How Personality Traits Influence Negotiation Outcomes? A Simulation based on Large Language Models

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Abstract

Psychological evidence highlights the influence of personality traits on decision-making. For instance, agreeableness and openness enhance negotiation outcomes positively, whereas neuroticism can lead to unfavorable outcomes. This paper introduces a simulation framework that integrates LLM agents endowed with synthesized personality traits. These agents negotiate within a traditional bargaining domain with customizable personalities and negotiation objectives. The experimental results indicate that the behavioral tendencies of LLM-based simulations generally mirror those observed in human negotiations. A case study based on synthesized bargaining dialogues reveals intriguing behavioral dynamics, including deceitful and compromising behaviors. The contribution is twofold. First, we propose a simulation methodology that harnesses LLM agents' linguistic and economic capabilities. Secondly, we offer empirical insights into the impact of Big-Five personality traits on bilateral negotiation outcomes.

1 Introduction

Recent Large language models (LLMs) have demonstrated their capacity to emulate diverse human traits (Park et al., 2022; Serapio-García et al., 2023). Such models can now simulate intricate human behaviors and provide valuable insights into various linguistic, psychological, and economic aspects of human cognition. Real-world decision-making is an example of a cognitive processes that has long been exciting for psychologists and economists. Economic theory posits that decisions assume a certain level of rationality and comprehension of available options (Gibbons, 1992). However, behaviorists contend that humans are not entirely rational but are influenced by psychological factors (Evans, 2014), cognitive biases (Daniel, 2017) and personality traits (Bayram and Aydemir, 2017). An important research question is how individual personality traits differences impact decision patterns. For instance, evidence suggests that certain personality traits might give individuals certain advantages in negotiation settings (Falcão et al., 2018; Barry and Friedman, 1998; Amanatullah et al., 2008). Extraversion tends to result in a slight disadvantage in competitive negotiation settings while being an advantage in cooperative settings (Barry and Friedman, 1998).

In this paper, we explore how personality traits affect negotiation. We specifically focus on negotiations that involve the exchange of offers in the form of dialogues in natural language. We attempt to answer a long-standing question in psychology: *"How does a difference in personality traits influence negotiation outcomes?"*, in the context of LLMs.

To address such question, we propose an LLM-based negotiation simulation framework incorporating LLM negotiation agents with synthesized personality traits (Figure 1). First, we use in-context learning to configure LLM agents with specific personality profiles given target negotiation objectives. Our personality profiles follow the framework of Big-Five personality theory (Costa Jr and McCrae, 1995; John et al., 1999) and assign to the LLM agent personality traits instructions through personality-describing adjectives (Goldberg, 1992). For the negotiation objectives, we introduce an instruction on the task-specific negotiation goals of the agent. Specifically, we consider a competitive bargaining scenario between a buyer and seller agent. With LLM agents, we perform negotiation simulations in the form of dialogues, in which agents exchange offers. To evaluate the outcomes of the negotiation, we extract and analyze the negotiation states and the offer prices (if any) made in utterances. By varying the personality traits of the negotiation agents, we observe changes in negotiation outcomes and behavioral patterns. We investigated which personality traits lead to

