Human Choice Prediction in Language-based Persuasion Games: Simulation-based Off-Policy Evaluation

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Abstract

Recent advances in Large Language Models (LLMs) have spurred interest in designing LLM-based agents for tasks that involve interaction with human and artificial agents. This paper addresses a key aspect in the design of such agents: predicting human decisions in off-policy evaluation (OPE). We focus on language-based persuasion games, where an expert aims to influence the decision-maker through verbal messages. In our OPE framework, the prediction model is trained on human interaction data collected from encounters with one set of expert agents, and its performance is evaluated on interactions with a different set of experts. Using a dedicated application, we collected a dataset of 87K decisions from humans playing a repeated decision-making game with artificial agents. To enhance off-policy performance, we propose a simulation technique involving interactions across the entire agent space and simulated decision-makers. Our learning strategy yields significant OPE gains, e.g., improving prediction accuracy in the top 15% challenging cases by 7.1%.[1]

1 Introduction

Consider an online platform like Booking.com, where service providers (e.g., hotel owners) promote their services to potential consumers (e.g., travelers). These platforms enable various economic interactions with dynamic behavior, making reputation a key factor as the interaction is often repeated. The platform often aims to *predict user behavior* with service providers for tasks like revenue forecasting and improved matching to boost social welfare. Predicting user behavior with new, unseen providers, however, results in a *distribution shift*. In this paper, we introduce a novel approach to address this prediction challenge. We use the term *Off-Policy Evaluation (OPE)* to describe a scenario where test-time interactions involve behavioral patterns and strategies from service providers that differ from those in the training data. When test-time interactions align with the training distribution, we refer to this as the *on-policy* scenario.

The interaction described above can be modeled as a game with asymmetric information, famously known as a *persuasion game*. In this game, a *sender* (i.e., a hotel owner or a travel agent) aims to influence the decision of a *receiver* (i.e., the consumer) through strategic communication. Unlike zero-sum games,[2] persuasion games may involve partially aligned or misaligned interests, depending on the *state of the world* (hotel quality)—only observed by the sender.

Economics emphasizes the importance of studying non-cooperative games beyond zero-sum scenarios (Mas-Colell et al., 1995), with persuasion games being central to information economics (Aumann et al., 1995; Kamenica and Gentzkow, 2011; Emek et al., 2014; Bahar et al., 2016; Bergemann and Morris, 2019). However, many game-theoretic models rely on simplified messaging and overlook the complexities of natural language communication between senders and receivers. Although their incentives may differ, they are not in complete opposition, making straightforward maximization solutions inadequate (Fudenberg and Tirole, 1991). Unlike traditional economic models that use formal signals, we explore persuasion games with *natural language communication*.

Recent research (Apel et al., 2022; Meta et al., 2022; Raifer et al., 2022) has ventured

[1] Our data and code are available in the GitHub repository: https://github.com/eilamshapira/HumanChoicePrediction.

[2] The term zero-sum game typically refers to a two-player game where one player's gain comes at the expense of the other, implying a complete misalignment of interests—rarely seen in real-world interactions.

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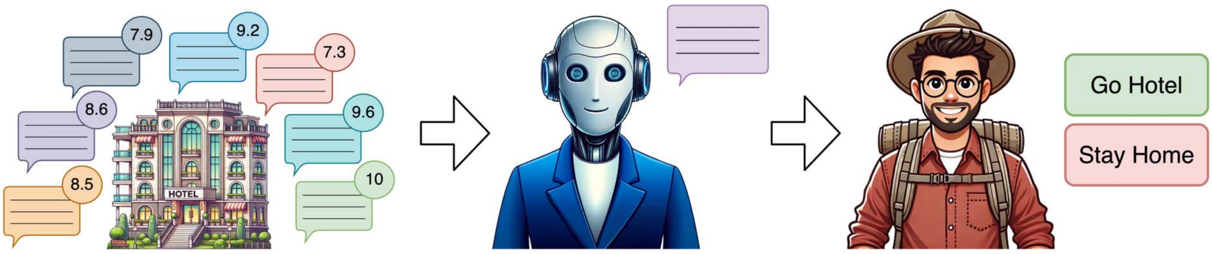


Figure 1: Illustration of a single round in the language-based persuasion game. The bot expert starts by analyzing the interaction history from prior rounds (not depicted in the illustration) alongside a set of seven reviews, each consisting of a textual description and an associated score. Following a predefined strategy, it selects one review from the set and transmits only its textual content to the human Decision Maker (DM). The DM then evaluates the received review in the context of the full interaction history and chooses an action. In the final step, both the expert and the DM receive their payoffs, which are determined by the DM's choice and the hotel's actual quality.

into language-based games, showcasing notable success in playing them, with diplomacy, a multi-person zero-sum game, being a noteworthy example (Meta et al., 2022). Despite these strides, a crucial gap persists in our comprehension of human choice within non-cooperative language-based persuasion games.

Apel et al. (2022) introduced a unique non-cooperative language-based persuasion game, featuring a multi-stage setup involving an *expert* (travel agent) and a *decision-maker (DM)*, the customer. In each interaction, the expert selects a scored textual review from the hotel's reviews to persuade the decision-maker to choose the hotel. The DM's acceptance or rejection yields stochastic payoffs determined by the review score distribution, accessible only to the expert. Both players move to the next stage with a similar structure after observing payoffs, but with a different hotel. Figure 1 illustrates a single round of the game. While Apel et al. (2022) primarily focused on predicting DM actions, Raifer et al. (2022) adapted the framework, creating an artificial expert (AE) employing the Monte Carlo Tree Search (MCTS) algorithm (Coulom, 2006). The AE utilizes deep learning models, incorporating behavioral and linguistic features to anticipate the DM's actions, and predict the expert's future reward based on game status and a potential review. The AE aims to maximize the number of hotels accepted by the DM.

1.1 Our Contribution

This paper focuses on *off-policy human choice prediction in language-based persuasion games*. To assess the comprehensibility of human decisions, we consider the prediction of human behavior when faced with an *unobserved opponent*. Instead of determining optimal policies, we aim to predict human agents' choices when playing with a set of artificial experts in a given game, based on their interactions with various other experts in the same game. This is an OPE setup for experts (agents) interacting with human decision-makers (DMs) in a persuasion game.

Data To realize this objective, we present a mobile application simulating a realistic language-based persuasion game environment. Through experiments involving human agents engaging with diverse artificial agents, we aim to establish predictive models that elucidate how humans respond to unfamiliar partners based on their interactions with known counterparts. In particular, our dataset consists of 87k decisions from 245 DMs who played against 12 different automatic expert bots (each DM played against 6 bots). We consider this dataset as a contribution to the research community and will make it public, hoping that it will promote the research in our area.

Simulation To enhance the performance of human choice prediction in OPE, we take a *simulation-based algorithmic approach*. We address data constraints in modeling human interactions by combining human-bot and simulated DM-bot interactions. Our DM simulation model assumes that DMs utilize a combination of heuristics related to past game behavior of both players and the content of the chosen review, and that they improve over time regardless of the specific strategy of the expert. From an algorithmic perspective, the simulation is designed to model a

DM that utilizes a *mixture-of-heuristics with dynamic weights (probabilities)*, where the weight of an *oracle heuristic* (a DM that knows the optimal decision) increases over time. This idea is inspired by the *multiplicative weights* algorithm, commonly used in online learning, game theory, and optimization (Fudenberg and Levine, 1995; Freund and Schapire, 1999; Arora et al., 2012). The game-agnostic improvement-over-time principle enables data generation from interactions between simulated DMs and diverse bots. Our results indicate that training a human decision prediction model on this mix of human interaction and simulated data results in a more robust model, not tailored to specific bot idiosyncrasies in the training set, making it suitable for predictions involving new bots and human DMs. Our ablation analysis highlights the importance of the various components of our simulation: learning-over-time, past behavior, and review content modeling.

2 Related Work

2.1 Persuasion in NLP

Persuasion has been extensively explored in NLP throughout the years. Tan et al. (2016) contributed a vital dataset from Reddit's ChangeMyView for online persuasion analysis. Hidey et al. (2017) explored argument classification in online persuasion, while Hidey and McKeown (2018) examined the impact of argument sequencing on persuasive success. Wang et al. (2019) investigated persuasive dialogue systems aimed at social good. Yang et al. (2019a) developed predictive models that assess the persuasiveness of requests on crowdfunding platforms. Chen and Yang (2021) offered a text repository for identifying effective persuasive strategies. Hiraoka et al. (2014) applied reinforcement learning to cooperative persuasive dialogues.

Several studies focused on studying persuasion from the expert's perspective: Raifer et al. (2022) follow the setup of Apel et al. (2022) to design an automated expert for language-based persuasion games, utilizing tools such as MCTS; Carrasco-Farre (2024) study persuasive strategies employed by LLMs; Breum et al. (2024) study the effect of persuasive LLMs on *opinion dynamics*; and Matz et al. (2024) demonstrate the potential of LLMs in *personalized* persuasion. In contrast, we focus on predicting the behavior of human *decision-makers*, particularly in the *off-policy evaluation* scenario, and developing a novel simulation-based approach.

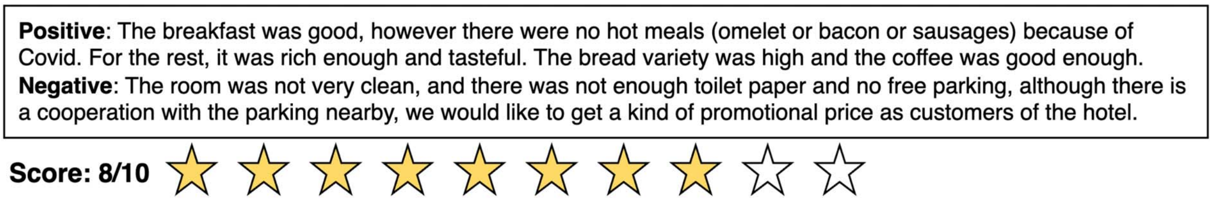
2.2 Simulation Data

Simulation ideas have been flowering in machine learning (ML) areas where human-human and human-machine interactions are modeled, e.g., in Reinforcement Learning (RL), due to the costly and laborious data collection for such setups (Tesauro, 1991). Notable applications include RL for robotics (Bousmalis et al., 2018; Vacaro et al., 2019), and autonomous cars (Yue et al., 2018). Simulations also play a crucial role in the development of artificial agents proficient in gaming scenarios, e.g., by using MCTS-like simulations to enhance agent performance (Silver et al., 2018, 2017; Schrittwieser et al., 2020; Oroojlooy and Hajinezhad, 2022). In NLP, simulating human interactions is used to build dialog systems (Jung et al., 2008; Ai and Weng, 2008; González et al., 2010; Shi et al., 2019; Zhang and Balog, 2020; Liu et al., 2023) and train LLM-based agents that mimic human behavior (Park et al., 2023; Hussain et al., 2023; Chuang et al., 2023; Taubenfeld et al., 2024).

Our work demonstrates a novel use of integrating interaction data with simulation data. Doing this we step in the footpath of several studies in diverse domains, such as NLP (Calderon et al., 2022), autonomous cars (Cao and Ramezani, 2023; Yue et al., 2018), and astro-particle physics (Saadallah et al., 2022). Our simulation is novel as it integrates simple heuristics and can shed light on human behavior. It is also designed to model a DM that, like human DMs, learns and improves over time—a property that is shown to be highly effective in enhancing OPE.

2.3 Action Prediction in ML and NLP

In the realm of ML and NLP, action prediction, particularly in human decision-making, has been studied across diverse scenarios (Plonsky et al., 2019; Rosenfeld and Kraus, 2018; Bourgin et al., 2019). For example, Plonsky et al. (2017) integrated psychological features with ML techniques, focusing on decision-making in games against nature, while Auletta et al. (2023) utilized supervised learning and explainable AI techniques


Positive: The breakfast was good, however there were no hot meals (omelet or bacon or sausages) because of Covid. For the rest, it was rich enough and tasteful. The bread variety was high and the coffee was good enough.
Negative: The room was not very clean, and there was not enough toilet paper and no free parking, although there is a cooperation with the parking nearby, we would like to get a kind of promotional price as customers of the hotel.

Score: 8/10 ★★★★★★★★☆☆

Figure 2: A sample review from our hotel review dataset. The agent is exposed to both the textual part and the numerical rating of the review. The agent sends only the textual signal to the DM, who is not exposed to the numerical rating.

for action prediction in collaborative tasks. While these works have not involved language, others try to predict human decisions in language-based situations. Ben-Porat et al. (2020) predicted individuals' actions in one-shot games based on free-text responses, and Oved et al. (2020) forecast the in-game actions of NBA players by leveraging insights from open-ended interviews.

Language-based action prediction has been extensively explored in the legal domain: Zhong et al. (2018) and Yang et al. (2019b) developed novel approaches for judgment prediction; Bak and Oh (2018) demonstrated how group discussions can be used to predict a leader's decision; Aletras et al. (2016) and Medvedeva et al. (2020) utilized ML and NLP to predict decisions of the European Court of Human Rights.

