# Impact of Probabilistic Behavior on Human-Bot Interactions

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## Abstract

Recent advancements in Large Language Models (LLMs) have fueled growing interest in developing LLM-based agents for tasks involving interactions between humans and bots. One of these tasks is persuasion in hotel recommendation games, where bot agents suggest hotels to human players, who then decide whether to accept or reject the recommendation. Building on the work of Shapira et al. (2024), my research focused on human-bot interactions, specifically on how the bot's additional statistical knowledge influences the decisions made by the decision-maker (DM). Furthermore, I explored how using similar strategies for both the bot and the DM could enhance the DM's decision-making process.

## 1 Introduction

The rapid advancement of Large Language Models (LLMs) in recent years has enabled the development of intelligent agents capable of complex interactions with humans. (Brown et al. (2020); Radford et al. (2019); Oroojlooy and Hajinezhad (2022)). These agents, leveraging their vast computational power and linguistic capabilities, can engage in tasks that require a high degree of adaptability and understanding. One intriguing area of application is in the realm of persuasion games, where human decision-makers interact with bots to make choices based on recommendations. In a recent study by Apel et al. (2022), a language-based persuasion game was introduced where players make decisions based on interactions with agents. In this game, the player assumes the role of a decision maker (DM) interacting with a bot, portrayed as an agent. Each round presents the DM with information about a specific hotel, with the task of determining whether the hotel is "good" based on a rating from 0 to 10. Hotels with an average score of 8 or higher are considered "good". The game consists of 10 rounds, during which the DM evaluates each hotel's information and the outcomes of previous decisions to maximize their overall utility by selecting only high-rated hotels. On the other hand, the bot's objective is to influence the DM into choosing the recommended hotels as often as possible, creating a strategic interaction between persuasion and decision-making. The interplay between the bot's suggestions and the human's choices becomes particularly compelling when probabilistic and statistical elements influence the bot's behavior. Recent studies suggest that integrating statistical decision-making into bots can significantly improve their ability to influence human behavior. (Ghose et al. (2014); Hertwig et al. (2009); Hooten et al. (2010)). My work builds on these insights by examining how probabilistic behavior and statistical strategies can further enhance the bot's influence on human decision-making in persuasion games.

## 2 Related Work

This research builds directly on the work by Shapira et al. (2024). I utilized their data and code, aiming to improve the accuracy of the DM's choices. My improvements are grounded in various statistical methods designed to enhance the bot's ability to offer better recommendations. I employed techniques such as T-tests, confidence intervals, and bootstrap to identify patterns and provide the bot with information that transforms it into an expert, enabling it to offer more informed advice to the DM.

Furthermore, these statistical methods draw heavily on the work presented in the book "Exploring the Efficacy of Persuasion Strategies for Different User Types in Games that Encourage Environmentally Responsible Behavior" by Yue and Gue (2023). This book discusses various persuasion strategies based on game theory, some of which were implemented for the bot, while others were adapted to enhance the decision-making process of the DM.

# 3 Model

In my subsequent work, I adopted the Long Short-Term Memory (LSTM) model due to its proven superiority in performance, as demonstrated in Shapira et al. (2024). The LSTM architecture itself was kept intact, with my focus on enhancing the simulation framework rather than altering the core model. The improvements involved introducing advanced statistical methods and probabilistic decision-making strategies into the simulation. This approach allowed the bot to better mimic expert behavior while maintaining a level of unpredictability to challenge the human decision-maker.

# 4 Data

You can find all relevant data and code in the following GitHub repository: HumanChoicePrediction.

## 4.1 Original Simulation

I used the dataset from Shapira et al. (2023), which encompasses games played by 210 distinct users. In the original game setup, the bot randomly selects its persuasion strategies from a strategy space of 1,179 possibilities. However, many of these strategies are quite simple and do not significantly help the DM in arriving at the correct decision. This is primarily because the strategies do not involve deep insights into the hotel's data, even though the bot is exposed to the reviews for the hotel in each round. Additionally, the DM also has a limited toolkit of strategies and is constrained in how they can respond to the bot's persuasive attempts.

## 4.2 Improved Simulation

In the first part of my study, I focused on the bot's ability to adjust its behavior based on a probabilistic approach. Depending on the drawn probability, the bot uses statistics-based strategies so it could act as an expert or adopt a more random strategy to enhance adaptability and effectiveness in persuasion. This method introduces a level of unpredictability into the bot's decision-making, aiming to reflect real-life scenarios where uncertainty exists and where even experts can make mistakes.