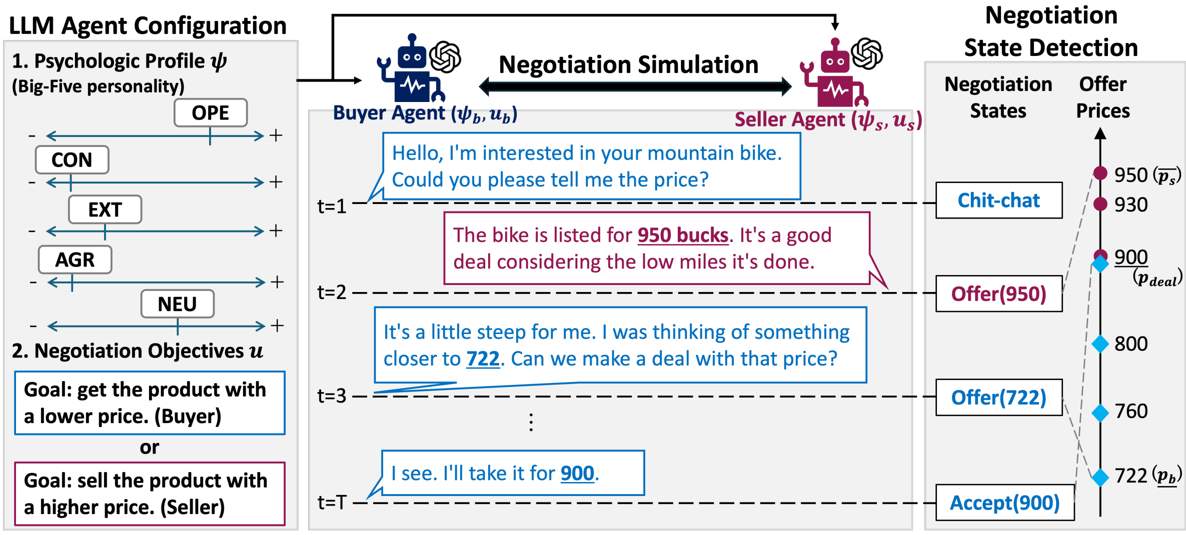


Figure 1: System Overview.

better/worse negotiation outcomes. More importantly, we want to see whether the LLM-based simulation results align with the findings of previous research conducted on human subjects. Our experimental results show that the tendencies in LLM-based simulation generally align with those observed in human-based results. In addition, the case analysis based on synthesized bargaining dialogue reveals intriguing behavioral patterns such as deceiving and deceptive behaviors, compromising behaviors, take-it-or-leave-it strategies, and so forth. The results obtained in this work illustrate that LLM not only mimics various styles of talking but is also capable of capturing the behavioral patterns of humans. The contribution of the paper is twofold. (1) We propose a simulation methodology that leverages LLM agents with linguistic and economic capabilities. (2) We provide insights on the effect of Big-Five personality traits on simulated negotiation outcomes and compare them with the negotiation outcomes of psychology experiments.

The paper is structured as follows. Section 2 covers some research on the links between personality traits and decision-making instances. Section 3 outlines our methodology. Section 4 presents the experimental results. Section 5 concludes the paper.

2 Related Work

Recent advances in LLMs allowed the development of systems capable of emulating various human behaviors, emotions, and personalities (Akata et al., 2023; Serapio-García et al., 2023). Decision-making is a particular type of human behavior that is still challenging to reproduce with LLM agents because it relies on reasoning capabilities that they lack (Tamkin et al., 2021). Decision-making generally entails choosing an action from various options in response to a particular situation, often reflecting personal preferences or beliefs (Simon, 1990). Moreover, real-world decisions are challenging because they are susceptible to environmental and cognitive constraints (Phillips-Wren and Adya, 2020).

Narrowing down the scope of decision-making problems, we focus on negotiation as an example that we claim could be studied comprehensibly using LLMs. In a negotiation, two parties interact with each other to exchange bids and attempt to reach a mutual agreement (Raiffa, 2007; Jennings et al., 2001). Looking at negotiations from the classical economics perspective, we often presuppose several assumptions, such as rationality (Evans, 2014). Such assumptions often fail when the negotiations are conducted through natural language, which conveys various aspects that cannot be studied economically, such as emotions or personality traits. There is in fact evidence showing the effect of Big-Five personality traits on decisions (Bayram and Aydemir, 2017; Urieta et al., 2021; Erjavec et al., 2019; Toledo and Carson, 2023; El Othman et al., 2020). In negotiations, certain personality traits are considered disadvantageous (Falcão et al., 2018; Amanatullah et al., 2008). Extraversion and agreeableness, for example, constitute liabilities in competitive bargaining problems while being advantageous in cooperative settings (Barry and Friedman, 1998). Part of our results reproduce such cases in addition to other instances.

3 Methodology

This section introduces our proposed simulation framework with LLM agents possessing synthesized personalities. In Section 3.1, we explain the formulation of the negotiation model and the basic syntax. In Section 3.2, we introduce the method to configure a LLM negotiation by providing instructions regarding personality traits and negotiation objectives. We then describe the process of simulating negotiation dialogues with the LLM agents in section 3.3.