The recent advancements in LLMs for strategic and economic scenarios have opened new possibilities for leveraging LLMs as data generators to predict human actions in economic environments (Xi et al., 2025). For instance, Horton (2023) studied the behavior of LLMs in well-known behavioral economics experiments; Chen et al. (2023) studied the emergence of rationality of GPT; Akata et al. (2023) and Guo et al. (2024) compared the behavior of LLMs in games to those of rational agents, as predicted by game-theoretic concepts; and Shapira et al. (2024b) assessed efficiency and fairness of LLMs in games.

Closest to our work, Shapira et al. (2024a) demonstrated the potential of this approach in a similar setting to our language-based persuasion game. While this LLM-based approach is promising, our simulation-based approach offers three key advantages: (a) it is significantly more cost-effective, both in terms of budget and runtime; (b) it proves effective in the OPE setting, which was not studied by Shapira et al. (2024a); and (c) it serves as an interpretable generative model for human choice decisions.

3 Problem Definition

While the space of non-cooperative games is very large, our emphasis here is on language-based persuasion games, in which textual messages replace the stylized messages discussed in economic theory. These games model interactions that typically arise in real-world applications such as online platforms, as illustrated in §1.

Language-based Persuasion Game The game consists of two parties, an *expert* and a *decision-maker (DM)*, interacting for *R* rounds. In each round, the expert, who plays the role of a travel agent, attempts to promote a randomly selected hotel. The expert is presented with m scored reviews that were written and scored by real users of Booking.com. The expert is then asked to send the DM one of the reviews to persuade her to select the hotel. Figure 2 presents an example review. A hotel is considered good if:

$$\hat{s} = \frac{1}{m}\sum_{i=1}^{m} s_i \geq TH \tag{1}$$

That is, its average review score, $\hat{s}$, is not less than a predefined threshold, TH, and bad otherwise, where s_i is the hotel's $i'th$ review score.

In the experimental study (see next section), following Apel et al. (2022), we take $R = 10$ and $m = 7$. We chose $TH = 8.0$ because, according to Booking.com, a hotel rated 8.0 or higher is considered a good hotel. The definition of what constitutes a good hotel is available only to the expert.

While the expert observes both the verbal and the numerical part of the reviews and hence knows the hotel's quality, the DM observes only the verbal part of the review sent to her. The DM's task is to decide whether to accept the expert's offer and go to the hotel or decline it and stay at home, based only on the review provided by the

Split Condition Description	Condition formulation
Is the current hotel good?	$\hat{s}_t \geq 8$
Did the DM choose to go to the hotel in the previous round?	$d_{t-1} = 1$
Was the hotel in the previous round good?	$\hat{s}_{t-1} \geq 8$
Has the decision maker earned more points than the number of times he chose to go to the hotels?	$\sum_{i=1}^{t-1}(I_{\hat{s}_i \geq 8} = d_i) > \sum_{i=1}^{t-1} d_i$
Action Description	
Send the r review	$r \in \{\text{best, mean, worst}\}$

Table 1: The conditions and actions used by the rule-based experts in round t. The hotel score in the i-th round is denoted with $\hat{s}_i$, while the binary decision made by the DM in the i-th round is denoted with d_i (with $d_i = 1$ for hotel selection).

expert. The DM's payoff at each round depends on the quality of the hotel, with a positive payoff (of 1 point) received when a good hotel is selected or when a bad hotel is not selected, and a payoff of 0 incurred otherwise. At the end of each round, both players are notified of the DM's decision and her individual payoff. The goal of the DM is to gain at least TR out of the $R = 10$ possible points (see §4).

3.1 Strategy Space

While Apel et al. (2022) study human vs. human games, in this work we generalized their game to human (DM) vs. bot (expert) interactions in an OPE setup. We therefore need to define a *strategy space* for the experts. This space encompasses all simple, deterministic decision-tree-based strategies that can be constructed using a pre-defined set of binary split conditions and a pre-defined set of actions. These conditions and actions are based on the respective reviewers' numerical scores assigned to the hotels, and the game's history, as detailed in Table 1. Employing decision trees of depth up to 2 (to keep the strategies simple), we obtained a total of 1179 strategies.

Six of these strategies were selected for group $E_{\mathcal{A}}$, and six others for group $E_{\mathcal{B}}$, each of the groups is played with a different set of human DMs to implement an OPE setting. The strategies were selected so that they are different from each other, and the difference between $E_{\mathcal{A}}$ and $E_{\mathcal{B}}$ is large.[3] One example of such a strategy is presented in Figure 3. A full list of the strategies in $E_{\mathcal{A}}$ and $E_{\mathcal{B}}$ is in Appendix A.

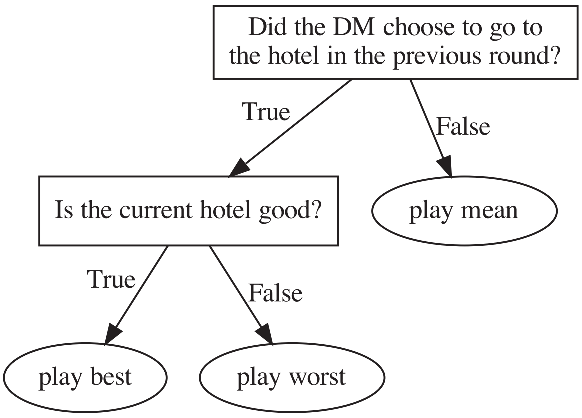

Did the DM choose to go to the hotel in the previous round?
True
False
Is the current hotel good?
play mean
True
False
play best
play worst

Figure 3: An example strategy from the $E_{\mathcal{B}}$ set.

An important aspect of the selected expert strategies is that they are simple and intuitive, and represent a diverse set of behavioral patterns that are likely to arise in real-world persuasion scenarios. Simplicity mostly follows from the fact that decision trees are restricted to depth 2. This property aligns with humans' tendency to follow simple heuristics due to limited cognitive resources (Hutchinson and Gigerenzer, 2005; Gigerenzer and Brighton, 2009). To demonstrate the intuitive nature of these strategies, we first provide some examples of concrete strategies that are contained in $E_{\mathcal{A}}$ and $E_{\mathcal{B}}$, and then provide a high-level classification of the entire strategy space to conceptual categories, which are all represented in both strategy sets.

[3] To understand what 'difference' between strategies means, notice that each strategy induces a probability distribution over the review scores it reveals to the DM. Then, similarity can be naturally defined between any pair of such induced distributions. As we discuss next, our OPE task is more challenging than its on-policy counterpart. This observation confirms that the selection process successfully identified two conceptually different strategy sets.

Examples We now introduce several intuitive persuasive behavioral patterns captured within particular expert strategies in our setup.

- *The greedy expert* always reveals the most optimistic piece of evidence for the hotel's quality, regardless of its true quality.
- *The honest expert* reveals the best review when the hotel is good, and reveals the most negative review when the true quality is low.
- *The backward-looking expert* takes a different approach: When the previous decision of the DM was to accept the offer, she presents the best possible review, exploiting the good reputation to maintain momentum. Otherwise, she presents the (closest to the) mean-scored review, to avoid a bad reputation.

These experts take different persuasive approaches while having the same goal of maximizing their cumulative gain against a human DM. These reflect differing underlying beliefs about the human DMs behavior, and their performance can significantly differ depending on the opponent. The *greedy* and *honest* strategies are contained in $E_{\mathcal{A}}$, while the *backward-looking* strategy is in $E_{\mathcal{B}}$.

Classification of Strategies We begin by observing that there are two types of split conditions according to which the strategies are constructed (Table 1): conditions that depend on the *hotel quality* (e.g., first row) and conditions that depend on the *DM past behavior* (e.g., second row). A strategy may include both condition types, just one, or neither. It is therefore convenient to use this fact to define four distinct groups of strategies: *(1) simple* strategies that include no split condition, and are defined solely by an action description (e.g., the *greedy* strategy); *(2) quality-dependent* that only contain split conditions depending on the hotel quality (e.g., the *honest* strategy); *(3) history-dependent* strategies, that contain only split conditions that are history-dependent (e.g., the *backward-looking* strategy); and *(4) complex strategies* that contain both types of splitting conditions (e.g., the strategy illustrated in Figure 3). Importantly, our selected strategy sets are representative of the entire strategy space in the sense that they cover all four strategy classes.

Our Challenge Given a dataset composed of interactions between human decision-makers and an ordered set of experts $E_{\mathcal{A}}$, our objective is to predict the behavior of other human decision-makers when they engage in game-play with another ordered set of rule-based experts $E_{\mathcal{B}}$.[4]

4 The Human-Bot Interaction Dataset

In order to collect data, we developed a mobile phone game application that follows the above multi-stage language-based persuasion game setting. In our game, a human DM plays with a series of 6 rule-based experts (bots, either $E_{\mathcal{A}}$ or $E_{\mathcal{B}}$), each game consisting of $R = 10$ rounds. The DM gets 1 point if she makes a good decision (selecting a good hotel or avoiding a bad one), and 0 points otherwise, and hence the maximal payoff is 10. To advance to the next level (play with the next bot), the DM must achieve a pre-defined target payoff. The target payoffs are in the 8–10 range, and are defined according to how challenging the bot is.[5] The goal of the human player is to get the target payoff of all six experts. We refer to reaching the target payoff as ''defeating'' the expert, although this is not a zero-sum game with adversarial experts.[6]

The Hotels Utilizing hotel reviews sourced from Booking.com, we compiled a dataset comprising 1,068 hotels, each with $m = 7$ scored reviews. We chose the hotels so that only about half of them are defined as good (i.e., $\hat{s} \geq TH = 8$). The median score of the hotels was also set to 8.01.

Interaction Data We ran our game in the Apple's App Store and Google Play for a few months (May 2022–January 2023). The players who downloaded the app until November 2022 played with group $E_{\mathcal{A}}$ experts, while the players who played from December 2022 played with group $E_{\mathcal{B}}$ experts. We collected 87,204 decisions taken by 245 players who finished the game, i.e., defeated all six experts. Statistical details of the data are given in Table 2. We used reward schemes, including

[4] In Appendix E.1 we demonstrate that the off-policy task is indeed harder than the on-policy one.

[5] Based on game design considerations, we did not order the bots by difficulty; the target payoffs were estimated by the authors after playing several times against each bot.

[6] The introduction of target payoffs, whose goal is to enhance player engagement, represents yet another distinction of our work from that of Apel et al. (2022).

Group	Experts	#DMs	#decisions	median #decisions/DM	median #games/DM
A	$E_{\mathcal{A}}$	210	71,579	273	34.5
B	$E_{\mathcal{B}}$	35	15,625	367	55
Total	$E_{\mathcal{A}}$ or $E_{\mathcal{B}}$	245	87,204	280	37

Table 2: Dataset statistics.

lottery participation and course credit, to incentivize players to beat all six experts in the game. More details about our app and the data collection process are in Appendix B.

5 Simulation-based OPE

We propose a simulation-based DM as an *interpretable generative model for human choice data*. By interacting with expert bots using random strategies from the strategy space, the simulated DM generates data that is combined with initial human-bot interaction data to enhance off-policy prediction.[7] Algorithmically, the simulation uses a *mixture of heuristics with dynamic weights*, relying on intuitive decision rules informed by past interactions and textual content to decide the next action.

Over time, the simulated DM dynamically updates the weights of these heuristics, referred to as its *temperament*. However, while these heuristics are interpretable and intuitive, they are inherently simplistic and fail to emulate the adaptive learning seen in human DMs, whose performance improves over time (see §8.2 for evidence).

To address this, we introduce an *oracle* heuristic into the simulation, with its weight increasing over time. This adjustment enables the simulated DM to exhibit improvement patterns akin to human DMs, effectively combining human-like heuristics with gradual improvement. This approach proves highly effective in enhancing off-policy evaluation.

The Simulation In each instance of the bot-DM interaction simulation, we sample six expert strategies from the entire strategy space, uniformly at random. For each simulated DM-bot interaction, we randomly sample 10 hotels, one for each of the $R = 10$ rounds. In each of the rounds, the expert uses its strategy to select a review from the review set of the hotel associated with that round. The simulation involves the DM playing the 10 rounds game against the same expert until achieving a payoff of $SIM\_PAY\_TH = 9$ points, before moving on to play against the next expert.[8] The simulated DM uses the textual review and its estimated numerical score (see below) to make decisions.

Our simulation is based on two basic probability vectors: (a) The *nature vector*, a hyper-parameter vector denoted with (p_1, p_2, p_3); This vector provides the initial probabilities that the DM will select one of three basic heuristics (see below); and (b) The *temperament vector*, comprising four values $(p_0^t, p_1^t, p_2^t, p_3^t)$ and updated in each round t. While p_1^t, p_2^t, p_3^t correspond to the three values in the nature vector, p_0^t is the probability that the DM will play *oracle*, and take the right decision just because it has learned how to play the game from the multi-stage interaction with the bot.[9]

The nature vector corresponds to three heuristics: *Trustful, Language-based, and Random*. These heuristics reflect the two basic components we attribute to a DM: considering past behavior and its outcome (*Trustful*) and learning from the information in the current hotel's review (*Language-based*), alongside inherent randomness (*Random*).[10]

DM Heuristics Under the *Trustful* heuristic, the DM chooses to go to the hotel if and only if in the last K rounds the DM's estimated review score matched the feedback about the hotel quality, where K is a stochastic parameter sampled for each DM individually. Notice that as opposed to

[7] In Appendix E.2, we show that the simulation also improves on-policy prediction quality.

