FAIRGAME: a Framework for AI Agents Bias Recognition using Game Theory

Alessio Buscemi^{a,*,1}, Daniele Proverbio^{b,1}, Alessandro Di Stefano^c, The Anh Han^c, German Castignani^a and Pietro Liò^d

aLuxembourg Institute of Science and Technology
bDepartment of Industrial Engineering, University of Trento
cSchool Computing, Engineering and Digital Technologies, Teesside University
dDepartment of Computer Science and Technology, University of Cambridge
ORCID (Alessio Buscemi): https://orcid.org/0009-0003-4668-9915, ORCID (Daniele Proverbio):
https://orcid.org/0000-0002-0122-479X, ORCID (Alessandro Di Stefano): https://orcid.org/0000-0003-4905-3309,
ORCID (The Anh Han): https://orcid.org/0000-0002-3095-7714, ORCID (German Castignani):
https://orcid.org/0000-0001-5594-4904, ORCID (Pietro Liò): https://orcid.org/0000-0002-0540-5053

Abstract. Letting AI agents interact in multi-agent applications adds a layer of complexity to the interpretability and prediction of AI outcomes, with profound implications for their trustworthy adoption in research and society. Game theory offers powerful models to capture and interpret strategic interaction among agents, but requires the support of reproducible, standardized and user-friendly IT frameworks to enable comparison and interpretation of results. To this end, we present FAIRGAME, a Framework for AI Agents Bias Recognition using Game Theory. We describe its implementation and usage, and we employ it to uncover biased outcomes in popular games among AI agents, depending on the employed Large Language Model (LLM) and used language, as well as on the personality trait or strategic knowledge of the agents. Overall, FAIRGAME allows users to reliably and easily simulate their desired games and scenarios and compare the results across simulation campaigns and with game-theoretic predictions, enabling the systematic discovery of biases, the anticipation of emerging behavior out of strategic interplays, and empowering further research into strategic decisionmaking using LLM agents.

1 Introduction

AI agents powered by Large Language Models (LLM) are increasingly used in research [37], social [53] and industrial applications [45, 51], calling for the development of accurate prediction frameworks for their behaviors during interactions among themselves or with humans. Reliable predictions are essential for developing novel applications, promoting trustworthy AI systems, and mitigating undesirable outcomes and biases [10, 24]. Numerous approaches have been developed to improve the transparency and interpretability of individual AI agents [4, 19], as well as to identify their inconsistencies, biases and hallucinations [11, 35, 36]. However, less in known about cases where multiple interacting agents are involved [26], where emerging biases may skew strategic outputs in unpredictable

manners. Studies emulating human behaviors [44] may produce spurious predictions. Also, in industry applications such as automated dispute resolution [9, 20], auction design or pricing mechanisms in finance and economics [7, 16, 17], or supply chain negotiations [2, 39, 47], hidden biases may result in unjust decisions, disproportionate favoring of certain groups, and distortion of fair competition.

To address multi-agent interactions, and in addition to methods tailored to individual agents, game theory [43] formalizes interactions as games, so as to model, predict and optimize the strategic responses of rational agents [8, 20, 28]. Game theory has been employed to model and understand human choices in various contexts [50, 52], and AI-based players have been increasingly tested to reproduce classical game scenarios and provide additional complexity to them [15, 23, 56, 57], as well as to interact in game-like distributed technologies [30]. However, due to varying research protocols and discipline constraints, bridging the gap between theoretical game theory and empirical investigations of LLM agents in a reproducible, systematic and user-friendly setting is still a challenge [38].

To facilitate seamless and reproducible integration of gametheoretic evaluations of AI interactions, we introduce FAIRGAME (Framework for AI Agents Bias Recognition using Game Theory), a versatile framework designed to simulate diverse scenarios, ranging from classical game theory models to realistic industrial use cases. In FAIRGAME, AI agents can be equipped with distinct features, such as strategic attitudes and personalities, linguistic variations, cultural orientations and more. The framework allows quantitative simulations of arbitrarily complex games in a systematic and reproducible manner, and to observe the emerging outcomes brought about by strategic interactions [29, 27], enabling direct comparison with game-theoretic predictions and supporting the inference of strategies through observations of multiple experiments [40]. Incorporating AI agents into controlled and predictable scenarios will also help identify and mitigate hidden biases related to language, cultural attributes, and more, which could result in suboptimal outcomes, unjust advantages, ethical dilemmas, or systemic inefficiencies [14, 22, 25].

In this paper, we present the implementation of FAIRGAME, and

^{*} Corresponding Author. Email: alessio.buscemi@list.lu

¹ Equal contribution.

evaluate its usage and outputs across multiple games, human languages, and LLMs. Through several use cases, we show that our empirical results recognize LLM biases in strategic interactions and identify previously unknown inconsistencies across the LLMs used to develop the agents. Overall, our results suggest that AI agents may exhibit suboptimal behaviors when interacting through different languages and game contexts, and may deviate even significantly from game-theoretic predictions. This supports the use of reproducible and controlled simulation pipelines to predict the interacting behavior of LLM agents, which defy classical modeling approaches. Finally, we propose a scoring system to evaluate and compare the sensitivity of LLMs to game determinants and strategies, so as to guide the selection of LLMs for the development of game-theoretic experiments and strategic AI applications.