3.1 Negotiation Model

We consider a classical *bargaining* scenario in which a buyer and a seller negotiate over the price of an item or product. Typically, the buyer aims to reduce the purchase price while the seller seeks to maximize it, resulting in the competitive nature of the negotiation scenario. This is also an example of a *zero-sum game* in which one party's gain leads to the other party's loss, showing the competitive nature of the task (Gibbons, 1992). In our LLM-based negotiation simulations, the seller and the buyer are LLM agents. Since our goal is to study the effect of personality traits on negotiation, we characterize the two agents by their psychological and economic profiles as in (Eq. 1).

$$\begin{aligned} \text{Seller } s &= (\psi_s, u_s) \\ \text{Buyer } b &= (\psi_b, u_b) \end{aligned} \tag{1}$$

The psychological profiles ψ_s and ψ_b will be instantiated with predefined personality traits. That is, we adopt the five-factor model of personality (Big-Five) (Costa Jr and McCrae, 1995; John et al., 1999), which decomposes human personality into five dimensions: **Openness (OPE)**, **Conscientiousness (CON)**, **Extraversion (EXT)**, **Agreeableness (AGR)**, and **Neuroticism (NEU)**. Each personality dimension is a spectrum with negative and positive polarities. These five dimensions encompass a comprehensive range of human personality patterns. Additionally, the economic profiles of the agents are reflected in their utility functions, denoted as u_s for sellers and u_b for buyers. A utility function is a mathematical way to describe the preferences or objectives of the agents depending on the case where the agent is minimizing (buyer) or maximizing the price (seller) (Gibbons, 1992).

The seller and the buyer negotiate in a dialogue D around a product. The dialogue is a sequence of T utterances $D = \{d_1, d_2, \ldots, d_T\}$. Each utterance d_t is associated with a negotiation state s_t and the current offer price p_t.

3.2 LLM Agent Configuration

We configure an LLM negotiation agent with specific personality traits by introducing a personality instruction (Section 3.2.1) and a negotiation objective instruction (Section 3.2.2), with in-context learning.

3.2.1 Personality Traits Instruction

We configure a LLM agent with a synthetic personality profile as in (Eq. 1). An agent k, with $k \in \{s, b\}$, possesses a 5-dimensional personality profile as described in (Eq. 2).

$$\begin{aligned} &\psi_k = (\psi_k^{OPE}, \psi_k^{CON}, \psi_k^{EXT}, \psi_k^{AGR}, \psi_k^{NEU}) \\ &\psi_k \in \mathbb{L}^5, \quad \mathbb{L} = \{\text{---}, \text{--}, \text{-}, \text{+}, \text{++}, \text{+++}\} \end{aligned} \tag{2}$$

Each element of ψ_k represents the corresponding personality dimension's polarity (negative or positive) and degree (high/moderate/low). For instance, ψ_k^{AGR} takes on one the values in $\mathbb{L}$, which respectively represents a spectrum from highly disagreeable (---), moderately disagreeable (--), lowly disagreeable (-), lowly agreeable (+), moderately agreeable (++), highly agreeable (+++). Following previous work, we use personality-describing adjectives to instruct personality traits (Serapio-García et al., 2023). We use the list of 70 bipolar adjective pairs proposed by Goldberg (1992), which are adjectives that statistically correlate with certain Big-Five personality traits (Table 1). For instance, prompting an LLM with adjectives such as *unsure* and *irresponsible* is likely to result in an LLM with *negative conscientiousness* traits.

For each personality dimension in ψ_k, we randomly pick n adjectives out of all the personality-describing adjectives associated with the polarity of the given dimension. Further, we apply the modifiers based on the degree of the personality traits. We use "very" as a modifier for a high degree and "a bit" for a low degree. No modifier is used for the moderate degree. Following this process, we use $5 \times n$ adjectives associated with any given personality profile ψ_k. We then generate a personality trait instruction with the template *"Act as a person*

Dimension	Negative	Positive
OPE	unimaginative, uncreative, unaesthetic, ...	imaginative, creative, aesthetic, ...
CON	unsure, messy, irresponsible, ...	self-efficacious, orderly, responsible, ...
EXT	unfriendly, introverted, silent, ...	friendly, extroverted, talkative, ...
AGR	distrustful, immoral, stingy, ...	trustful, moral, generous, ...
NEU	relaxed, at ease, easygoing, ...	tense, nervous, anxious, ...