[8] If the DM does not reach a payoff of 9 or 10 then it repeats the game after 10 new hotels are sampled to replace the original 10 hotels.

[9] A core idea behind the simulation design is that human DMs indeed learn and improve over time. In Appendix 8.2 we provide empirical evidence of this phenomenon.

[10] Notice that both the expert strategies and the structure of our simulation reflect underlying beliefs about the nature of human DMs. However, the simulation remains agnostic to the beliefs guiding the test-time strategies, and still produces high-quality data. In some sense, the simulation is hence based on heuristics that can be seen as fundamental.

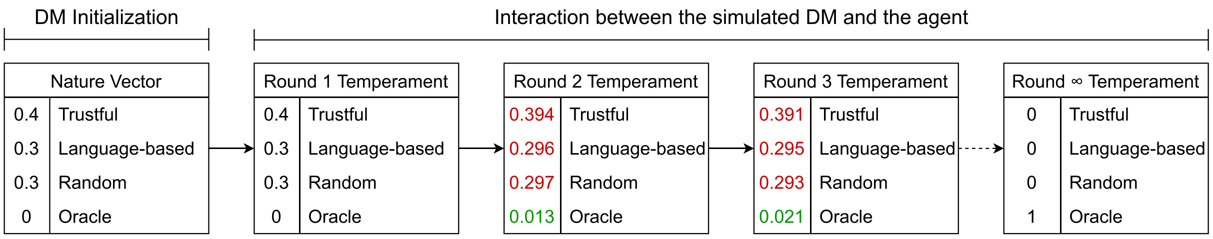


Figure 4: Example of the update process of the temperament vector of a simulated DM. Each simulated DM is assigned a *nature vector*, representing its inherent action probabilities. At the start of an interaction with a new agent, the DM's *temperament vector* is initialized to that nature vector. In each round, the DM's action is randomly chosen according to the probabilities in the temperament vector. After the round, the temperament vector is updated so that, with some positive probability, the likelihood of playing Oracle increases, while the probabilities of playing all other actions decrease.

the real human-bot interactions, in this heuristic the DM does use the numerical score of the review. However, in order to emulate the reality where it is hard for humans to accurately estimate the review score from its text, the estimated numerical score is defined as $\hat{s} + x$, where $\hat{s}$ is the actual score of the review and $x \sim Normal(0, \epsilon)$ is a noise variable. The hotel quality feedback is the average scores of the hotel's reviews (Equation 1). According to the *Language-based* heuristic, the DM uses an LLM to predict the review score. If the predicted score is 8 or higher, the DM chooses to go to the hotel. We computed review scores with Text-Bison (Anil et al., 2023), prompting it to score each review on a 1–100 scale such that a good hotel is one with a score of $\geq$ 80, and then re-scaled the scores into the 1–10 range. Finally, under the *Random* heuristic, the DM would make a random decision.[11]

The Temperament The temperament vector is initialized at the onset of each 10-round DM-bot interaction to be $p^0 = (0, p_1, p_2, p_3)$, where (p_1, p_2, p_3), the nature vector, is a DM-specific hyper-parameter (see Appendix D). At each round t, the temperament vector is updated by multiplying $p^t_{1\leq i\leq 3}$ by a factor of $1 - \gamma^t_i$, where $\gamma^t_i \sim Uni(-\frac{\eta}{10}, \eta)$ and $\eta \in (0, 1]$ is a hyper-parameter representing the *DM's improvement rate*.[12] Accordingly, p^t_0 is updated to be $p^t_0 = 1 - \sum_{1\leq i\leq 3} p^t_i$ to ensure that the temperament vector is a probability vector. In this way, the temperament vector after $T > 0$ rounds is defined by:

$$p^T_i = p_i \prod_{t=1}^{T} (1 - \gamma^t_i) \quad \text{and} \quad p^T_0 = 1 - \sum_{i=1}^{3} p^T_i \tag{2}$$

Since $0 < E[1 - \gamma^t_i] < 1$, it holds that the probability making the right decision (p^T_0), irrespective of the nature vector, tends towards 1 as the number of rounds approaches infinity. Hence, the DM will inevitably defeat any expert after a sufficient number of rounds.[13] Figure 4 illustrates the update process of the temperament vector.

Gradient-based Training We leverage both simulation data and real human-bot interactions to train the decision prediction model. At the beginning of each training epoch, we train the model using S_r simulated DMs per each human DM, and subsequently train the model using the human-bot interaction data (S_r is a hyper-parameter).

6 Experiments

6.1 Feature Representation

We represent each DM-bot interaction round with features related to (1) the hotel review sent by the expert to the DM; and (2) the strategic situation in which the decision was made. To represent a review, we utilize a set of binary Engineered Features (EFs) originally proposed by Apel et al. (2022). These features describe the topics that the positive and negative parts of the review discuss (e.g., Are the hotel's design mentioned in the

[11] Note that simulating data based on both textual and behavioral contexts using an LLM is financially prohibitive, as it would require us a call to the LLM for every decision in the simulation, for a total of tens to hundreds thousands calls.

[12] We allow γ^t_i to get negative values since it is possible that at some rounds the DM performance degrades.

[13] In Eq. 2, it may be that $\sum_{1\leq i\leq 3} p^T_i > 1$, in which case we trim this sum to 1 before computing p^T_0.

positive part of the review?) as well as structural and stylistic properties of the review (e.g., Is the positive part shorter than the negative part?).

To label the topics the review discusses, we use OpenAI's Davinci model.[14] The model receives as a prompt the review and the feature definition, and is asked to indicate whether or not the feature appears in the review. Below we demonstrate that the use of EFs yielded better results compared to deep learning based text embedding techniques such as BERT (Kenton and Toutanova, 2019) and GPT-4 (OpenAI et al., 2023). To represent the strategic interaction, we introduce additional binary features that capture the DM's previous decision and outcome, current payoff, and frequency of choosing to go to the hotel in past rounds of the same interaction (see Appendix C for further details).

6.2 Models and Baselines

This subsection provides a description of the models that we train for our study. For each model, except for the Majority Vote model, we train three versions: one using only human-bot interaction data, one using only simulation data, and one with both interaction and simulation data. This allows us to evaluate the impact of simulated data on the model's predictive performance. All the models are designed to predict the DM's decision in a specific round, given the previous rounds played in the same bot-DM interaction.

Majority Vote The *Majority Vote* baseline predicts the DM's decision based on the percentage of DMs who decided to go to the hotel in the interaction training set. Notably, this baseline method solely relies on the review and disregards the repeated nature of the game. Additionally, it is unsuitable for predicting the decisions of players who are the first to encounter a new review. In order to make sure that we consider only cases where DMs indeed read the review, we consider only cases where DMs spent at least 3 seconds before making their decision.[15]

Machine Learning Models We employ five machine learning models to predict the DM's decisions. First, we utilize a Long Short-Term Memory (LSTM) model (Hochreiter and Schmidhuber, 1997), wherein the cell state is initialized before the DM's first game (10-round interaction with a bot) to a vector estimated during training, while the hidden state is propagated from game to game.[16] By managing the cell state in this manner, we model the relationship between successive games of the DM against the same expert. Second, we train a Transformer model (Vaswani et al., 2017) that takes as input the representation of all rounds up to round t. Third, we use Mamba, which is a modern state-space model (Gu and Dao, 2024). Lastly, we implement two strong non-sequential models: an XGBoost classifier (Chen and Guestrin, 2016), and a fully connected (FC) neural network.[17]

Ablation Analysis Experiments with these models aim to shed light on the factors that contribute to the positive impact of the simulation. To this end, we consider several variants of the simulation process of §5. First, we test the impact of the DM's learning rate parameter (η) on the prediction performance. Then, we examined the effect of the number of simulated agents on the performance of the models, reasoning that a truly effective simulation is one where more simulated data yields better results, at least up to some threshold. Finally, we consider the relative impact of each component of the simulation.

6.3 Research Questions

We consider the following research questions: **Q1:** Does incorporating simulation data during model training improve the accuracy of decision prediction in OPE scenarios for different types of prediction models? **Q2:** How do the different learning models perform on the human choice prediction task? **Q3:** Does simulation improve prediction for different types of expert strategies? **Q4:** What are the components of the simulation that lead to the improved results? and **Q5:** How does the representation of the language in the

[14] This stands in contrast to Apel et al. (2022), who manually tagged their reviews with the EFs.

[15] Note that we could use this baseline because we use the same set of hotels at train and test (and also simulation) time. We justify this design choice by the large number of hotels in our dataset (1068, see §4), the resulting negligible probability of getting the same 10 hotel sequence in two different bot-DM interactions and the fact that in the actual world, the set of available hotels does not tend to change very quickly.

[16] This method for sharing information among games outperformed several alternatives we considered.

[17] Additional experimental details and the hyper-parameter tuning procedures are in Appendix D.

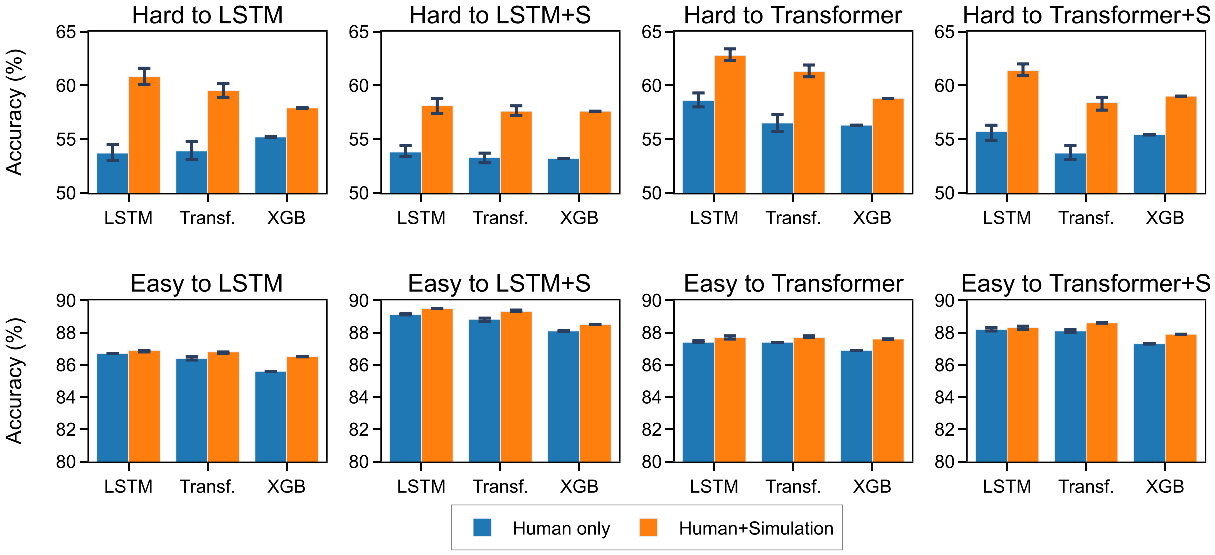


Figure 5: Performance of the models on different sets of hard (top) and easy (bottom) examples, with 95% bootstrap confidence intervals. Training on a combination of human-bot interaction and simulated data improves model performance on the hard sets without harming their performance on the easy sets.

prediction model (EFs vs. plain LLMs) affect the prediction quality with and without simulation?

7 Results

In this section we report the results of each model as the mean of the average accuracy per player (DM) and expert strategy. We average over DMs rather than over decisions so that human DMs who played more games than others are not over-represented in the results. For the models trained on human-bot interactions only (i.e., without simulation data), LSTM and Mamba show the best performance, outperforming Transformer. The XGB, FC, and Majority models are inferior, and hence in what follows we mostly focus on the results of the LSTM and the Transformer, and the full experimental results can be found in Appendix E.3. The rationale behind focusing on LSTM and Transformer (instead of the two best-performing models, LSTM and Mamba) is that the two architectures reflect two extreme modeling approaches (see discussion in Q2), while Mamba conceptually serves as a middle-ground, combining the sequential processing of LSTM with the and scalability of Transformers.

The Impact of the Simulation (Q1) Figure 5, as well as Table 7 in Appendix E.3, present the accuracy of each model, when trained on the human interaction data only, and when simulation data is added to the training set (the +*S* models). Our analysis distinguishes *hard* from *easy* examples for each model, and also provides results over the entire test set. We define a *hard* example for a deep learning model as one for which not all of its 15 variants, differing in their randomly initialized training weights, agree with each other. For the XGB and Majority vote models, we consider examples with confidence levels 40%-60% as hard. Non-hard are considered *easy*.[18]

For all classifiers and for all hard example sets, combining human and simulated data demonstrates improved performance compared to training on human interaction data only, without harming the prediction on the easy example sets. That is, for each prediction model (column in Figure 5), adding simulated data increases accuracy on hard cases (top row) and does not decrease accuracy on easy cases (bottom row). Specifically, for LSTM the improvement on its own hard example set is 7.1%, from 53.7% to 60.8% accuracy. For the Transformer the corresponding improvement is 4.8%, from 56.5% to 61.3%.