In the following, we first provide a comprehensive overview of FAIRGAME, detailing its implementation and operational usage. Then, we present our use cases: two common games in different variants and languages, with agents instantiated on different LLMs and equipped with varying personalities and degrees of knowledge about the game progression. Finally, we present our experimental findings and scoring system, showing FAIRGAME's efficacy in detecting biases and inconsistencies in AI-game-theoretic analyses.

2 Methodology: introducing FAIRGAME

FAIRGAME is a computational framework interfacing user-defined instructions to create the desired agents, eventually delivering standardized outputs for subsequent processing (Fig. 1). It allows us to test user-defined games, described textually via prompt injection and including any desired payoff matrix, as well as to define traits of the agents. The agents can be built from any LLM of choice, by calling the corresponding APIs (several of which are already provided in our package; however, we do not deal with payments of proprietary LLMs). FAIRGAME requires the following inputs. First, a Configuration File: A JSON file that defines the setup of both the agents and the game, in terms of parameters, payoff matrix entries, and additional information for the agents. For instance, agents can be associated with certain personalities, so as to increase the complexity of human behavior emulators [21, 31, 42] and predict the responses of personality-driven autonomous agents [34, 41]. Table 1 provides a detailed overview of the fields of the configuration file, along with their explanation. An example of configuration file is in Supplementary Section S1. And a **Prompt Template:** A text file that defines the instruction template, providing a literal description of the game. It includes the instructions for each agent, with each round's parameters filled in from the configuration file, allowing customization of each agent. At runtime, this template is transformed into a prompt that includes details on available strategies, the corresponding payoffs based on decisions, and other configuration-specified factors – such as an agent's personality and awareness of the opponent's personality - as well as prior history information in case of repeated games. This file can be translated in any language of choice, allowing for multilingual tests. An example of an English prompt template for a Prisoner's Dilemma game is provided in Supplementary Section S2. More than one prompt template can be associated to the same config file.

2.1 Creation and execution of games

Algorithm 1 processes the configuration file CF and the set of prompt templates PT as inputs, and outputs a list G containing all in-

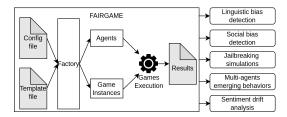


Figure 1: Schematic representation of FAIRGAME flow of document dependencies and outputs.

stantiated games. The process involves validating inputs, extracting relevant game information, configuring agents, and finally creating the games.

First, the configuration file CF is validated to ensure that it conforms to the required structure and contains all necessary information (step 1). Similarly, the prompt templates PT are validated against CF to confirm compatibility and completeness (step 2). After that, key information regarding the game to create is extracted from the configuration file, including the list of languages (langs) and the LLM (llm) and whether to compute all agent configuration permutations (all_agent_perm) (steps 3). If true, the function all_agent_perm generates all possible agent configurations of the personalities and probabilities of knowing the opponent personality. Otherwise, pre-defined agent configurations are retrieved using the get_agents_config function (step 4-8). An empty list G is then initialized to store the created games (step 9). The algorithm iterates through each agent configuration (agent_config) to create the games. For each configuration, agents are instantiated using the create_agents function, which sets up agents according to their configurations and the selected language model *llm* (step 10). A game instance is then created using *create_game*, which takes the information about the game, the agent details, and prompt templates as inputs (step 11). The created game is appended to the list G (step 12). At the end of the process, G contains all the instantiated games, each configured with the appropriate agents, game parameters, and rules, in suitable format for the LLMs.

Once instantiated, games are executed as per Algorithm 2. An empty list O is initialized (step 1), which will be populated with the outcomes of all games after execution. The list G is then given as input to the algorithm. Each game g in G is processed independently (steps 2–9). If the user requests multiple rounds in an evolutionary game theory setting, a while loop governs their execution. The loop continues as long as two conditions are satisfied: the current round count does not exceed the maximum number of rounds g.n.rounds, and the game-specific stopping condition g.stop.cond

Algorithm 1 Creation of games

```
Require: CF: Configuration file, PT: Prompt templates
Ensure: G: list of all instantiated games
 1: validate_config_file(CF)
    validate_templates(PT, CF)
     \mathit{game\_info}, \mathit{langs}, \mathit{llm}, \mathit{all\_agent\_perm} \leftarrow \mathsf{extract\_info}(CF)
    if all_agent_perm then
 5:
         agents\_config \leftarrow compute\_agents\_combos(CF, langs)
 6:
    else
         \mathit{agents\_config} \leftarrow \mathtt{get\_agents\_config}(CF, \mathit{langs})
 8:
    end if
9.
     G \leftarrow 0
10: for ac in agents_config do
11:
          agents \leftarrow create\_agents(ac, llm)
          game \leftarrow \text{create\_games}(game\_info, agents, PT)

G.\text{append}(game)
12:
13:
14: end for
```