Table 1: The big-five personality dimensions and their corresponding personality-describing adjective pairs.

with the following personality: $\${L}$.", where L is a comma-separated list of the associated adjectives (including the modifiers). The personality traits instructions are given to the LLM agents through in-context learning.

3.2.2 Negotiation Objective Instructions

To configure the economic profiles of the LLM negotiation agents (u_s and u_b in (Eq. 1), we incorporate negotiation objective instructions that define the negotiation goals of each agent. Specifically, we focus on a bargaining scenario where the seller agent aims to sell the product at a higher price, reaching its ideal price as closely as possible. Conversely, the buyer agent seeks to secure a deal at a lower price and strives to achieve its ideal target price (Raiffa, 1982). The instructions are the following:

- (Buyer) Act as a buyer and try to strike a deal for a $\${PRODUCT}$ with a lower price through conversation. You would like to pay for $\underline{p}_b$. Your reply should not be too long.
- (Seller) Act as a seller that bargains with the buyer to get a higher deal price. Your listing price for this $\${PRODUCT}$ is $\bar{p}_s$: $\${DESCRIPTION}$ Your reply should not be too long.

Here, $PRODUCT$ and $DESCRIPTION$ are the product name and short description of the negotiation item. These linguistic instructions could theoretically be mapped into utility functions, which will later be used to evaluate negotiations. We avoid making assumptions about the shape of the utility functions, as the behaviors of the agents are primarily shaped by the LLM instructions, which may not follow any specific mathematical representation of their preferences.

3.3 Negotiation Simulation

Using the methods in Section 3.2, we configure the buyer LLM agent and the seller LLM agent and conduct a negotiation simulation between them. The seller and buyer agents exchange offers, with the seller kick-starting the conversation with the fixed utterance *"Hi, how can I help you?"*. After an utterance d_t is generated, the response is fed to the other agent as a prompt. The process continues until the termination condition is met. In this fashion, we collect a negotiation dialogue $D = \{d_1, d_2, \ldots, d_T\}$. Following (Fu et al., 2023), we introduce a dialogue state detector to extract negotiation-related information from each utterance. First, we detect the negotiation state s_t of d_t, which is one of the following states:

- *Offer*: the agent makes a price offer.
- *Accept*: the agent accepts the current offer.
- *Deal-break*: the agent refuses the last offer and walks away from the negotiation table.
- *Chit-chat*: utterances whose intent is not directly related to the negotiation, such as greetings.

In addition, we extract the current offer price p_t for each utterance. After generating each utterance d_t, the dialogue state detector takes d_t and its context (previous h utterances) as input and extracts the negotiation state s_t and the current offer price p_t (if any.) In this work, we use another LLM as the dialogue state detector.

For the termination condition of the negotiation is based on the detected negotiation states. We terminate the negotiation dialogue if an *Accept* or a *Deal-break* is reached. Also, we set a length limit of $T = T_{max}$ of the dialogue. If the length of the generated dialogue reaches this limit, we terminate the process and automatically regard it as a failed negotiation.

4 Experimental Results

In this section, we first provide details on the experimental settings (Section 4.1). The rest of the section is dedicated to analyzing the results of the simulations.

4.1 Experimental Settings

For buyer and seller agents, we adopt GPT-4 (gpt-4-0613) (OpenAI, 2023) as the choice of the LLM model.

We additionally utilized the CraigsListBargain dataset (He et al., 2018) to set several negotiation variables. The dataset is a commonly used dataset of negotiation, consisting of bargaining dialogues in an online platform. For each negotiation entry in the dataset, we extract the name and the description of the product, and the 'listing price' of the seller and a 'target price' of the buyer. We use the listing price as the ideal price $\bar{p}_s$ for the seller and the target price as the ideal price $\underline{p}_b$ for the buyer. Note that an agent's ideal price is not disclosed to the other party in our setting. We randomly sampled a total of 1500 negotiation entries from the dataset.