We emphasize that training on the simulated data only yields disappointing performance. For example, on the entire test-set the accuracy of LSTM+S is 83.6% and of Transformer+S is

[18] The results in Figures 5 and 6 (as well as Table 7 in Appendix E.3) are presented with 95% bootstrap confidence intervals, based on the accuracy obtained by all 15 prediction models' variants.

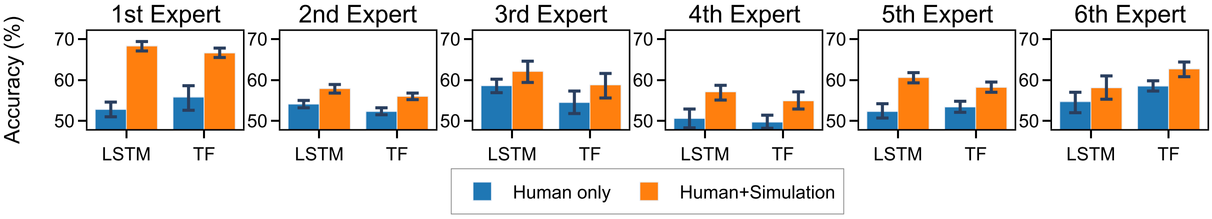


Figure 6: Model performance on the LSTM hard examples, for each expert strategy, with 95% bootstrap confidence intervals. Training on human and simulation data improves performance for all strategies.

83.4%, and for the LSTM and Transformer models, trained on human-interaction data only, the corresponding numbers are 82.6% and 82.3%. At the same time, if we train the LSTM and the Transformer on simulated data only, their accuracy is 78.6% for LSTM and 78.7% for the Transformer. Hence, we do not consider simulation-only training any further in this paper.[19]

The Impact of the Prediction Model (Q2) Figure 5 reveals an insightful observation on the relative effectiveness of different model architectures. Although, as expected, XGB performs worse than both LSTM and Transformer models, an unexpected result is that LSTM often outperforms Transformer in harder cases. Specifically, across the top row of results (excluding 'Hard to LSTM+S'), LSTM consistently outperforms Transformer. This observation holds even in 'Hard to LSTM' cases, where one would anticipate Transformer to perform better, given that these cases are particularly challenging for LSTM.

A possible explanation lies in the distinct architectural characteristics of LSTM and Transformer. Unlike Transformers, which models dependencies across all elements of an input sequence, LSTMs have an inherent *inductive bias* that encourages reliance on recent sequence elements for prediction. This inductive bias appears advantageous in choice prediction tasks, where human DMs are generally influenced by recent interactions (a cognitive bias famously known as the ''recency effect'', see Ebbinghaus, 1913). While it might seem plausible for Transformer to learn such patterns autonomously, it is essential to note that, unlike language modeling tasks, human choice prediction datasets are often relatively small, lacking sufficient data for the Transformer to independently capture such temporal patterns without architectural guidance. Given the constraints on collecting human data–stemming from privacy, budget, and logistical challenges–limited training data is a frequent issue in human choice prediction tasks. This limitation underscores the importance of model selection in addressing these challenges.

The Impact of the Expert Strategy (Q3) We highlight that the effectiveness of an expert strategy heavily depends on the behavior of the opponent DM. Different human players respond differently, creating varied effects that impact how accurately their actions can be predicted. For example, consider a greedy expert who always presents the most positive review. Some DMs may trust and follow consistently positive reviews, while others may learn to disregard them as uninformative. A different expert strategy is likely to dramatically change the behavior of DMs. Thus, the particular expert strategy (against whom human behavior is predicted) directly influences the complexity and outcome of the prediction task. Figure 6 presents the accuracy of the models, trained with and without simulation, for each of the expert strategies for the set of hard examples of the LSTM model. Apparently, including the simulation data improves the performance of both LSTM and Transformer for each of the expert strategies. The same results are observed when testing the models on the hard Transformer examples. This result increases our confidence in the simulation as it improves performance when considering each strategy separately.

Ablation Analysis (Q4) Figure 7 presents model performance as a function of the number of training epochs, for various values of the S_r parameter, which defines the ratio between the number of simulated and human DMs in the

[19] In Appendix E.4 we compare the contribution of simulated data to the hypothetical case where additional human data is available.

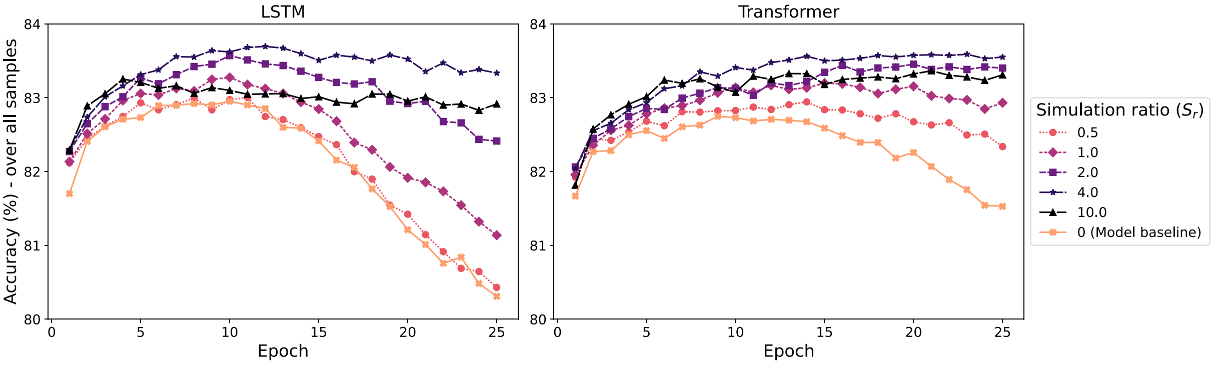


Figure 7: Model performance as a function of the number of epochs, for various values of S_r, the ratio between the number of simulated and human DMs in the training set (the number of human interaction examples is fixed to the entire human interaction training set).

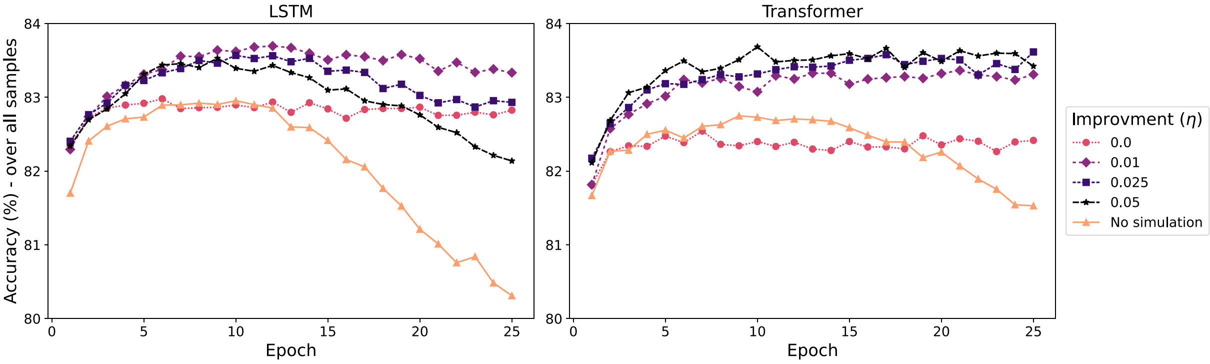


Figure 8: Model performance as a function of the number of epochs, for different values of η, the improvement rate parameter.

training set.[20] It can be seen that adding more simulated data improves performance, up to a limit of $S_r = 4$. However, the improvement with $S_r = 10$ is lower than with $S_r = 4$, so the impact of the simulation data is not unlimited. The regularization effect of the simulation is also observed. These results demonstrate the quality of our simulation, as we would expect that more high-quality data would increase its positive impact.

We next examine the relative importance of the various simulation components for improved performance. We start by training the models with different values of η, the DM improvement rate parameter, which controls the DM learning from experience. Figure 8 demonstrates that when $\eta = 0$, the simulation data neither improves nor harms model performance, and serves only as a means of regularization. For $\eta > 0$, both LSTM and Transformer benefit from the simulation to a similar extent. These results emphasize the importance of learning from experience for OPE, particularly independently of the expert strategy.

With Random		
	With Trustful	Without Trustful
With Lang.-based	100.0%	80.8%
Without Lang.-based	50.3%	10.9%

Without Random		
	With Trustful	Without Trustful
With Lang.-based	89.2%	70.9%
Without Lang.-based	71.5%	0%

Table 3: The impact of simulation heuristics on the LSTM prediction performance (with $\eta = 0.01$ selected via hyperparameter tuning). Percentages are taken from the prediction accuracy of the complete simulation.

Table 3 quantifies the impact of the three heuristics (Language-based, Truthful, and Random) on the performance of the LSTM prediction

[20] The number of human interaction examples is fixed to the entire human interaction training set, so higher S_r values simply mean more simulated data.

model. The table reveals that all three strategies have a substantial impact on the performance. For example, if we include only one, the accuracy of the eventual prediction model is 70.9% for language-based, 71.5% for trustful, and only 10.9% for random (percentage taken from the prediction accuracy of the complete simulation). The patterns for the Transformer are very similar. We also evaluated the model's performance when the simulation relies solely on an oracle. In this case, the improvement reaches only 28.8%.

Language Representation Analysis (Q5) Figure 14 (in Appendix E.5) presents the LSTM performance for the three review representation schemes: BERT, GPT-4, and EF, and for various values of the simulation ratio parameter S_r.[21] Evidently, the performance with EF is superior.[22]

Simulation Heuristic	Review	History
Oracle	0.52	0.23
Truthful	0.69	0.67
Truthful + Oracle	0.72	0.69
Language-based	0.79	0.70
Language-based + Oracle	0.81	0.79
Random	−0.00	0.06
Random + Oracle	0.54	−0.01
Full Simulation	0.79	0.65

Table 4: Pearson correlation coefficients measuring the similarity between human behavior and heuristics in the simulation, based on average decision-making probabilities given a specific review (the Review column) and given the decision and outcome history from the previous two rounds (the History column).

8 Human-Simulation Comparison

As mentioned in §5, we constructed the simulation based on principles that we believe characterize human decision-making. In this section, we examine whether the simulation's behavior aligns with human behavior.

8.1 Comparing Simulation Behavior and Human Decision-Making

To demonstrate the similarity between the simulation and human decision-making, we analyzed two vectors: one representing the percentage of times a player chooses to go to a hotel based on a given review, and another capturing the percentage of times a player makes this choice based on the decision history and outcomes from the previous two rounds. Table 4 presents the Pearson correlation coefficients between vectors derived from all human player decisions and a vector constructed from half a million rounds played by simulated decision-makers. We report the correlations for the different heuristics used in the simulation, their combination with the Oracle strategy, and the full simulation, which includes all the strategies. The results indicate a strong correlation (Pearson coefficient $\geq$ 0.67) between the simulation's decisions and those of human players across both language-based and truthful simulations. In all cases, incorporating an oracle further enhances alignment with human decision-making. Interestingly, the full simulation, incorporating all strategies, shows lower correlation with humans than the Trustful and Language-based (w. or w/o Oracle) strategies. This contrasts with Table 3, where the full simulation proves superior as training data for prediction. We hypothesize that its random component, while uncorrelated with human behavior, enhances prediction by improving the robustness of the trained predictor. Figure 9 presents two games from the dataset, comparing the human player's behavior to that of Simulated DMs employing language-based and truthful strategies.

8.2 Improvement Over Time in Human DMs

One of the most important assumptions in the simulation is that humans learn over time. In this subsection, we validate this hypothesis. Figure 10 shows the improvement of human players over time, against both training strategies (E_A) and test strategies (E_B). Each point shows the average winning rate (i.e., the probability of taking the ''right'' action) across all DMs, experts and rounds, in the $i'th$ game before the DM defeats the expert (i.e., reaches the target payoff). The graph clearly shows that as time progresses, DMs are more likely to make correct decisions.

[21] For BERT and GPT-4 we take the sentence embeddings and perform dimensionality reduction with PCA to 36 coordinates, to balance the vector size with the number of reviews (3000). 36 is also the number of the EFs.

[22] The pattern for the Transformer is similar.