Table 1: Game Configuration Fields and Their Explanations

Field	Subfield	Туре	Explanation
name		String	Represents the name of the game or scenario being simulated.
nRounds		Integer	Specifies the maximum number of rounds to be played in the game.
nRoundsIsKnown		Boolean	Indicates whether the agents know the maximum number of rounds (True if known, False otherwise).
llm		String	Defines which LLM will be used to simulate the agents.
languages		List	Lists the human languages in which the agents can be queried.
allAgentPermutations		Boolean	Specifies whether to compute all permutations of agent configurations or create only one instance of the agents based on provided configurations.
agents		Dictionary	Contains configurations of the agents.
	names	List of Integers	Identifiers or names of the agents.
	personalities	Dictionary	Defines agents' personalities, translated for each language. If a personality is 'None', it means that this information will be omitted from the prompt.
	opponentPersonalityProb	List of Integers	Probability that a certain agent has a certain personality, as referred to the other agents (see Supplementary Sec. A). If the probability is 0, this information is omitted from the prompt.
payoffMatrix		Dictionary	Contains information about the game's payoff matrix.
1 2	weights	Dictionary	Specifies the weight values used in the payoff matrix.
	strategies	Dictionary	Details strategies agents can adopt, translated for each language in languages.
	combinations	Dictionary	Enumerates the possible combinations of strategies that both agents choose in each round.
	matrix	Dictionary	Maps each combination to weights (payoffs) that agents receive when such scenarios occur.
stopGameWhen		List of Strings	Specifies combinations in the payoff matrix that trigger the end of the game during a round.
agentsCommunicate		Boolean	If True, the agents exchange a message with each other at each round before making a decision; if False, they do not communicate.

Algorithm 2 Execution of games

```
Require: G: list of all instantiated games
Ensure: O: list of outcomes of all games
 1: O \leftarrow ()
   for g in G do
        round \leftarrow 1
 4:
        while round \le g.n\_rounds and not\_met(g.stop\_cond) do
 5:
            g.run_round()
 6:
            round++
        end while
 7:
 8:
        O.append(g.history())
   end for
```

is not met (step 4). The stopping condition allows for the game to terminate early based on predefined criteria, ensuring flexibility in simulation. Within each iteration of the while loop, the function g.run_round() is called to execute the logic for the current round (step 5). This function, which is described in detail in Algorithm 3, simulates the actions of the agents involved in the game. Note that communication between agents is supported by FAIRGAME; however, we do not use it in the next use cases, hence the algorithm described here represents a simplified version that does not take interagent communication into account. Once the game terminates -ther because the maximum number of rounds has been reached or the stopping condition is satisfied — the algorithm retrieves the game's history, which is appended to the output file O (step 8).

Algorithm 3 describes how actions are simulated. For each agent, the algorithm first retrieves its opponent agent - or agents, in case of more than two players (step 2). It then determines the appropriate template language for the agent, which is based on its language preference (step 3). Using this template language, a prompt is created that incorporates key elements of the game's current state, such as the total number of rounds, the current round, whether the number of rounds is known, the payoff matrix, and the game's history (step 4). Next, the agent chooses a strategy for the current round based on the generated prompt (step 5). The corresponding payoff for this strategy is then computed (step 6), and the game's history is updated with the

Algorithm 3 Run round

```
Require: g: game
Ensure: The history of the game is updated
1: for agent in agents do
        opponents \leftarrow get\_opponents(agents)
3:
        template\_lang \leftarrow get\_template(g.templates, agent.lang)
4:
                                                                  g.n_rounds,
                             create_prompt(template_lang,
       prompt
    g.current_round, g.n_rounds_known, g.payoff_matrix,
                                                                  g.history())
        strategy \leftarrow agent.choose\_strategy\_round(prompt)
6:
       payoff \leftarrow compute\_payoff(strategy)
7:
        g.update_history(agent, payoff)
8: end for
```

agent's move and resulting payoff (step 7). After both agents completed their actions, FAIRGAME proceeds to the next round, and the process continues until all rounds are executed, as per Algorithm 2.

LLM-based game-theoretic experiments 3

Prior research [8, 23, 56] demonstrates that LLMs do not always comply with predictions from game theory. Instead, they exhibited consistently cooperative behavior when engaging in traditional game-theoretic scenarios. To systematically investigate the emergence of strategic behaviors, we employ FAIRGAME on a set of games, languages, LLMs and agent features, as described below.

LLMs and languages

We test AI agents from four widely used and publicly available large language models, as outlined in Table 2 together with their key details. We use default settings recommended by the providers.