For the personality traits instruction, we consider the following three variations:

- Mixed-dimension agent: We define the spectrum of personality traits based on the Big-Five theory. For an agent, we first generate a personality profile by randomly sampling from the personality space $\mathbb{L}^5$ (such as [**OPE++**, **CON---**, **EXT--**, **AGR+**, **NEU++**].) We select $n = 3$ personality-describing adjectives associated with the sampled polarity and degree values for each Big-Five dimension. The 5000 adjectives across all dimensions are then randomly shuffled to give $\$\{L\}$.

- Single-dimension agent: We pick one out of five Big-five dimensions and only give personality traits instruction along this dimension. We select the personality dimension, the polarity, and the degree (such as **AGR+**) and randomly sample $n = 3$ personality-describing adjectives associated with it.

- No-personality agent: An LLM agent is only given the instructions for negotiation objectives but not regarding personality traits.

For the dialogue simulation process, we set a maximum length of $T_{MAX} = 20$ utterances. We use GPT-4 (gpt-4-0613) and the function calling module provided by Open AI to implement the negotiation state detector. The target utterance and its preceding $h = 5$ utterance are given as context for negotiation state detection. We consider the following two types of experiment settings:

- Mixed-personality setting: We conduct negotiation simulation with both the seller and the buyer being mixed-dimension agents. The personality profiles of both agents are set randomly, as described above.

- Single-personality setting: In a mixed-personality setting, personality traits of all five dimensions influence the negotiation outcomes together. We conduct negotiation simulation with single-dimension agents to better discriminate the influence of each big-five dimension. Further, to simplify the matter, we randomly pick one of the LLM agents (either buyer or seller) to give personality traits instruction. The other agent is always a no-personality agent.

4.2 Evaluation of the Negotiations

We mainly evaluate the negotiations in terms of utility and whether the negotiations are successful or not (Baarslag et al., 2016; Cao et al., 2015; Lin et al., 2023). Recall that utility functions serve as mathematical tools for quantifying the quality of decision outcomes (Simon, 1990). Below we list our used metrics.

Intrinsic utility (UI). Based on the negotiation instructions, the utility of buyer and seller for a particular price p could be expressed in (Eq. 3).

$$
\begin{aligned}
u_s, u_b &: \mathbb{R}^+ \to [0,1] \\
u_s(p) &= \frac{p - \underline{p}_s}{\bar{p}_s - \underline{p}_s} \\
u_b(p) &= \frac{\bar{p}_b - p}{\bar{p}_b - \underline{p}_b}
\end{aligned} \tag{3}
$$

As illustrated in the example of figure 1, the prices $\underline{p}_s$ and $\bar{p}_s$ are the seller's reservation price and initial price, and $\underline{p}_b$ and $\bar{p}_b$ are the buyer's initial price and reservation price. Here, $\underline{p}_s$ is the price the seller is willing to accept without losing money. Similarly, the buyer's reservation price $\bar{p}_b$ is the maximum price it is willing to pay. Generally, the agreement zones of the agents are defined as the intersection between $[\underline{p}_b, \bar{p}_b]$ and $[\underline{p}_s, \bar{p}_s]$. We set $\underline{p}_s$ and $\bar{p}_b$ by assuming that the agreement zone is defined as a percentage of $[\underline{p}_b, \bar{p}_b]$. Second, $[\underline{p}_b, \bar{p}_b]$ and $[\underline{p}_s, \bar{p}_s]$ are private to the agents. It is important to note that an off p is not guaranteed to fall within the intervals due to the language model.

Joint utility (JU). We measure the quality of a bargaining solution p using a normalized joint utility u_{sb} inspired by Nash solution (Luce and Raiffa, 1989) as in (Eq. 4).

$$u_{sb}(p) = \frac{(p - \underline{p}_s)(\bar{p}_b - p)}{(\bar{p}_b - \underline{p}_s)^2} \tag{4}$$

For instance, the joint utility reaches a maximum of 0.25 when p is the arithmetic average of $\underline{p}_s$ and $\bar{p}_b$. This measure is often used to measure the level of fairness of a given outcome p.