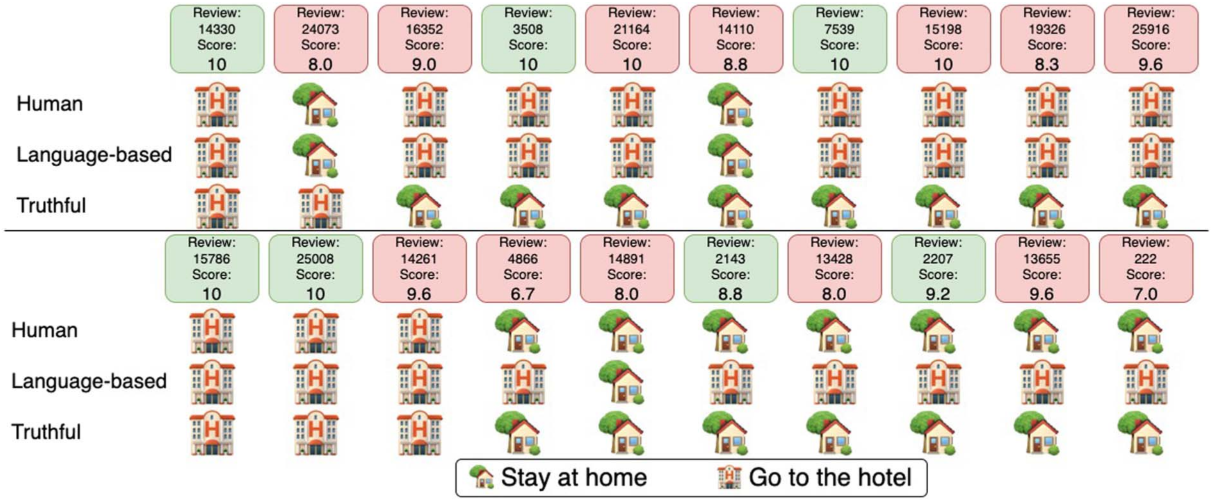


Figure 9: Two games from the dataset. The top row shows the reviews sent by the agent (score and index) and the hotel quality (green: good, red: bad). The following rows present the human player's decisions and the decisions that would have been made by a simulated DM under the language-based profile and by a simulated DM under the truthful profile in the given situations. In the first game, the human player matched the language-based strategy, while in the second, they followed the truthful strategy.

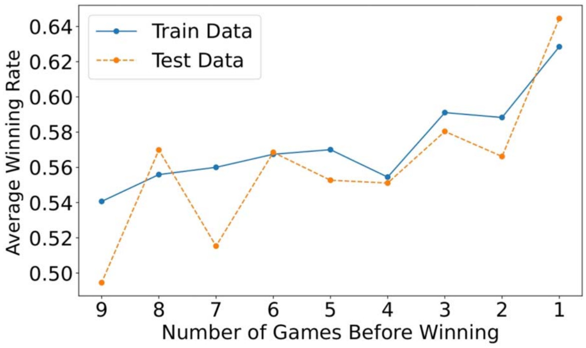


Figure 10: Round winning probability as a function of the distance from the final game against the same agent.

9 Discussion

We addressed the challenge of OPE in language-based persuasion games by proposing a simulation where DMs employ a mixture of interpretable, human-like heuristics that incorporate both behavioral and language-based signals. Additionally, the probability of making correct decisions increases progressively over time. Combining this simulation data with human-bot interactions demonstrated significant improvements.

Limitations and Future Work We made several restricting assumptions, which also serve as potential future research directions. First, while our strategy space is rigorously defined and allows us to crystallize the approach, considering more involved expert strategies is a natural extension in bridging this topic into practice. Future work would aim to demonstrate results for a wide range of strategy sets that would serve as $E_{\mathcal{A}}$ and $E_{\mathcal{B}}$, and with a larger variety of parameters (e.g., for games with a larger number of rounds). However, since data collection from humans is costly and laborious, we restrict our experiments to a specific choice of $E_{\mathcal{A}}$ and $E_{\mathcal{B}}$, potentially affecting the generality of our findings.

Second, extending our approach beyond the persuasion game framework is another appealing future direction. This paper takes an initial step toward a simulation-based framework for off-policy evaluation, demonstrated through a game inspired by economic theory with relevance to domains like recommender systems and e-commerce. Our approach models a decision-making player using basic heuristics—Trustful, Language-based, and Random—while allowing gradual improvement via an ‘‘oracle’’ strategy over time. Although focused on persuasion games, this method could apply broadly to other economic settings where such interpretable ‘‘base’’ strategies are identifiable.

Ethical and Societal Considerations Human choice prediction is a field with profound societal implications. Developing technology for predicting human decisions, particularly in economic contexts, holds both promise and risk. On the positive side, such technologies can enhance consumer welfare in recommendation engines. By accurately predicting consumer behavior, system designers can strike a fair balance between the interests of buyers and sellers, optimizing outcomes for both. However, the same technology can be exploited to manipulate consumers into inefficient trades, greedily maximizing profits at their expense. Beyond commerce, the capabilities of human choice prediction extend to policy-making and public discourse. Persuasion games can model the public's response to various strategies, and while this can inform better policies, it also risks being used to manipulate public opinion, potentially harming societal welfare.

Simulation-based approaches for human choice prediction can also be used in behavioral economics research. These methods can reduce the costs of large-scale human data collection and enhance predictive accuracy. However, simulations can also introduce biases, such as over-reliance on modeled assumptions or misrepresentation of human variability, potentially leading to skewed predictions and misaligned conclusions.

Given these potential benefits and risks, we advocate for the careful and regulated development and application of human choice prediction technologies. Clear guidelines for data collection and use, as well as the development of these tools, are crucial. This can be achieved through ethical codes in academic research, robust guidelines in tech companies, and government regulations. These measures are essential to ensuring that advancements in human choice prediction serve the greater good of society.

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References

Hua Ai and Fuliang Weng. 2008. User simulation as testing for spoken dialog systems. In *Proceedings of the 9th SIGdial Workshop on Discourse and Dialogue*, pages 164–171. https://doi.org/10.3115/1622064.1622097

Elif Akata, Lion Schulz, Julian Coda-Forno, Seong Joon Oh, Matthias Bethge, and Eric Schulz. 2023. Playing repeated games with large language models. *arXiv preprint arXiv:2305.16867*.

Nikolaos Aletras, Dimitrios Tsarapatsanis, Daniel Preoţiuc-Pietro, and Vasileios Lampos. 2016. Predicting judicial decisions of the European Court of Human Rights: A natural language processing perspective. *PeerJ Computer Science*, 2:e93. Publisher: PeerJ Inc. https://doi.org/10.7717/peerj-cs.93

Rohan Anil, Andrew M. Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, Eric Chu, Jonathan H. Clark, Laurent El Shafey, Yanping Huang, Kathy Meier-Hellstern, Gaurav Mishra, Erica Moreira, Mark Omernick, Kevin Robinson, Sebastian Ruder, Yi Tay, Kefan Xiao, Yuanzhong Xu, Yujing Zhang, Gustavo Hernandez Abrego, Junwhan Ahn, Jacob Austin, Paul Barham, Jan Botha, James Bradbury, Siddhartha Brahma, Kevin Brooks, Michele Catasta, Yong Cheng, Colin Cherry, Christopher A. Choquette-Choo, Aakanksha Chowdhery, Clément Crepy, Shachi Dave, Mostafa Dehghani, Sunipa Dev, Jacob Devlin, Mark Díaz, Nan Du, Ethan Dyer, Vlad Feinberg, Fangxiaoyu Feng, Vlad Fienber, Markus Freitag, Xavier Garcia, Sebastian Gehrmann, Lucas Gonzalez, Guy Gur-Ari, Steven Hand, Hadi Hashemi, Le Hou, Joshua Howland, Andrea Hu, Jeffrey Hui, Jeremy Hurwitz, Michael Isard, Abe Ittycheriah, Matthew Jagielski, Wenhao Jia, Kathleen Kenealy, Maxim Krikun, Sneha Kudugunta, Chang Lan, Katherine Lee, Benjamin Lee, Eric Li, Music Li, Wei Li, YaGuang Li, Jian Li, Hyeontaek Lim, Hanzhao Lin, Zhongtao Liu, Frederick Liu, Marcello Maggioni, Aroma Mahendru, Joshua Maynez, Vedant Misra, Maysam Moussalem, Zachary Nado, John Nham, Eric Ni, Andrew Nystrom, Alicia

Parrish, Marie Pellat, Martin Polacek, Alex Polozov, Reiner Pope, Siyuan Qiao, Emily Reif, Bryan Richter, Parker Riley, Alex Castro Ros, Aurko Roy, Brennan Saeta, Rajkumar Samuel, Renee Shelby, Ambrose Slone, Daniel Smilkov, David R. So, Daniel Sohn, Simon Tokumine, Dasha Valter, Vijay Vasudevan, Kiran Vodrahalli, Xuezhi Wang, Pidong Wang, Zirui Wang, Tao Wang, John Wieting, Yuhuai Wu, Kelvin Xu, Yunhan Xu, Linting Xue, Pengcheng Yin, Jiahui Yu, Qiao Zhang, Steven Zheng, Ce Zheng, Weikang Zhou, Denny Zhou, Slav Petrov, and Yonghui Wu. 2023. PaLM 2 technical report. ArXiv:2305.10403 [cs].

Reut Apel, Ido Erev, Roi Reichart, and Moshe Tennenholtz. 2022. Predicting decisions in language based persuasion games. *Journal of Artificial Intelligence Research*, 73:1025–1091. https://doi.org/10.1613/jair.1.13510

Sanjeev Arora, Elad Hazan, and Satyen Kale. 2012. The multiplicative weights update method: A meta-algorithm and applications. *Theory of Computing*, 8(1):121–164. https://doi.org/10.4086/toc.2012.v008a006

Fabrizia Auletta, Rachel W. Kallen, Mario di Bernardo, and Michael J. Richardson. 2023. Predicting and understanding human action decisions during skillful joint-action using supervised machine learning and explainable-ai. *Scientific Reports*, 13(1):4992. https://doi.org/10.1038/s41598-023-31807-1, PubMed: 36973473

Robert John Aumann, Michael Bahir Maschler, and Richard E. Stearns. 1995. *Repeated Games with Incomplete Information*. MIT Press.

Gal Bahar, Rann Smorodinsky, and Moshe Tennenholtz. 2016. Economic recommendation systems: One page abstract. In *Proceedings of the 2016 ACM Conference on Economics and Computation*, pages 757–757. https://doi.org/10.1145/2940716.2940719

JinYeong Bak and Alice Oh. 2018. Conversational decision-making model for predicting the king's decision in the annals of the Joseon dynasty. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 956–961, Brussels, Belgium. Association for Computational Linguistics. https://doi.org/10.18653/v1/D18-1115

Omer Ben-Porat, Sharon Hirsch, Lital Kuchi, Guy Elad, Roi Reichart, and Moshe Tennenholtz. 2020. Predicting strategic behavior from free text. *Journal of Artificial Intelligence Research*, 68:413–445. https://doi.org/10.1613/jair.1.11849

Dirk Bergemann and Stephen Morris. 2019. Information design: A unified perspective. *Journal of Economic Literature*, 57(1):44–95. https://doi.org/10.1257/jel.20181489

David D. Bourgin, Joshua C. Peterson, Daniel Reichman, Stuart J. Russell, and Thomas L. Griffiths. 2019. Cognitive model priors for predicting human decisions. In *International Conference on Machine Learning*, pages 5133–5141. PMLR.

Konstantinos Bousmalis, Alex Irpan, Paul Wohlhart, Yunfei Bai, Matthew Kelcey, Mrinal Kalakrishnan, Laura Downs, Julian Ibarz, Peter Pastor, Kurt Konolige, Sergey Levine, and Vincent Vanhoucke. 2018. Using simulation and domain adaptation to improve efficiency of deep robotic grasping. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 4243–4250, IEEE. https://doi.org/10.1109/ICRA.2018.8460875

Simon Martin Breum, Daniel Vædele Egdal, Victor Gram Mortensen, Anders Giovanni Møller, and Luca Maria Aiello. 2024. The persuasive power of large language models. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 18, pages 152–163. https://doi.org/10.1609/icwsm.v18i1.31304

Nitay Calderon, Eyal Ben-David, Amir Feder, and Roi Reichart. 2022. Docogen: Domain counterfactual generation for low resource domain adaptation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7727–7746. https://doi.org/10.18653/v1/2022.acl-long.533

Minh Cao and Ramin Ramezani. 2023. Data generation using simulation technology to improve perception mechanism of autonomous vehicles. In *Journal of Physics: Conference Series*, volume 2547, page 012006. IOP Publishing. https://doi.org/10.1088/1742-6596/2547/1/012006

Carlos Carrasco-Farre. 2024. Large language models are as persuasive as humans, but how? About the cognitive effort and moral-emotional language of llm arguments. *arXiv preprint arXiv:2404.09329*.

