotional state). When reviewing the regression results for Models 1, 2, and 3, the use of empathetic language did increase the perceived the helpfulness, which contradicted the ANOVA results as the results did not yield significant evidence to support the fist hypotheses; however, upon reviewing the regression results, it could be determined that the empathy in language display has a positive effect on helpfulness. Second, the results support the use of empathetic language increased the perceived trustworthiness while the inducement of anger negatively affects the effect of both using chatbot and empathetic language. When reviewing the regression results for Trustworthiness, both hypotheses are supported; however, the ANOVA only supports the second hypothesis. This can be explained when reviewing the regression results support that the use of empathetic language improves the the trustworthiness; however, when the negative emotion of anger is introduced, the empathetic language has the opposite effect (Alam et al., 2018; Cox and Ooi, 2022; Liebrecht et al., 2021; Pelau et al., 2021). Finally, the use of empathetic language does not have significant impact on cognitive effort needed to perform the task; however, a bot significant outperformed the FAQ site.

5.2. Literature on emotion display in conversations

As discussed earlier, the results show that empathy in language display, both in a syntactical and rhetorical context, impact the perceived helpfulness and trustworthiness. Additionally, the results suggest that negative emotions like anger hinders and even reverses the effect of empathy in language display, which suggests that more research in emotional alignment is needed. The influence of emotion display in conversations within our chatbot depends on the chatbot's perceived social intelligence from the receiver as previously detailed in Table 1 because it is important to note that the introduction of anger, as a moderating effect, had various reactions while using the empathetic chatbot. Although prior studies sought to explore whether the perception of more human-like qualities of the chatbot led to a greater perceived empathetic response, our research seeks to expand by exploring the perceived psychological anthropomorphic characteristics of an AI device influence in a significant positive way can impact the perceived empathetic characteristics of the robot (Pelau et al., 2021) and how to build trust between the user and the conversational agent during a difficult time. As Cuff et al., 2016 defined empathy as ”*the emotional response, dependent upon the interaction between trait capacities and state influences. [These] processes are automatically elicited but are also shaped by top-down control processes. The resulting emotion is similar to one's perception (directly experienced or imagined) and understanding (cognitive empathy) of the stimulus emotion, with recognition that the source of the emotion is not one's own.*” One such study which our study is based on explored the effects of mimicry from the injection of empathy, the use of pronouns, verb tense, and punctuation; and found that (i) mimicry did not have much impact to elicit a high empathetic response, (ii) used personal pronouns such as ”*[*you]” over ”*the*”, (iii) verb tense was used in the present, (iv) proper punctuation, more so, a formal writing style, was indicative of more empathetic writing style.

We theorized the empathetic chatbot have be perceived as empathetic between the user and the chatbot and eliciting the appropriate response from the user from the lexical cues such as ”*let us*” and ”*shall we*”, which would try to engage the user through collective reasoning and using the first person plural conjugation (Alam et al., 2018. Additionally, additional lexical cues such as changing the order of object centered and subject centered verbs in the sentence structure, will detail who the person is giving preferential treatment in terms of empathy towards the