Concession rate (CR). Given the negotiation objectives, the offers could be assumed to undergo some form of decay akin to concessions. That is, an agent k will make an offer at round $t \in [1, T]$ based on a discounted utility function (5), with concession rate $c_k \in [0, 1]$.

$$u_k^{(t)} = \underline{p}_k + (\bar{p}_k - \underline{p}_k) \times \left(\frac{T-t}{T}\right)^{c_k} \tag{5}$$

Applied to the utility functions of the buyer and seller (Eq. 3), we obtain the concession rates (6).

$$\begin{aligned} CR_s &= \sum_{t=1}^{T} \log\left(\frac{\bar{p}_s - p_t}{\bar{p}_s - \underline{p}_s}\right) \\ CR_b &= \sum_{t=1}^{T} \log\left(\frac{p_t - \underline{p}_b}{\bar{p}_b - \underline{p}_b}\right) \end{aligned} \tag{6}$$

Negotiation success rate (NSR). Defines the ratio of the successful negotiations T_{succ} relative to the total number of negotiation rounds T.

$$NSR = \frac{T_{succ}}{T} \tag{7}$$

Average Negotiation Round (ANR). Refers to the speed of successful negotiation (Lin et al., 2023).

$$ANR = \frac{1}{T_{succ}} \sum_{k=1}^{T_{succ}} R_k \tag{8}$$

where R_k is the number of rounds of the k^{th} successful negotiation.

4.3 Correlation Analysis

The intrinsic utility (IU) is the most direct way to quantify the negotiation outcome. Thus, we include the visualization of intrinsic utility (IU) values for both single and mixed-personality settings in Figure 2. To analyze the correlations between each of the Big Five personality dimensions and the negotiation metrics, we conduct Spearman's rank correlation analysis. Table 2 illustrates the results for both single and mixed settings. The statistically significant correlations (with p-values smaller than 0.05 and 0.1) are highlighted in the table. It is clear from the coefficients in the single and mixed cases that when personality traits are combined, the correlation level decreases across traits. The results indicate that agreeableness (AGR) diminishes intrinsic utility gain for single and mixed cases, whereas conscientiousness (CON) contributes to increased utility gain. Openness (OPE) decreases utility in the single case, with correlation coefficients of -0.2471 ($p < 0.05$). The negative correlation of extraversion (EXT) and agreeableness (AGR) with utility reflects a well-known effect of these traits in competitive settings, where they are considered liabilities in distributive bargaining encounters (Barry and Friedman, 1998).

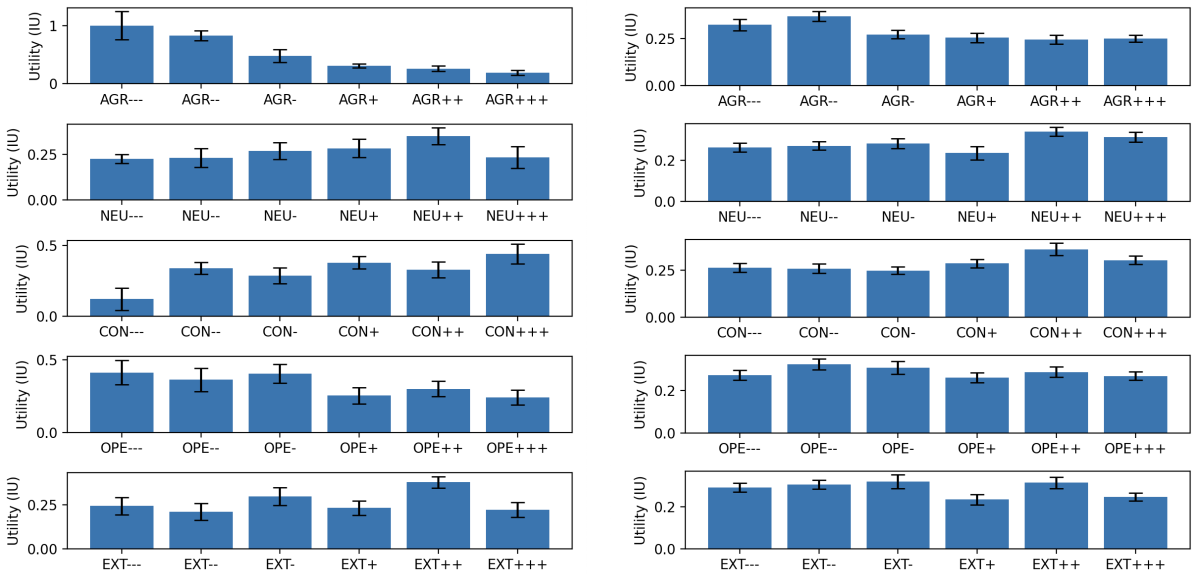
In terms of joint utility gain, also interpreted as the fairness of the negotiation deals for both agents, the joint utility correlates positively with agreeableness, suggesting that negotiators with high levels of agreeableness jointly achieve better utility with a correlation of 0.101 ($p < 0.05$) in the mixed case. Neuroticism is found to correlate negatively with the joint utility gain at -0.0419 ($p < 0.1$), which corroborates the negative effect of neuroticism on the outcomes of distributive negotiations (Sass and Liao-Troth, 2015).