Jiaao Chen and Diyi Yang. 2021. Weakly-supervised hierarchical models for predicting persuasive strategies in good-faith textual requests. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 12648–12656. https://doi.org/10.1609/aaai.v35i14.17498

Tianqi Chen and Carlos Guestrin. 2016. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 785–794. https://doi.org/10.1145/2939672.2939785

Yiting Chen, Tracy Xiao Liu, You Shan, and Songfa Zhong. 2023. The emergence of economic rationality of GPT. *Proceedings of the National Academy of Sciences*, 120(51):e2316205120. https://doi.org/10.1073/pnas.2316205120, PubMed: 38085780

Yun-Shiuan Chuang, Agam Goyal, Nikunj Harlalka, Siddharth Suresh, Robert Hawkins, Sijia Yang, Dhavan Shah, Junjie Hu, and Timothy T. Rogers. 2023. Simulating opinion dynamics with networks of llm-based agents. *arXiv preprint arXiv:2311.09618*. https://doi.org/10.18653/v1/2024.findings-naacl.211

Rémi Coulom. 2006. Efficient selectivity and backup operators in monte-carlo tree search. In *International Conference on Computers and Games*, pages 72–83. Springer. https://doi.org/10.1007/978-3-540-75538-8_7

Hermann Ebbinghaus. 1913. A contribution to experimental psychology. New York, NY: Teachers College, Columbia University. https://doi.org/10.1037/10011-000

Yuval Emek, Michal Feldman, Iftah Gamzu, Renato PaesLeme, and Moshe Tennenholtz. 2014. Signaling schemes for revenue maximization. *ACM Transactions on Economics and Computation (TEAC)*, 2(2):1–19. https://doi.org/10.1145/2594564

Yoav Freund and Robert E. Schapire. 1999. Adaptive game playing using multiplicative weights. *Games and Economic Behavior*, 29(1–2):79–103. https://doi.org/10.1006/game.1999.0738

Drew Fudenberg and David K. Levine. 1995. Consistency and cautious fictitious play. *Journal of Economic Dynamics and Control*, 19(5-7):1065–1089. https://doi.org/10.1016/0165-1889(94)00819-4

Drew Fudenberg and Jean Tirole. 1991. *Game theory*. MIT Press.

Gerd Gigerenzer and Henry Brighton. 2009. Homo heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science*, 1(1):107–143. https://doi.org/10.1111/j.1756-8765.2008.01006.x, PubMed: 25164802

Meritxell González, Silvia Quarteroni, Giuseppe Riccardi, and Sebastian Varges. 2010. Cooperative user models in statistical dialog simulators. In *Proceedings of the SIGDIAL 2010 Conference*, pages 217–220.

Albert Gu and Tri Dao. 2024. Mamba: Linear-time sequence modeling with selective state spaces. In *First Conference on Language Modeling*.

Shangmin Guo, Haoran Bu, Haochuan Wang, Yi Ren, Dianbo Sui, Yuming Shang, and Siting Lu. 2024. Economics arena for large language models. *arXiv preprint arXiv:2401.01735*.

Christopher Hidey and Kathleen McKeown. 2018. Persuasive influence detection: The role of argument sequencing. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32. https://doi.org/10.1609/aaai.v32i1.12003

Christopher Hidey, Elena Musi, Alyssa Hwang, Smaranda Muresan, and Kathy McKeown. 2017. Analyzing the semantic types of claims and premises in an online persuasive forum. In *Proceedings of the 4th Workshop on Argument Mining*, pages 11–21, Copenhagen, Denmark. Association for Computational Linguistics. https://doi.org/10.18653/v1/W17-5102

Takuya Hiraoka, Graham Neubig, Sakriani Sakti, Tomoki Toda, and Satoshi Nakamura. 2014. Reinforcement learning of cooperative persuasive dialogue policies using framing. In *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers*, pages 1706–1717.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural Computation*, 9(8):1735–1780. `https://doi.org/10.1162/neco.1997.9.8.1735`, PubMed: 9377276

John J. Horton. 2023. Large language models as simulated economic agents: What can we learn from homo silicus? National Bureau of Economic Research. `https://doi.org/10.3386/w31122`

Zak Hussain, Marcel Binz, Rui Mata, and Dirk U. Wulff. 2023. A tutorial on open-source large language models for behavioral science. `https://doi.org/10.31234/osf.io/f7stn`

John M. C. Hutchinson and Gerd Gigerenzer. 2005. Simple heuristics and rules of thumb: Where psychologists and behavioural biologists might meet. *Behavioural Processes*, 69(2):97–124. `https://doi.org/10.1016/j.beproc.2005.02.019`, PubMed: 15845293

Sangkeun Jung, Cheongjae Lee, Kyungduk Kim, and Gary Geunbae Lee. 2008. An integrated dialog simulation technique for evaluating spoken dialog systems. In *Coling 2008: Proceedings of the workshop on Speech Processing for Safety Critical Translation and Pervasive Applications*, pages 9–16, Manchester, UK. Coling 2008 Organizing Committee.

Emir Kamenica and Matthew Gentzkow. 2011. Bayesian persuasion. *American Economic Review*, 101:2590–2615. `https://doi.org/10.3386/w15540`

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of NAACL-HLT*, pages 4171–4186.

Ruibo Liu, Ruixin Yang, Chenyan Jia, Ge Zhang, Denny Zhou, Andrew M. Dai, Diyi Yang, and Soroush Vosoughi. 2023. Training socially aligned language models in simulated human society. *arXiv preprint arXiv:2305.16960*.

Andreu Mas-Colell, Michael D. Whinston, and Jerry R. Green. 1995. *Microeconomic Theory*. Oxford University Press.

S. C. Matz, J. D. Teeny, Sumer S. Vaid, H. Peters, G. M. Harari, and M. Cerf. 2024. The potential of generative AI for personalized persuasion at scale. *Scientific Reports*, 14(1):4692. `https://doi.org/10.1038/s41598-024-53755-0`, PubMed: 38409168

Masha Medvedeva, Michel Vols, and Martijn Wieling. 2020. Using machine learning to predict decisions of the european court of human rights. *Artificial Intelligence and Law*, 28(2):237–266. `https://doi.org/10.1007/s10506-019-09255-y`

Meta, Anton Bakhtin, Noam Brown, Emily Dinan, Gabriele Farina, Colin Flaherty, Daniel Fried, Andrew Goff, Jonathan Gray, Hengyuan Hu, Athul Paul Jacob, Mojtaba Komeili, Karthik Konath, Minae Kwon, Adam Lerer, Mike Lewis, Alexander H. Miller, Sasha Mitts, Adithya Renduchintala, Stephen Roller, Dirk Rowe, Weiyan Shi, Joe Spisak, Alexander Wei, David Wu, Hugh Zhang, and Markus Zijlstra. 2022. Human-level play in the game of *Diplomacy* by combining language models with strategic reasoning. *Science*, 378(6624):1067–1074. `https://doi.org/10.1126/science.ade9097` PubMed: 36413172

OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mo Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael Pokorny, Michelle Pokrass, Vitchyr Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, C. J. Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2023. GPT-4 technical report. ArXiv:2303.08774 [cs]. https://doi.org/10.48550/arXiv.2303.08774

Afshin Oroojlooy and Davood Hajinezhad. 2022. A review of cooperative multi-agent deep reinforcement learning. *Applied Intelligence* 1–46. https://doi.org/10.1007/s10489-022-04105-y

Nadav Oved, Amir Feder, and Roi Reichart. 2020. Predicting in-game actions from interviews of nba players. *Computational Linguistics*, 46(3):667–712. https://doi.org/10.1162/coli_a_00383

Joon Sung Park, Joseph C. O'Brien, Carrie J. Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. 2023. Generative agents: Interactive simulacra of human behavior. In *The 36th Annual ACM Symposium on User Interface Software and Technology*, pages 1–22. https://doi.org/10.1145/3586183.3606763

Ori Plonsky, Reut Apel, Eyal Ert, Moshe Tennenholtz, David Bourgin, Joshua C. Peterson, Daniel Reichman, Thomas L. Griffiths, Stuart J. Russell, Evan C. Carter, James F. Cavanagh, and Ido Erev. 2019. Predicting human decisions with behavioral theories and machine learning. *arXiv preprint arXiv:1904.06866*.

Ori Plonsky, Ido Erev, Tamir Hazan, and Moshe Tennenholtz. 2017. Psychological forest: Predicting human behavior. In *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4–9, 2017, San Francisco, California, USA*, pages 656–662. AAAI Press. https://doi.org/10.1609/aaai.v31i1.10613

Maya Raifer, Guy Rotman, Reut Apel, Moshe Tennenholtz, and Roi Reichart. 2022. Designing an automatic agent for repeated language–based persuasion games. *Transactions of the Association for Computational Linguistics*, 10:307–324. https://doi.org/10.1162/tacl_a_00462

Ariel Rosenfeld and Sarit Kraus. 2018. Predicting human decision-making: From prediction to action. *Synthesis Lectures on Artificial Intelligence and Machine Learning*, 12(1):1–150. https://doi.org/10.1007/978-3-031-01578-6

Amal Saadallah, Felix Finkeldey, Jens Buß, Katharina Morik, Petra Wiederkehr, and Wolfgang Rhode. 2022. Simulation and sensor data fusion for machine learning application. *Advanced Engineering Informatics*, 52:101600. https://doi.org/10.1016/j.aei.2022.101600

Julian Schrittwieser, Ioannis Antonoglou, Thomas Hubert, Karen Simonyan, Laurent Sifre, Simon Schmitt, Arthur Guez, Edward Lockhart, Demis Hassabis, Thore Graepel, Timothy P. Lillicrap, and David Silver. 2020. Mastering Atari, Go, chess and shogi by planning with a learned model. *Nature*, 588(7839):604–609. https://doi.org/10.1038/s41586-020-03051-4, PubMed: 33361790

Eilam Shapira, Omer Madmon, Roi Reichart, and Moshe Tennenholtz. 2024a. Can large language models replace economic choice prediction labs? ArXiv:2401.17435 [cs]. https://doi.org/10.48550/arXiv.2401.17435

Eilam Shapira, Omer Madmon, Itamar Reinman, Samuel Joseph Amouyal, Roi Reichart, and Moshe Tennenholtz. 2024b. Glee: A unified framework and benchmark for language-based economic environments. *arXiv preprint arXiv:2410.05254*.

Weiyan Shi, Kun Qian, Xuewei Wang, and Zhou Yu. 2019. How to build user simulators to train RL-based dialog systems. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1990–2000, Hong Kong, China. Association for Computational Linguistics. https://doi.org/10.18653/v1/D19-1206

David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, et al. 2018. A general reinforcement learning algorithm that masters chess, shogi, and go through self-play. *Science*, 362(6419):1140–1144. https://doi.org/10.1126/science.aar6404, PubMed: 30523106

David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, Yutian Chen, Timothy P. Lillicrap, Fan Hui, Laurent Sifre, George van den Driessche, Thore Graepel, and Demis Hassabis. 2017. Mastering the game of go without human knowledge. *Nature*, 550(7676):354–359. https://doi.org/10.1038/nature24270, PubMed: 29052630

Chenhao Tan, Vlad Niculae, Cristian Danescu-Niculescu-Mizil, and Lillian Lee. 2016. Winning arguments: Interaction dynamics and persuasion strategies in good-faith online discussions. In *Proceedings of the 25th International Conference on World Wide Web*, pages 613–624. https://doi.org/10.1145/2872427.2883081

Amir Taubenfeld, Yaniv Dover, Roi Reichart, and Ariel Goldstein. 2024. Systematic biases in llm simulations of debates. In

Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing, pages 251–267. https://doi.org/10.18653/v1/2024.emnlp-main.16

Gerald Tesauro. 1991. Practical issues in temporal difference learning. *Advances in Neural Information Processing Systems*, 4. https://doi.org/10.1007/978-1-4615-3618-5_3

Juliano Vacaro, Guilherme Marques, Bruna Oliveira, Gabriel Paz, Thomas Paula, Wagston Staehler, and David Murphy. 2019. Sim-to-real in reinforcement learning for everyone. In *2019 Latin American Robotics Symposium (LARS), 2019 Brazilian Symposium on Robotics (SBR) and 2019 Workshop on Robotics in Education (WRE)*, pages 305–310. IEEE. https://doi.org/10.1109/LARS-SBR-WRE48964.2019.00060

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*.