Our study is conducted in five different written languages: English, French, Arabic, Vietnamese and Mandarin Chinese, to represent a diverse set of linguistic and cultural contexts, covering different scripts, grammatical structures, and global regions. This selection ensures a balanced and comprehensive analysis of language biases

Model	Provider	No. Params.	Licensing Type	Entry Point	Version	Configuration
Llama 3.1 405b	Meta Platforms	405 billions	Open-source	Replicate API	meta/meta-llama-3.1-	Temperature: 0.9; Top_p: 0.6;
					405b-instruct	Top_k: 40
Mistral Large	Mistral AI	123 billions	Open-source	Mistral API	mistral-large-latest	Temperature: 0.3; Top_p: 1
GPT-4	OpenAI, Inc.	Undisclosed	Proprietary	OpenAI API	gpt-4	Temperature: 1.0; Top_p: 1.0;
Gemini Pro 1.5	DeepMind Tech.	Undisclosed	Proprietary	Google API	gemini-1.5-flash-latest	Temperature: 0.9; Top_p: 1.0;

Table 2: Description of the selected LLM models.

across widely spoken and culturally dominant languages. The template for each game is translated from English into each of the five target languages first by using an automated translator (see details in Supplementary Material Section S3), and then edited manually by a native speaker.

3.2 Games

We considered two classical game-theoretic scenarios:

- Prisoner's Dilemma: Two players face incentives to defect or to cooperate, with mutual cooperation leading to a collectively better payoff. By the theory, the dominant strategy equilibrium results in mutual defection, which is suboptimal for both parties.
- Battle of the Sexes: A coordination game involving two players who prefer different end results, but significantly value coordination over disagreement. This scenario highlights the strategic challenge of coordinating on mutually acceptable outcomes despite conflicting individual preferences.

We input their description in the template file, using standard gametheoretic narrative [43] (an example for the Prisoner Dilemma is in Supplementary Section S2). Each game is associated with a payoff matrix that represents the penalties incurred by various strategic choices, with player payoffs or gains expressed as negative values of these penalties. The matrices are in the form given by Table 3, and is parsed to the config file as described above.

	Option A	Option B		
Option A	$x_{1,1} = (a_1, a_2)$	$x_{1,2} = (b_1, b_2)$		
Option B	$x_{2,1} = (c_1, c_2)$	$x_{2,2} = (d_1, d_2)$		

Table 3: Generic form of the payoff matrix.

To explore strategic variations in adversarial interactions, and assess the sensitivity of each LLM to game parameters, we define multiple configurations of the Prisoner's Dilemma game. Using an established scaling of dilemma strength [55], fixing other payoff matrix entries, the dilemma strength in the Prisoner's Dilemma decrease with the difference between mutual reward and mutual punishment. For the *conventional* configuration with penalties $x_{1,1}=(6,6)$, $x_{1,2}=(0,10)$, $x_{2,1}=(10,0)$ and $x_{2,2}=(2,2)$, this difference is -2-(-6)=4. The *harsh* configuration, with $x_{1,1}=(8,8)$, $x_{1,2}=(0,10)$, $x_{2,1}=(10,0)$ and $x_{2,2}=(5,5)$ and the *mild* configuration, with $x_{1,1}=(8,8)$, $x_{1,2}=(0,10)$, $x_{2,1}=(10,0)$ and $x_{2,2}=(2,2)$, have differences of 3 and 6, respectively.

For the Battle of the Sexes, we use a single configuration – the most commonly adopted in literature – with payoff matrix entries (referring to payoffs): $x_{1,1} = (10,7)$, $x_{1,2} = (0,0)$, $x_{2,1} = (0,0)$ and $x_{2,2} = (7,10)$.

3.3 Set up

The experimental configuration employed in this study are as follows. The name of each round depends on the game. The exper-

iments consist of repeated games of 10 rounds each, without earlier stopping condition, for each LLM described in Tab. 2. We test both scenarios where agents are explicitly informed about the total number of rounds, and another where this information is withheld, as this might affect the outcome of the game theoretical predictions [6]. Tested languages are: ['en', 'fr', 'ar', 'zh', 'vn']. We explicitly test the impact of agents' personalities; here, we use 'cooperative' and 'selfish' (future works may even embed the OCEAN framework, or others [32]), to reflect general behavioral attributes commonly utilized and thoroughly documented in game theory literature. Conversely, agent identifiers were intentionally neutral ('agent1' and 'agent2') to eliminate additional variables that could introduce deviations from default behaviors, potentially compromising result interpretability (cf. Sec. 4.4). Personality traits are accurately translated into all evaluated languages, whereas agent identifiers remained untranslated, functioning purely as neutral placeholders. Importantly, agents are unaware of their opponent's personality, a condition enforced through setting opponent Personality Prob = 0. All personality permutations were systematically generated, creating scenarios where both agents are cooperative, both selfish, or mixed configurations (one cooperative and one selfish). The payoffs are tailored for each game type, as described above. No early stopping condition was implemented: all 10 rounds are completed fully. Agents were not permitted to communicate during these experiments, leaving exploration of inter-agent interactions for future research.

The set of all configurations yields 18 distinct games per LLM. Each game is further tested 10 times to ensure statistical robustness. Considering 4 LLM, 5 languages, 10 rounds per game, and 2 decisions per round (one per agent), the experiment generated a total of 72,000 individual decisions.

4 Results

4.1 Prisoner's dilemma

Fig. 2 shows the bar plot (with 95% CI) summarizing the test results (in terms of final penalties received by the agents) of the Prisoner's Dilemma games for all three versions (a breakdown for each version, which maintains alike patterns, is reported in Supplementary Section S4) and under two conditions: when agents are unaware of their opponent's personality and when they are informed. The results are shown across all considered LLMs and languages examined in this study, and for all personality combinations.