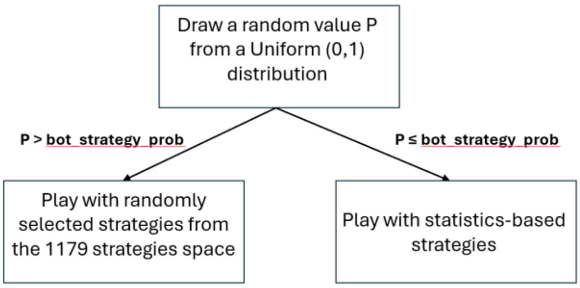


Figure 1: Bot's behavior involves probabilistic strategy selection

I introduced a new parameter called *bot_strategy_prob*, which serves as a threshold for $P$, the probability drawn to determine the bot's behavior. As shown in Figure 1, if $P$ is greater than this threshold, the bot acts as in the original game setting, randomly selecting persuasion strategies to recommend a hotel. However, if $P$ is less than or equal to the threshold, the bot operates as an expert, utilizing statistics-based strategies. These strategies involve analyzing the hotel's reviews using tools such as confidence intervals, T-tests, bootstrap, and leverage techniques like identifying tendencies from previous rounds to improve recommendations for the DM. If these complex criteria are met, the bot provides the DM with the hotel's average score, aiming to offer a balanced perspective. Otherwise, the bot delivers the lowest score to dissuade the DM from selecting the hotel. On the other hand, the DM continues to act as in the original game, selecting actions based on probability vector derived from strategies involving history, topic, LLM scores, random choices, or the oracle strategy. The oracle strategy ensures the DM makes the right decision (i.e., chooses the hotel) if the hotel's average score is $\geq 8$.

The second phase of my study expands on the idea of probabilistic strategies by incorporating them into the DM's toolkit. In this scenario, the DM is provided with statistical tools like those used by the bot, enabling a more informed decision-making process. This creates a scenario in which both the bot and the DM operate under almost the same probabilistic strategies, simulating a more sophisticated interaction where both parties act almost the same. As the DM becomes better equipped to evaluate the bot's recommendations, the study explores whether this symmetry in strategy leads to improved decision-making outcomes for both the bot and the DM. The DM's strategies were carefully designed to mirror the bot's approach while incorporating advanced statistical techniques. For example, the DM uses confidence intervals, bootstrap, t-tests, and mean evaluation strategies to assess the trustworthiness of the bot's recommendations.

The DM determines if the statistical criteria are satisfied and compares them to the bot's suggestion. In the absence of prior interaction history, the DM initially follows the bot's recommendation. However, once there is a history of decisions, the DM relies on both statistical criteria and the bot's previous actions to guide its decision-making. The bot is graded based on past performance, and if the bot has been correct in at least 75% of its recommendations, coupled with statistically significant evidence to favor going to the hotel, the DM will mimic the bot's behavior.
More complex strategies were also implemented for the DM. One such strategy involves assessing the bot's trustworthiness by comparing the bot's message to the score provided by a large language model (LLM). If the difference between the bot's score and the LLM score is equal or less than 2, and the bot has rated the hotel at least an 8, the DM will follow the bot's recommendation to go to the hotel.

The DM also employs strategies derived from the persuasion techniques discussed in Yue and Gue's (2023) book on persuasion strategies. These include game-theory-based methods such as the explore-and-exploit algorithm, Upper Confidence Bound (UCB) strategies, and Tit-for-Tat. The latter has already been successfully implemented in Shapira et al.'s (2024) original work. Additionally, the DM uses a "statistical consensus" strategy that synthesizes the results of all its statistical methods. If most of these methods suggest going to the hotel, the DM will opt to follow that recommendation.
This combination of statistical rigor and game-theory-inspired strategies allows the DM to make more sophisticated decisions, further exploring the dynamic between human and bot decision-making processes.

## 5 Experiments and Results

My experiments explore the hypothesis that probabilistic strategies enable the bot to interact more effectively with the DM by offering recommendations that could enhance the DM's decision-making accuracy over time.
These are the main results and conclusions of my study.

### 5.1 Bot as Expert with Probability, DM Uses Original Strategies


Figure 2: Test accuracies with 95% confidence intervals for part A

In the first part of the project, as illustrated in Figure 2, we observe an intriguing trend: as the probability increases that the bot will recommend more convincingly to the DM, the quality of the DM's decisions does not necessarily improve. In fact, when the bot strictly adheres to statistically based strategies with a probability of 1, the DM's performance tends to decline compared to when it follows a cluster of simpler strategies sampled from a set of 1179 strategies.

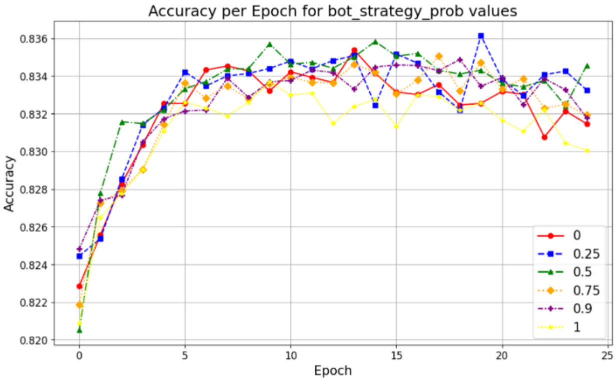


Figure 3: Accuracies per Epoch during Test

From Figure 3 we can see that this trend is consistent across all epochs. A key reason for this likely appears to be the DM's reliance on its established decision-making strategies. If the DM continues to utilize the same approaches as in the initial game setting, the bot's influence on the DM's decisions diminishes. To address this issue, I have incorporated a wider array of strategies into the DM's toolkit.