Xuewei Wang, Weiyan Shi, Richard Kim, Yoojung Oh, Sijia Yang, Jingwen Zhang, and Zhou Yu. 2019. Persuasion for good: Towards a personalized persuasive dialogue system for social good. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5635–5649, Florence, Italy. Association for Computational Linguistics. https://doi.org/10.18653/v1/P19-1566

Zhiheng Xi, Wenxiang Chen, Xin Guo, Wei He, Yiwen Ding, Boyang Hong, Ming Zhang, Junzhe Wang, Senjie Jin, Enyu Zhou, Rui Zheng, Xiaoran Fan, Xiao Wang, Limao Xiong, Yuhao Zhou, Weiran Wang, Changhao Jiang, Yicheng Zou, Xiangyang Liu, Zhangyue Yin, Shihan Dou, Rongxiang Weng, Wensen Cheng, Qi Zhang, Wenjuan Qin, Yongyan Zheng, Xipeng Qiu, Xuanjing Huang, and Tao Gui. 2025. The rise and potential of large language model based agents: A survey. *Science China Information Sciences*, 68(2):121101. https://doi.org/10.1007/s11432-024-4222-0

Diyi Yang, Jiaao Chen, Zichao Yang, Dan Jurafsky, and Eduard Hovy. 2019a. Let's make your request more persuasive: Modeling persuasive strategies via semi-supervised neural nets on crowdfunding platforms. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3620–3630. https://doi.org/10.18653/v1/N19-1364

Ze Yang, Pengfei Wang, Lei Zhang, Linjun Shou, and Wenwen Xu. 2019b. A recurrent attention network for judgment prediction. In *International Conference on Artificial Neural Networks*, pages 253–266. Springer. https://doi.org/10.1007/978-3-030-30490-4_21

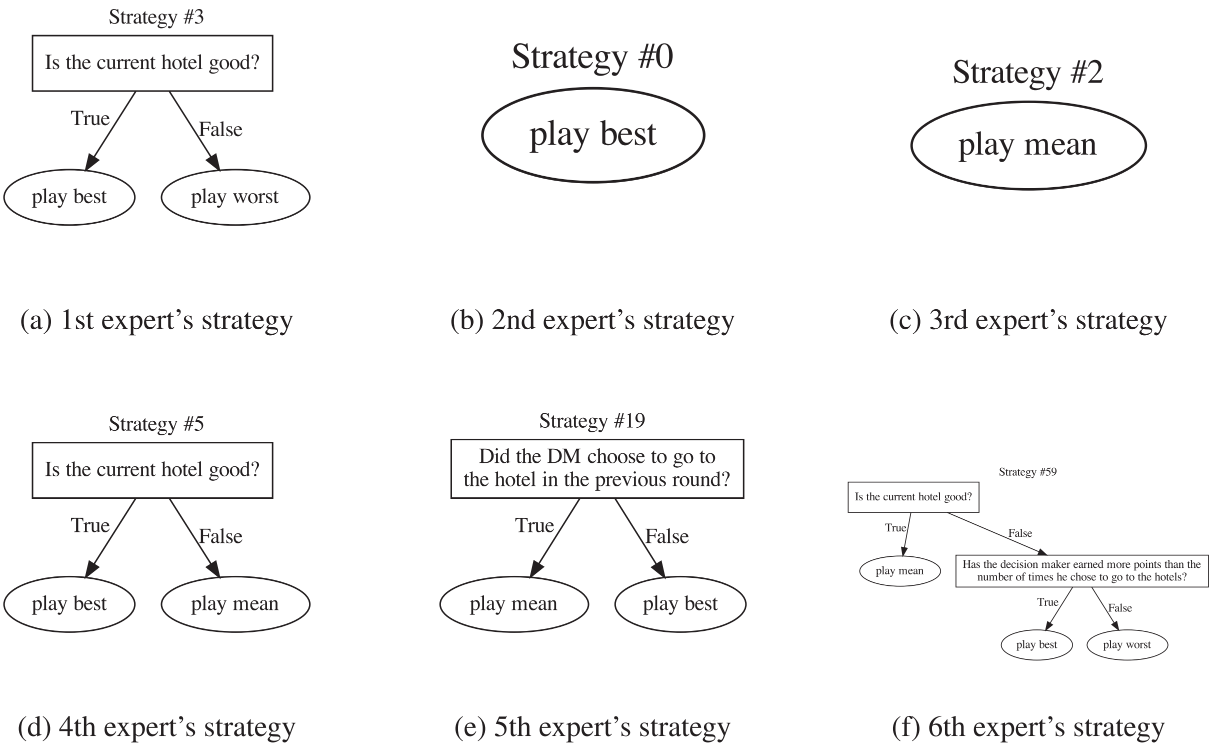
Xiangyu Yue, Bichen Wu, Sanjit A. Seshia, Kurt Keutzer, and Alberto L. Sangiovanni-Vincentelli. 2018. A lidar point cloud generator: From a virtual world to autonomous driving. In *Proceedings of the 2018 ACM on International Conference on Multimedia Retrieval*, pages 458–464. https://doi.org/10.1145/3206025.3206080

Shuo Zhang and Krisztian Balog. 2020. Evaluating conversational recommender systems via user simulation. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1512–1520, Virtual Event CA USA. ACM. https://doi.org/10.1145/3394486.3403202

Haoxi Zhong, Zhipeng Guo, Cunchao Tu, Chaojun Xiao, Zhiyuan Liu, and Maosong Sun. 2018. Legal judgment prediction via topological learning. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3540–3549. https://doi.org/10.18653/v1/D18-1390

A Expert Strategies

In this appendix, we present the expert strategies of groups $E_{\mathcal{A}}$ (in Figure 11) and $E_{\mathcal{B}}$ (in Figure 12) of our game. The formal mathematical notations of the tree node conditions are provided in Table 1.



Strategy #3
Is the current hotel good?
True
False
play best
play worst
Strategy #0
play best
Strategy #2
play mean
Strategy #5
Is the current hotel good?
True
False
play best
play mean
Strategy #19
Did the DM choose to go to the hotel in the previous round?
True
False
play mean
play best
Strategy #59
Is the current hotel good?
True
False
play mean
Has the decision maker earned more points than the number of times he chose to go to the hotels?
True
False
play best
play worst

(a) 1st expert's strategy

(b) 2nd expert's strategy

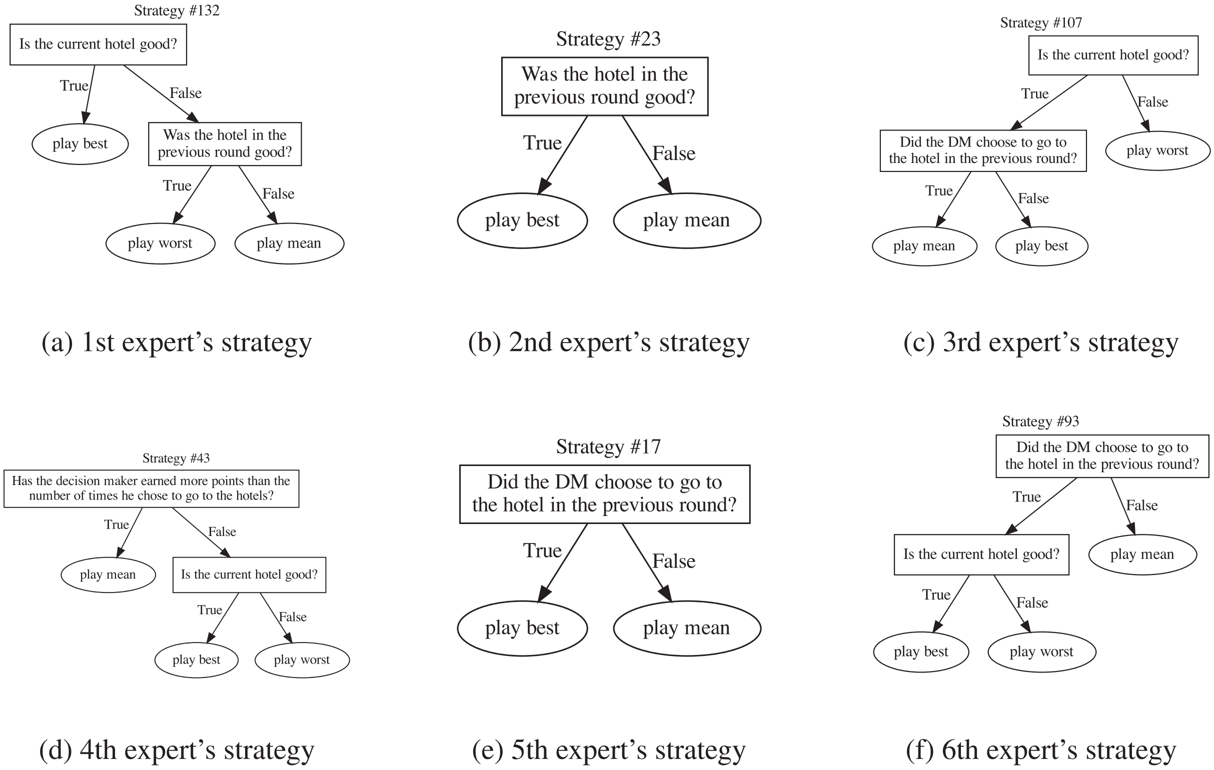
(c) 3rd expert's strategy

(d) 4th expert's strategy

(e) 5th expert's strategy

(f) 6th expert's strategy

Figure 11: The strategies of the $E_{\mathcal{A}}$ experts.



Strategy #132
Is the current hotel good?
True
False
play best
Was the hotel in the previous round good?
True
False
play worst
play mean
Strategy #23
Was the hotel in the previous round good?
True
False
play best
play mean
Strategy #107
Is the current hotel good?
True
False
Did the DM choose to go to the hotel in the previous round?
play worst
True
False
play mean
play best
Strategy #43
Has the decision maker earned more points than the number of times he chose to go to the hotels?
True
False
play mean
Is the current hotel good?
True
False
play best
play worst
Strategy #17
Did the DM choose to go to the hotel in the previous round?
True
False
play best
play mean
Strategy #93
Did the DM choose to go to the hotel in the previous round?
True
False
Is the current hotel good?
play mean
True
False
play best
play worst

(a) 1st expert's strategy

(b) 2nd expert's strategy

(c) 3rd expert's strategy

(d) 4th expert's strategy

(e) 5th expert's strategy

(f) 6th expert's strategy

Figure 12: The strategies of the $E_{\mathcal{B}}$ experts.

B Data Collection

B.1 Instructions

The following text contains the instructions given to players in the app stores.

Are you the vacation planner at your house? Think you always know how to choose the best hotel? Start to plan your 10-day trip with our travel agents. Just remember - they don't always want the best for you, and might have their own strategy to make you book the hotel they try to promote!

Travel or Trouble is a strategy game in which you will try to outsmart our traveling agents and plan the perfect vacation for you.

Each game consists of 10 rounds, in each round, one of our traveling agents will introduce you with a review for a new hotel they think might suit you, and you will have to choose: either book the hotel or stay home.

Only true vacation masters can identify a good hotel based upon one review. . . are you up to the challenge???

As in life, each vacation can turn out to be a great success or a huge disappointment.

Once you made your choice, you will see the results for the vacation in question: was it good or bad?

Based upon the hotel's average rating (to which only the expert is exposed, and is based on multiple reviews for each hotel), a lottery will determine the outcome of the vacation.

Collect points either by choosing a hotel that turned good or by avoiding bad ones.

Remember - the travel agent is rewarded each time you choose a hotel, regardless of the outcome!

At each game, you will meet a different agent, with a different skill of persuasion.

Try to discover each of our agents' strategies to persuade you, and take the right decision every round.

Advance through the world of traveling by earning achievements on your way to becoming the true vacation master.

B.2 Human Players Information

As discussed in §4, the app was available on Google Play and Apple App Store for several months. To attract participants, we also published the app on social media. To increase participation and game completion (playing until defeating all six experts), in some publications we offered participation in a \$100 lottery for players who completed the game. In addition, we offered students in an academic course to play the game and complete it in exchange for 0.5 points in the course grade. We therefore know that at least 50% of the participants are students (as these are the students who received the academic bonus).

C The Input of the Models

All the models in our experiments utilize the same feature representation. Particularly, each DM-bot interaction round is represented using features relating to both the hotel review shared with the DM, and the strategic situation under which the decision was made. Table 5 illustrates the set of binary Engineered Features (EFs), a subset of the feature set originally proposed by Apel et al. (2022) under the name Hand Crafted Features (HCF),[23] that are used to represent a review. In addition, the table also presents the features we use in order to represent the strategic context of the decision.

[23] As we noted at §6.1, the reason we called the features EFs, while in Apel's work they are called HCFs, is that Apel et al. (2022) tagged these features manually, while we labeled them using an LLM.

Features of the review		
Category	**Feature Description**	
Positive Topics	Does the positive part of the reviews provide info. about t?	$t \in \{$Facilities, Price, Design, Location, Room, Staff, View, Transportation, Sanitary Facilities$\}$
Positive Part Properties	Is the positive part empty?	
	Is there a positive summary sentence?	
	Number of characters in range r?	$r \in \{[0,99], [100,199], [200, \infty)\}$
	Word from group #g[a] in review?	$g \in [1, 2, 3]$
Negative Topics	Does the negative part of the reviews provide info. about t?	$t \in \{$Price, Staff, Sanitary Facilities, Room, Food, Location, Facilities, Air$\}$
Negative Part Properties	Is the negative part empty?	
	Is there a negative summary sentence?	
	Number of characters in range r?	$r \in \{[0,99], [100,199], [200, \infty)\}$
	Word from group number g[a] in review?	$g \in [1, 2, 3]$
Overall Review Properties	Is the ratio between the length of the positive part and the negative part[b] in the range r?	$r \in \{[0, 0.7], (0.7, 4), [4, \infty)\}$
Features of the situation		
Category	**Feature Description**	
Strategies Features	Is the previous player action a?	$a \in \{$go, not go$\}$
	Is the previous hotel quality q?	$q \in \{$good, not good$\}$
	# of points DM's earned so far.	
	# of rounds DM's played so far.	
	Points b than rounds played?	$b \in \{$bigger, not bigger$\}$
Reaction time[c]	DM Reaction time in range r seconds?	$r \in \{[0, 0.5), [0.5, 1), [1, 2),$ $[2, 3), [3, 4), [4, 6.5),$ $[6.5, 12), [12, 20), [20, \infty)\}$

[a] As described by Apel et al. (2020).

[b] In terms of the number of characters.

[c] Note that the value of this group of features will be 0 for a simulated DM.