In terms of the concession behavior of the LLM agents, a significant positive correlation exists between concession rates, agreeableness, and openness. Conversely, the single case has a negative correlation with neuroticism (NEU) at -0.2764 ($p < 0.05$). These results suggest that individuals with heightened agreeableness and openness are inclined to make more concessions, while those with heightened neuroticism tend to make fewer. Extraversion for the mixed case also shows a positive effect on concession behavior with a correlation of 0.0532 ($p < 0.1$).

Shifting the focus from the individual, utilitarian view of the negotiation to the macroscopic view, we look at personality traits impact on the average number of rounds (ANR), also interpreted as the number of utterances in the negotiation dialogue as illustrated in Figure 1. Our analysis uncovered a significant negative correlation between the average number of negotiation rounds and agreeableness and openness. This suggests that agreeable and open individuals tend to engage in negotiations

Personality Trait	AGR		NEU		CON		OPE		EXT	
	Single	Mixed	Single	Mixed	Single	Mixed	Single	Mixed	Single	Mixed
Intrinsic Utility (IU)	**-0.66****	**-0.11****	0.077	0.035	**0.20****	**0.071****	**-0.25****	-0.036	-0.25	**-0.075****
Joint Utility (JU)	**0.54****	**0.10****	-0.088	**-0.042***	-0.050	0.014	0.075	0.025	-0.028	0.031
Concession Rate (CR)	**0.51****	**0.087****	**-0.28****	**-0.046***	-0.11	**-0.033****	**0.13***	**0.047***	-0.090	**0.053***
Average Round (ANR)	**-0.50****	**-0.14****	0.034	0.030	**0.16***	0.031	**-0.28****	-0.0064	-0.12	**-0.10****
Success Rate (NSR)	**0.14***	**0.079****	0.000	-0.0001	0.014	**0.079****	0.035	0.026	**0.17****	0.026

Table 2: Spearman's rank correlation coefficients illustrating the relationships between negotiation metrics and Big-Five personality traits (AGR, NEU, CON, OPE, EXT). Bold numbers with asterisks indicate statistical significance, with * denoting $p < 0.1$ and ** denoting $p < 0.05$.



(a) Single personality dimension.

(b) Mixed personality dimension.

Figure 2: The intrinsic utility (IU) of different personality settings.

that end quickly. In contrast, there is a positive correlation between the average number of negotiation rounds and conscientiousness (CON) at 0.157 ($p < 0.1$) for the single case.

When looking at the negotiation success rate (NSR), we found a slight positive correlation between NSR and both agreeableness (AGR) and extraversion (EXT) at 0.1732 ($p < 0.05$) for the single case only. This suggests that the success of the negotiations is affected by the agents' agreeableness and extraversion levels. This aligns with the positive effect of agreeableness on the negotiators' distributive outcomes reported in (Sass and Liao-Troth, 2015). However, such traits are known to have an opposite, negative effect on initiating negotiations in distributive bargaining reported in (Reif and Brodbeck, 2011). More generally, extraversion, in particular, is positively related to confrontational conflict settings (our bargaining setting) and negatively to non-confrontational settings (Ma, 2005).

4.4 Case Study

We conduct qualitative analysis of the negotiation simulation results. Table 3 shows several examples of dialogues generated in the negotiation simulation process. It is easier to discriminate the influences of a specific personality trait, while in the mixed-personality settings multiple factors come into play at the same time and makes it less obvious which factors is dominant. Thus, all examples presented in the table are generated in the single-personality setting.