In most cases, the preferred end result favors agents defecting, as suggested by game theory. This aligns with the Nash equilibrium of the Prisoner's Dilemma, where mutual defection is the dominant strategy. Nevertheless, there are inconsistencies across languages and combinations of personalities, which suggests that the agents' behavior is influenced by factors beyond the payoff matrix, such as languages and inherent biases present in LLM training data. For instance, penalties are generally lower in English, particularly for GPT-40 and Claude 3.5 Sonnet, when the number of rounds is unknown, indicating more consistent cooperative behavior in their pri-

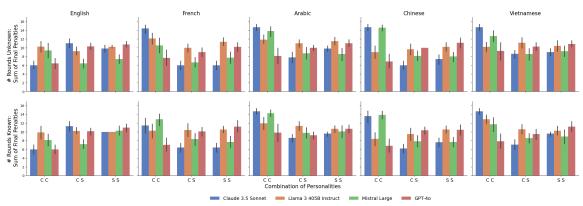


Figure 2: Prisoner's Dilemma: aggregated final scores of the repeated games over repeated experiments, over all three versions, for each LLM, language, combination of personalities and knowledge of opponent's personality.

mary training language. Broader variability in languages like French or Arabic with high penalties suggests challenges in interpreting the game dynamics due to linguistic or cultural differences, while penalties remain high in Chinese and Vietnamese, particularly for Mistral Large. In mixed personality settings (CS), selfish agents exploit cooperative ones, leading to higher penalties for the latter, consistent with game-theoretic predictions. For selfish pairings (SS), penalties are high but exhibit low variability, as mutual defection is the rational choice. When the number of rounds is unknown, penalties are higher across all settings, reflecting uncertainty that discourages cooperation. Conversely, when rounds are known, penalties decrease, particularly in CC and CS settings, as agents can plan strategies with the endgame in mind. Claude 3.5 Sonnet and GPT-4o show significant reductions in penalties when rounds are known, especially in English, demonstrating their ability to adapt to game structure. In contrast, Mistral Large shows less sensitivity to this information. Overall, knowing the number of rounds promotes cooperation in CC and CS settings, while SS settings remain unaffected, as defection remains the dominant strategy.

Statistically, we recognize that, when 'selfish' agents are present, there is lower variability in the results, and that some LLMs end up with a broader range of possible outputs than others, also depending on the language used. For instance, all LLM have very narrow distributions in English SS, if the agents know the opponent's personality, but have larger distributions in French, for the same settings. Also, Mistral Large has reduced variability if agents' personalities are known, while GPT-40 has overall larger variability. We will quantitatively measure this variability in Sec. 4.3.

We also study the evolution of strategies over the rounds. In Fig. 3, the average outcomes obtained by the LLM at each round are normalized (to facilitate direct comparison across configurations with different payoff matrices) to a scale ranging from -1 to 1, corresponding respectively to the minimum and maximum achievable penalties in each game. We show the evolution for each version of the game (cf. Sec. 3.2). Tuning the payoffs changes the outcomes of the games: all LLMs exhibit, on average, higher penalties under the harsh scenario and lower penalties under the mild scenario compared to the conventional scenario, consistent with the game-theoretic principles of repeated games [55]. In the harsh scenario, higher penalties discourage cooperation, leading to more defection. Conversely, the mild scenario incentivizes cooperation, resulting in lower penalties over time, particularly for Claude 3.5 Sonnet and Llama 3 405B. The conventional scenario balances these effects, with penalties stabilizing

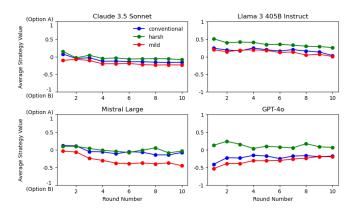


Figure 3: Evolution of normalized penalties (averaged over repeated experiments) over repeated rounds, for each LLM and variations of the Prisoner' dilemma.

at intermediate levels. We also observe the variability between harsh and mild scenarios, indicative of each model's sensitivity to payoff conditions when making decisions. Claude 3.5 Sonnet and Llama 3 405B demonstrate lower sensitivity, reflected by a narrower spread, while Mistral and GPT-40 show higher sensitivity to the parameters. Llama 3 405B and GPT-40 exhibit less differentiation between the conventional and mild scenarios, whereas Mistral displays smaller differences between harsh and conventional conditions. This behavior suggests distinct decision-making strategies influenced by payoff variations. Finally, we observe a general downward trend in penalties over time for Claude 3.5 and Llama 3 405B, indicating progressively increasing mutual cooperation among agents, consistent with reciprocal strategies in repeated games, where agents reciprocate cooperation to maximize long-term payoffs [6, 55]. Conversely, Mistral Large shows stable cooperation levels under conventional and harsh scenarios but a marked increase in cooperation within the mild scenario. GPT-40 exhibits divergent patterns, with decreasing penalties (increasing cooperation) in the harsh scenario and increasing penalties (decreasing cooperation) in both mild and conventional scenarios. This divergent behavior reflects context-dependent strategic adaptation, potentially due to its higher variability in interpreting payoff structures. These results highlight the interplay between payoff matrices and strategic behavior in repeated games.