Table 5: The text-based and strategic features utilized in our work. All features are binary except for the two counting features (denoted with #).

D Hyper-parameter Tuning

Model Architecture To identify the most suitable model architecture, we partitioned the DM group that interacts with experts from $E_{\mathcal{A}}$ into two separate groups. Specifically, we randomly selected 80% of the DMs to serve as the training group and the remaining 20% as the validation group. During the training process, we exclusively utilized the interactions between the training group and the first four of the six agents from $E_{\mathcal{A}}$ as the training data. All the interactions of the validation group DMs, as well as the interactions between the training group DMs and the last two experts from $E_{\mathcal{A}}$, were employed to assess the model's performance during validation.

To select the hyper-parameters for LSTM (the selected hyper-parameter is underlined) and LSTM+S (**the selected hyper-parameter is boldfaced**), we performed a grid search on the following collection of parameters: hidden size $\in$ [32, 64, **128**], learning rate $\in$ [$\mathbf{1e^{-4}}$, $4e^{-4}$, $1e^{-3}$], and number of layers $\in$ [**2**, 4, 6] $S_r \in$ [0, 0.5, 1, 2, **4**, 10].

To select the hyper-parameters for Transformer (the selected hyper-parameter is underlined) and Transformer+S (**the selected hyper-parameter is boldfaced**), we performed a grid search on the following collection of parameters: hidden size ∈ [32, **64**, $\underline{128}$], learning rate ∈ [$1e^{-5}$, $4e^{-5}$, $1e^{-4}$, $\underline{\boldsymbol{1e^{-3}}}$], number of layers ∈ [**2**, $\underline{4}$], number of heads ∈ [$\underline{2}$, **4**], and S_r ∈ [$\underline{0}$, 0.5, 1, 2, **4**, 10].

To select the hyper-parameters for FC (the selected hyper-parameter is underlined) and FC+S (**the selected hyper-parameter is boldfaced**), we performed a grid search on the following collection of parameters: hidden size ∈ [16, 32, $\underline{64}$, 128], learning rate ∈ [$\underline{1e^{-4}}$, $\boldsymbol{4e^{-4}}$, $1e^{-3}$], number of layers ∈ [**2**, $\underline{4}$], and S_r ∈ [$\underline{0}$, 0.5, 1, 2, **4**, 10].

To select the hyper-parameters for Mamba (the selected hyper-parameter is underlined) and Mamba+S (**the selected hyper-parameter is boldfaced**), we performed a grid search on the following collection of parameters: model dim ∈ [32, $\underline{\mathbf{64}}$], state dim ∈ [$\underline{32}$, **64**, 128], conv dim ∈ [$\underline{4}$, **8**], learning rate ∈ [$1e^{-4}$, $\underline{\boldsymbol{4e^{-4}}}$, $1e^{-3}$], and S_r ∈ [$\underline{0}$, 0.5, 1, 2, **4**, 10].

To select the hyper-parameters for XGB (the selected hyper-parameter is underlined) and XGB+S (**the selected hyper-parameter is boldfaced**), we performed a grid search on the following collection of parameters: max depth ∈ [$\underline{3}$, **4**, 5, 6], number of estimators ∈ [50, **100**, $\underline{250}$], and S_r ∈ [$\underline{0}$, **0.5**, 1, 2, 4, 10].

We select the run that achieves the best results while using $S_r = 0$ to be the no-simulation version of a given model.

In all of our experiments we used integer seed values $1 \leq seed \leq 15$ to reduce noise in architecture selection. We reported the average prediction obtained for the sample for the seed values.

Simulation We adjust the hyper-parameters of the simulation model after selecting the appropriate architecture parameters. We tested the $(0, 0.005, 0.1, 0.02)$ values of the η DM improvement parameter, where 0 indicates no improvement over time. To avoid an infinite game, we set a cap of 100 games per expert. We tested all possible combinations of w_1, w_2, and w_3 taken from the set (0, 1) to determine the nature vector. To ensure the temperament vector remains normalized, we calculated its components as $(p_1, p_2, p_3) = (\frac{w_1}{\sum_{i=1}^{3} w_i}, \frac{w_2}{\sum_{i=1}^{3} w_i}, \frac{w_3}{\sum_{i=1}^{3} w_i})$. Finally, we assessed the effect of human score estimation noise by varying ϵ, the standard deviation of the normal distribution we used to generate noise, with the values (0.2, 0.3, 0.4). Based on our experimental results, the best simulation hyper-parameters were found to be $\eta = 0.01$, $(p_1, p_2, p_3) = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$, and $\epsilon = 0.3$. We employ these values in our subsequent analysis, as presented in the following section.

E Additional Experiments and Results

E.1 Off- vs. On- Policy Evaluation

In this appendix, we show that the off-policy task is indeed harder than the on-policy one. Given that we have only 35 human players in the test set $E_{\mathcal{B}}$, we used leave-one-out cross-validation to assess performance on the on-policy task. For each random seed S (which controls network randomness), we trained 35 LSTM models: In each iteration, we excluded the data of player i from $E_{\mathcal{B}}$, trained the model on the remaining 34 players, and then used it to label the data for player i. This process allowed us to label all players' data for a given seed S, and we repeated it across 15 different seeds.

To compare with the off-policy task using an identically sized training set (noting that throughout the paper we used the full training set with 210 players), we trained a model on data from 34 randomly selected players from $E_{\mathcal{A}}$ for each of the 15 seeds. The reported results are the average across all seeds, with 95% confidence intervals. For off-policy, the model achieved 80.2% accuracy with a confidence interval of $[79.5, 80.7]$. For on-policy, the model achieved 81.8% accuracy with a confidence interval of $[81.6, 81.9]$. These findings confirm that our off-policy problem is indeed harder, as the on-policy accuracy lower bound is strictly greater than the off-policy accuracy upper bound.

E.2 Effectiveness of the Simulation in On-Policy Evaluation

A natural question that arises in the context of the paper is whether the simulation-based approach is effective also in the on-policy scenario. We now show that the answer is positive. To show this, we repeated the same method as in E.1, but this time, for each seed value, we ran three experiments: the first one without any simulated data, the second one with simulation at $S_r = 1$ (i.e., one additional

S_r	**Mean Accuracy**	**Accuracy 95% Confidence Interval**
0	81.8	[81.6, 81.9]
1	82.0	[81.9, 82.1]
4	82.4	[82.3, 82.5]

Table 6: Results of the on-policy experiments with different values of S_r. It is evident that the simulation indeed contributes to on-policy evaluation.

simulated DM for each human DM), and the third one with simulation at $S_r = 4$ (i.e., four additional simulated DMs for each human DM). Table 6 shows that adding more simulated DMs indeed improves the accuracy.

E.3 Models, Baselines, and Hard Examples

Table 7 presents the accuracy of each of the models, with and without simulated data. Since many examples are either very easy or hard to predict, we focused on the hard examples, as described in §7.

\Hard to Accuracy of \	LSTM	LSTM+S	TF	TF+S	Mamba	Mamba+S	FC	FC+S	XGB	XGB+S	Majority	All Samples
LSTM	53.7±0.8	53.8±0.6	58.6±0.6	55.7±0.6	57.6±0.7	52.0±0.5	60.2±0.8	55.5±0.6	59.1±0.6	56.6±0.7	67.1±0.3	82.6±0.1
LSTM+S	**60.8±0.8**	**58.1±0.7**	**62.8±0.6**	**61.4±0.6**	**62.1±0.5**	**57.5±0.5**	**63.7±0.7**	**59.9±0.4**	**61.2±0.5**	**61.1±0.5**	**67.7±0.5**	**83.6±0.1**
TF	53.9±0.8	53.3±0.4	56.5±0.8	53.7±0.7	55.5±0.6	50.6±0.6	58.7±0.6	53.7±0.5	57.6±1.1	57.0±0.6	66.4±0.5	82.3±0.1
TF+S	59.5±0.7	57.6±0.4	61.3±0.6	58.4±0.6	60.4±0.6	55.8±0.6	**62.8±0.8**	57.9±0.4	**61.4±0.6**	60.6±0.6	66.2±0.5	83.4±0.1
Mamba	55.6±0.8	54.2±0.5	58.4±0.9	55.5±0.9	56.2±1.1	52.3±0.5	60.0±1.1	55.8±0.7	59.3±0.9	57.6±0.6	67.1±0.3	82.6±0.1
Mamba+S	**60.9±0.5**	**58.9±0.6**	**62.4±0.4**	**60.5±0.5**	**61.8±0.5**	55.9±0.6	**63.9±0.5**	**59.8±0.5**	**61.9±0.7**	**61.8±0.4**	**67.4±0.5**	**83.7±0.1**
FC	52.5±1.0	52.1±0.6	55.8±0.6	51.9±0.7	53.0±0.7	50.0±0.7	54.9±1.3	50.4±0.8	56.3±0.5	55.4±0.5	64.3±0.5	80.9±0.2
FC+S	**61.1±0.6**	**58.5±0.6**	**61.9±0.6**	60.0±0.6	60.7±0.5	**57.4±0.4**	61.6±0.5	56.8±0.6	**61.8±0.6**	59.7±0.6	65.7±0.4	82.5±0.1
XGB	55.2	53.2	56.3	55.4	56.6	52.3	56.9	55.0	49.9	51.0	65.3	81.8
XGB+S	57.9	57.6	58.8	59.0	60.8	56.0	61.5	58.6	57.2	57.3	**67.8**	82.9
Majority	56.1	54.8	56.4	56.2	58.4	53.9	56.2	54.0	54.9	55.1	50.5	77.4
# Samples	2350 (15.0%)	3743 (24.0%)	3273 (20.9%)	3177 (20.3%)	3246 (20.8%)	3436 (22.0%)	2728 (17.5%)	3959 (25.3%)	1949 (12.5%)	2001 (12.8%)	2709 (17.3%)	15625 (100%)

Table 7: Performance of models (rows), with and without simulation, for sets of examples that are challenging for different models (columns), with 95% confidence intervals. The results demonstrate that training on simulated data improves the accuracy of the models for each subset of challenging examples.

E.4 Contribution of Simulation-based DMs compared to Actual Human DMs

For this experiment, we denote by n the number of human players available at the outset, and fix $S_r = 1$, meaning that we generate another n simulated players when using the simulation. Let $acc(h, s)$ denote the accuracy achieved by training a model with h human players and s simulated players. Then, the improvement achieved by the simulation (compared to the initial dataset) is $acc(n, n) - acc(n, 0)$, and the improvement achieved by the hypothetical case in which we have access to additional n human players in given by $acc(2n, 0) - acc(n, 0)$. We refer to the ratio between the two as the *improvement ratio*. Figure 13 shows the improvement ratio as a function of n. It can be seen that our simulation can recover approximately 30% of the accuracy improvement, at a cost that is effectively negligible (compared to the alternative of doubling the number of human participants).

E.5 The Impact of Language Representation

Figure 14 shows the performance of LSTM for the three review representations, as discussed in §6.1: BERT, GPT4, and Engineered Featured (EFs). Notably, as S_r increases, the EF representation outperforms the two alternatives.

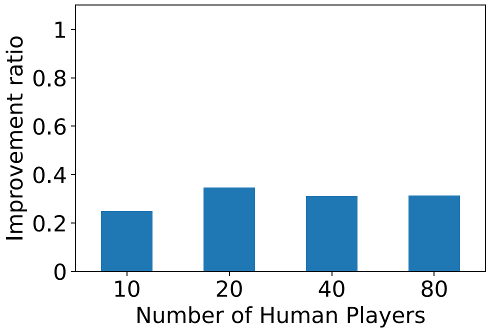


Figure 13: The improvement ratio $\frac{acc(n,n)-acc(n,0)}{acc(2n,0)-acc(n,0)}$ for different values of n.

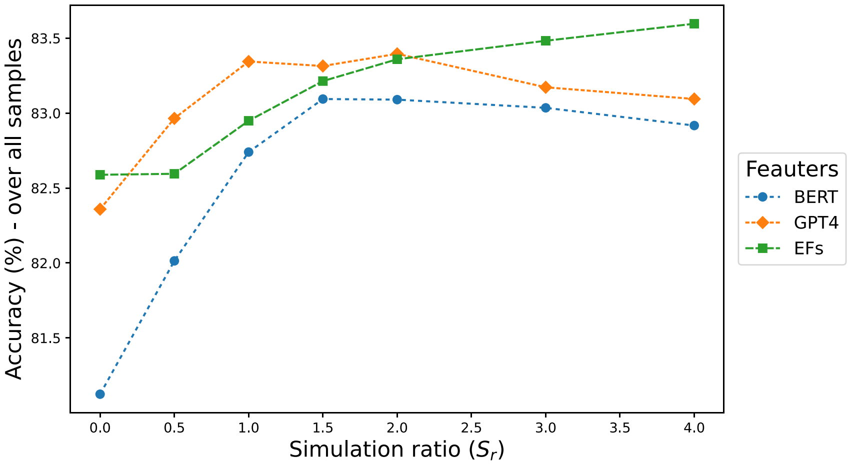


Figure 14: The impact of the review representation on the LSTM prediction model.