### 5.2 Bot as Expert with Probability, DM Uses Bot-Like Strategies

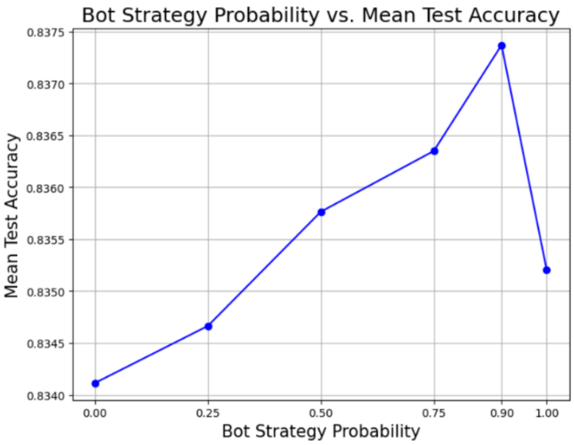


Figure 4: Accuracies per Epoch during Test

The graph presented in Figure 4 illustrates that when the DM adopts strategies like the bot's, there is a noticeable increase in accuracy. However, most of the improvements are marginal and falls within the confidence interval observed earlier in part 5.1. This suggests that aligning the DM's strategies with those of the bot may lead to a slight accuracy boost. Full results for both 5.1 and 5.2 sections can be seen in table 1, where 'Accuracy' refers to the mean value of the measure 'ENV Test accuracy per mean user and bot' over all seeds. The accuracy in 5.1 when *bot_strategy_prob* equals 0, is the score obtained in Shapira et al.'s (2024) setting.

| *bot_strategy_prob* | Accuracy in 5.1 | Accuracy in 5.2 |
|---|---|---|
| 0 | $0.835 \pm 0.002$ | $0.834 \pm 0.006$ |
| 0.25 | $0.836 \pm 0.001$ | $0.834 \pm 0.004$ |
| 0.5 | $0.836 \pm 0.004$ | $0.836 \pm 0.0002$ |
| 0.75 | $0.835 \pm 0.003$ | $0.836 \pm 0.002$ |
| 0.9 | $0.835 \pm 0.003$ | $0.837 \pm 0.001$ |
| 1 | $0.834 \pm 0.002$ | $0.835 \pm 0.001$ |

Table 1: Main Results for Different *bot_strategy_prob* Values

As a result, I decided to further explore this aspect by introducing multiple probability distributions for the DM's strategy selection.

### 5.3 Bot as Expert, DM Chooses Strategies from Different Distributions

In Shapira et al.'s (2024) work, the *basic_nature* parameter was used to determine how the DM selects strategies. This parameter consists of probability vectors guiding the DM's strategy choice. In this experiment, *bot_strategy_prob* was set to 1, meaning the bot is treated as a statistical expert. Several *basic_natures* were tested, where the DM played both pure and mixed strategies. In Figure 5 *Basic_natures* 18-22 represent pure strategies based on my statistical methods, while 23 is a mixed strategy that equally weighs game theory strategies and the difference between bot and LLM scores. *Basic_nature* 26 emphasized a consensus strategy combining statistical strategies with the bot-LLM score difference, assigning lower probabilities to game theory strategies.

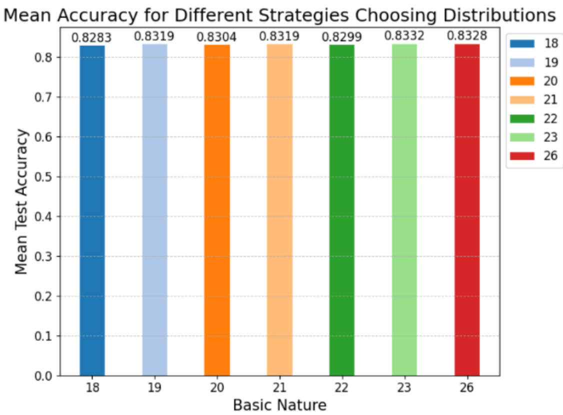


Figure 5: Accuracies per *Basic nature*

Overall, Figure 5 shows results consistent with Shapira et al.'s findings. *Basic_nature* 23, which combines the statistics-based consensus strategy with game theory strategies, performed slightly better than others, but showed no significant improvement.

## 6 Acknowledgments

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## 7 References

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