The first example is a negotiation dialogue between a highly disagreeable (**AGR---**) seller and a buyer without any personality setting. We can see that when the buyer asked about the product's price, the seller answers a price ($180) that is higher than the listing price ($160) in the instruction. We discover the kind of deceiving behavior in the negotiations involving disagreeable agents.

The second example is a negotiation involving a non-neurotic Buyer (**NEU--**). We can observe a

Agent	Negotiation Dialogue	$\bar{p}_s$	$\underline{p}_b$	p_{deal}
Seller (AGR---)	Buyer: Hello, I'm interested in your Smartphone. Could you please tell me the price? **Seller: Sure, for you, just because I like your spirit, I am willing to let it go for $180.** ... Buyer: Thanks for your patience. Although it's still over my budget, I'll take it for $160.	160	80	160
Buyer (NEU--)	**Buyer: As much as I'd want to meet your price, $260 is a bit steep for me... I'm willing to push my budget a notch to $245. What do you say?** Seller: I understand, times are tough. Given your genuine interest, I can accommodate the price at $250 for this wonderful piece. It's really a great bed and your children will certainly love it. Final deal at $250? **Buyer: I appreciate your flexibility and understanding. And an extra $5 won't hurt, I guess. Let's wrap it up at $250 then!** ...	290	203	250
Seller (OPE---)	Buyer: I see. I'm in a bit of a tight spot financially, and I was hoping for something around 114. ...Can we strike a deal at this price point? **Seller: I can understand your situation, but my final price is 190. ... I believe you won't find a better deal elsewhere.** Buyer: I understand your stance and you're right, it's a great offer. Yet, I can push my budget up to 130. ... **Seller: I see you're really interested. But the price is set at 190. That's the deal, it's clear and simple. It's the best I can offer for a new LG G4 with a protective case.** Buyer: I respect your offer, but considering my budget, the highest I can go is 150. **Seller: I appreciate your situation, and I understand money can be tight. But I can't sell it for less than 190.** ...	190	114	-

Table 3: Case study. The examples are generated with the single-personality setting. The third example did not reached the final deal, the p_{deal} is marked as "-".

compromising behavior here: when the seller offer the price of $250, the buyer concedes and accept the deal easily (*"And an extra* $5 *won't hurt, I guess."*). On the other hand, in the third example of negotiation involving a seller of negative openness (**OPE---**), we can see that the seller adopts a 'take-it-or-leave-it' strategy. Despite the constant effort of the buyer to make a concession to find a common ground with the seller, the seller is not willing to change the offer price ($190). This also results in a breakdown in negotiation, with the buyer leaving the negotiation table without reaching an agreement. The above examples showcase a range of negotiation behaviors such as deception compromising, hard-headed behavior, etc. This illustrates how specific personality traits influence negotiation dynamics and outcomes.

5 Conclusion

We introduced a simulation framework that integrates LLM agents possessing synthesized Big-Five personality traits. The agents were instructed to negotiate within a traditional bargaining setting. The experimental results indicate that the behavioral tendencies of LLM-based simulations generally mirror those observed in human interactions. We additionally proposed a case study based on synthesized bargaining dialogues which revealed interesting cases of deceitful and compromising behaviors. Our contribution is twofold. First, we proposed a simulation methodology that harnesses LLM agents' linguistic and economic capacities. Secondly, we offer empirical insights into the impact of Big-Five personality traits on bilateral negotiation outcomes.

6 Limitations

Our simulation framework presents possesses limitations that we will address in the future.

- The negotiation problem is relatively simple and could be rendered more complex by introducing additional issues and constraints. Also, we only focus on one negotiation scenario (bargaining) in this work. However, it should be straightforward to apply the proposed framework to other negotiation scenarios.

- We randomly sample from the personality space $\mathbb{L}^5$ to generate the personality profile.

However, the personality distribution of the personality is not uniform.

- It is possible to investigate various combinations of personality traits and and their interactions in a negotiation setting.

- The used preference models of the agents are relatively simplistic and do not account for other factors such as risk attitudes, etc.

- The strategies of the negotiating agents are missing from the persona definition.

- Addressing the risks of deploying the proposed negotiating agents within assistive technologies like Chatbots on financial and banking platforms.

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