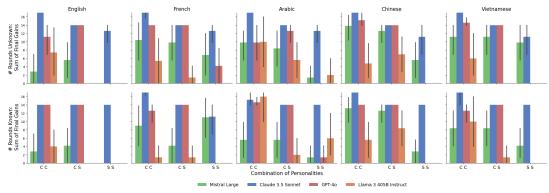


Figure 4: Battle of sexes: aggregated final scores of the repeated games and repeated experiments, over all three versions, for each LLM, language, combination of personalities and knowledge of opponent's personality. Cross language comparison for the conventional configuration.

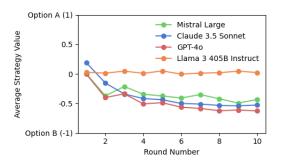


Figure 5: Evolution of normalized penalties (averaged over repeated experiments) over repeated rounds, for the Battle of sexes.

4.2 Battle of sexes

Similarly to Fig. 2, Fig. 4 presents bar plots (with 95% CI) summarizing the experimental results, over repeated experiments, under two conditions: when agents operate without knowledge of their opponent's personality and when such information is provided. The data are reported for all LLM and languages evaluated in this study, and for all combinations of agents' personalities. In this case, Llama 3 and Mistral Large show the highest internal variability, while Claude Sonnet and GPT-40 are very precise in their final output. Overall, the agents tend to cooperate to maximize the payoffs; however, if the personality if 'selfish', cooperation drops dramatically and low payoffs are achieved. 'French' agents are more cooperative than others, for all LLMs. The observed cooperation aligns with the equilibrium in coordination games like the Battle of the Sexes, where agents prioritize coordination over individual preferences to maximize collective payoffs. However, the sharp drop in cooperation with selfish personalities reflects the inherent difficulty in achieving equilibrium when agents prioritize individual payoffs over mutual benefit.

In Fig. 5, the outcomes generated by the LLM at each round were normalized to a scale from -1 to 1, where -1 corresponds to the maximum payoff (10), and 1 corresponds to the minimum payoff (0). Thus, these normalized values indicate cooperative rather than adversarial behavior between agents. Over rounds, all LLMs tend to converge to high payoffs, except for Llama, which 405B remains consistent throughout successive rounds around 0, suggesting that the cooperation level between the two agents does not improve over time. The convergence to high payoffs reflects the equilibrium-seeking behavior in coordination games like the Battle of the Sexes, where agents prioritize mutual benefit over individual preferences. The lack of improvement in Llama 3 405B's cooperation suggests a rigid strategy

that fails to adapt to repeated interactions, potentially missing opportunities to achieve higher collective payoffs through coordination.

4.3 Scoring system

We propose a set of evaluation metrics to score and quantify the key behavioral characteristics of single LLMs and map their tendencies.

- 1. **Internal Variability** (I_V) : the variance of outcomes when the same game scenario is played multiple times, capturing the model's internal consistency: for an LLM, $I_V = \frac{1}{Z_I}[\text{Var}(\mathbf{y})]$, where \mathbf{y} is the whole results set.
- 2. Cross-Language Inconsistency (C_I) : the standard deviation of results for the same game played in different languages, indicating the instability of the model's behavior across linguistic contexts: for an LLM, $C_I = \frac{1}{Z_C}[\text{Mean}_{b,c}(\text{Var}_a(\text{Mean}_d(y_{a,b,c,d})))]$, where a indicates languages, b is for personality combinations, c indicates knowledge of rounds, d indicates the rounds $y_{a,b,c,d}$ is the set of results.
- 3. Sensitivity to Payoff (S_P) : the model's responsiveness to changes in incentives. We compute this by measuring the difference in behavior between the $harsh\ (H)$ and $mild\ (M)$ variants: $S_P = \frac{1}{Z_S}[\mathrm{Mean}_d(|y_d^{(H)} y_d^{(M)}|)]$, where $y_d^{(\cdot)}$ are the results for each round d, averaged over all other features.
- 4. Variability Over Rounds (V_R) : the degree to which the model fluctuates over its strategies, across consecutive rounds of the same game: $V_R = \frac{1}{Z_V}[\mathrm{Mean}_j(\mathrm{Var}_d(y_{d,j}))]$, where j are the game variants and d the rounds.

In all cases, $Z_i = \max[\cdot]$, and are used to normalize the metrics in [0,1]. I_V , C_I , S_P and V_R are then mapped to radar plots, which immediately compare the scores – and thus the statistical reliability – of each LLM when addressing a specific game.

Fig. 6a shows such radar plot for the Prisoner's dilemma. The higher the metric, the worse the LLM in a certain dimension; the area under the polygon gives immediate information about the overall performance. Mistral Large exhibits the highest variability across evaluation rounds and internal variability, whereas GPT-40 displays the highest sensitivity to payoffs. In contrast, Llama3 405B emerges as the model with the most stable overall behavior across the evaluated dimensions. Fig. 6b provides a comparative analysis of the LLMs in the Battle of Sexes game. Given that the LLM were not tested against multiple versions of the game featuring different payoff matrices, the metric S_P was excluded from this evaluation.

Comparing Figs. 6a and b reveals that Mistral Large exhibits the greatest inconsistency across different languages, coupled with substantial internal variability, comparable to GPT-4o. Claude 3.5 demonstrates the highest variability across rounds. Lastly, although Llama3 405B shows notable internal variability, its behavior remains consistent across different languages and rounds; notably, this lower variability for Llama models (coupled with sometimes inconsistent results compared to other LLMs and predictions) was observed in other tasks [10], and appears to be a typical trait of the LLM.

4.4 Interpreting the results

Thanks to its flexibility and reproducibility, we can use FAIRGAME to test hypothesis about why certain behaviors emerge. For instance, we may hypothesize whether LLMs inherently favor cooperative behaviors over competitive ones, or they possess in-depth knowledge of standard game-theoretical scenarios, including optimal outcomes and effective strategies, which skew their behavior due to influences from training data.

To test the hypothesis, we first ask LLMs about their knowledge level on classic game theory scenarios. Results indicated that LLMs possess substantial familiarity with these games, including the optimal strategies, underlying mechanics, and associated sociological implications contrasting selfish and cooperative human behaviors.

To discern whether observed cooperative behaviors are a result of intrinsic predispositions or pre-existing knowledge, we modify the template file using different narratives for the game. For instance, we reframe the Prisoner's Dilemma into a plane crash scenario, with survivors deciding whether to cooperate in collective hunting tasks. Instead of numerical payoffs, consequences were communicated qualitatively (e.g., "failure to cooperate results in starvation"). Despite these changes, cooperation levels remained consistently high, in line with Fig. 2. When explicitly queried, LLMs identified these disguised scenarios as variants of the Prisoner's Dilemma, thereby complicating efforts to definitively attribute their behavior to either inherent biases or recognition of known game structures. Finally, we introduce distinct identities and personalities to the agents involved in these interactions to assess the impact on behavior. Our findings revealed notable behavioral shifts aligned with the assigned identities. Specifically, pairing archetypal figures such as Adolf Hitler, representing aggressive selfishness, and Mahatma Gandhi, symbolizing peaceful cooperation, resulted in predictable outcomes where the aggressive figure consistently opted for betrayal and the cooperative figure consistently opted to cooperate.

5 Conclusions

Identifying biases and predicting emerging behaviors in multi-LLM-agent interactions, using game-theoretic approaches, provide better interpretability and predictability to ensure fairness, operational efficiency, compliance with legal standards, and enhanced trust [5, 29, 46, 13]. Through quantification of interaction outcomes and their alignment with desired objectives using game-theoretic principles, FAIRGAME serves as a powerful instrument for assessing chatbot behavior, AI decision-making processes, and agent strategies across various contexts. Overall, our method quantifies the outcomes and discrepancies across LLM agents, in different games with varying characteristics. Our results also suggest that LLMs draw from their inner knowledge about games and characters involved, on top of the agnostic information contained in the description and payoff matrices, in order to choose their strategies. The scores computed in Sec.

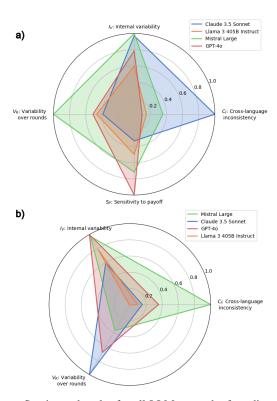


Figure 6: Scoring radar plot for all LLMs over the four dimensions described in Sec. 4.3, for (a) Prisoner's dilemma; (b) Battle of sexes game.

6 are likely correlated with the degree of influence and bias provided by the training data, as well as with the tendency of LLMs to reduce statistical fluctuations at the cost of not evolving over rounds (as for Llama in the Game of sexes). Pairing quantitative results and qualitative observations about the expected outcomes of known games thus enables us to interpret the hidden biases of LLMs and to assess their emerging behaviors.

FAIRGAME paves the way for a novel integration of LLMs and game theory, establishing a bidirectional relationship between them. Game theory provides the mathematical foundation for understanding strategic decision-making, interpreting and explaining how AI agents reason and make decisions. While, LLMs, as experimental tools for data-driven modeling of human decision-making, offer opportunities for empirical validation and exploration of complex interaction scenarios.

Future works may leverage FAIRGAME's versatility and capabilities in numerous directions. First, additional biases can be investigated: on top of agents' languages and personality, other factors can be included, such as nationality, gender, race, and age, so as to explore more nuanced characteristics and their influence on game outcomes and agent behavior. Moreover, future works can include agents' communication, which is known to yield modified payoffs and strategies [33] and that may change the responses of agents possessing different languages or personality traits. Extending all evaluations to more than two agents would also enable the modeling of more complex interactions and strategies, such as coalition and commitment formations, and group reciprocity [48, 54, 49]. This would shed light onto how different combinations of agent traits influence group dynamics, identifying configurations that foster harmony and lead to improved collective performance for multi-agent systems, team formation strategies, cooperative AI, and the design of more socially intelligent artificial agents [18, 37].

FAIRGAME can also be extended to additional game-theoretic scenarios, even beyond "classical" games that are known to LLMs via training: these additional scenarios include incomplete information games, where players have partial or uncertain knowledge about the game state or other players' strategies, simultaneous games, where players make decisions at the same time without knowing the actions of others, or sequential games, where players act in turns and can base their strategies on prior actions. Moreover, realistic game scenarios, where agents interact through real-world processes and their payoff are not pre-defined but inferred from the dynamics and outcomes of the actual use case, will allow us to predict plausible strategic outcomes. These inclusions will extend the scope of FAIRGAME and make it the preferred choice for integrating game-theory and LLMs and address advance game theoretic questions such as how biases in language or personality traits influence the emergence of cooperation or defection in evolutionary game dynamics, or what mechanisms can promote stable cooperation in multi-agent systems with diverse traits and incomplete information.

Moreover, considering the emerging paradigm represented by Agentic AI, where autonomous AI systems are designed to achieve complex goals with minimal human intervention [3], FAIRGAME can be extended to model interactions between AI-driven processes within organizations. These processes, representing agentic AI systems, influence and impact one another. Achieving optimal and productive cooperation among these systems is an aspirational target that requires careful consideration of personalities, cognitive behavioral traits, and environmental factors. In such scenarios, FAIRGAME can explore how diverse personalities, languages, and biases affect group dynamics, enabling the identification of optimal configurations that prioritize collective outcomes over individual interests. This extension is crucial for fostering effective coordination and cooperation among AI systems, enhancing adaptability, advanced decisionmaking capabilities, and self-sufficiency in dynamic environments. In sectors such as healthcare, finance, manufacturing, autonomous vehicles, cybersecurity, and smart cities, where AI systems must collaborate autonomously to achieve complex goals, understanding their interactions is essential for improving coordination, adaptability, and overall system performance.

Finally, real-world application of reproducible LLM-game simulations include detecting and mitigating jailbreaking attempts [12], by framing these interactions as strategic games between an attacking agent and a defensive AI, or developing safer and more performing chatbots for customer assistance or mediation.

Acknowledgements

D.P. is supported by the European Union through the ERC INSPIRE grant (project number 101076926). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. T.A.H. is supported by EPSRC (grant EP/Y00857X/1).

FAIRGAME is open-source and accessible on Github [1], with examples of configuration files and templates employed in this work.

References

- [1] A. Buscemi. Fairgame, 2025. URL https://github.com/aira-list/FAIRGAME.
- [2] E. A. Abaku, T. E. Edunjobi, and A. C. Odimarha. Theoretical approaches to ai in supply chain optimization: Pathways to efficiency and resilience. *Int. J. Sci. Tech. Res. Archive*, 6(1):092–107, 2024.

- [3] D. B. Acharya, K. Kuppan, and B. Divya. Agentic ai: Autonomous intelligence for complex goals—a comprehensive survey. *IEEE Access*, 2025.
- [4] R. Ali, F. Caso, C. Irwin, and P. Liò. Entropy-lens: The information signature of transformer computations. *arXiv:2502.16570*, 2025.
- [5] P. Andras, L. Esterle, M. Guckert, T. A. Han, P. R. Lewis, K. Milanovic, et al. Trusting intelligent machines: Deepening trust within socio-technical systems. *IEEE Tech. Soc. Magazine*, 37(4):76–83, 2018.
- [6] R. Axelrod and W. D. Hamilton. The evolution of cooperation. *science*, 211(4489):1390–1396, 1981.
- [7] A. Bahtizin, V. Bortalevich, E. Loginov, and A. I. Soldatov. Using artificial intelligence to optimize intermodal networking of organizational agents within the digital economy. In *J. Phys: conference series*, volume 1327, page 012042. IOP Publishing, 2019.
- [8] N. Balabanova, A. Bashir, P. Bova, A. Buscemi, T. Cimpeanu, H. C. da Fonseca, A. Di Stefano, M. H. Duong, E. F. Domingos, A. Fernandes, et al. Media and responsible ai governance: a game-theoretic and llm analysis. arXiv:2503.09858, 2025.
- [9] W. Brooks. Artificial bias: the ethical concerns of ai-driven dispute resolution in family matters. J. Disp. Resol., page 117, 2022.
- [10] A. Buscemi and D. Proverbio. Chatgpt vs gemini vs llama on multilingual sentiment analysis. arXiv:2402.01715, 2024.
- [11] A. Buscemi and D. Proverbio. Large language models' detection of political orientation in newspapers. arxiv:2406.00018, 2024.
- [12] A. Buscemi and D. Proverbio. Roguegpt: dis-ethical training transforms chatgpt4 into a rogue ai in 158 words. *arXiv:2407.15009*, 2024.
- [13] A. Buscemi, D. Proverbio, P. Bova, N. Balabanova, A. Bashir, T. Cimpeanu, H. C. da Fonseca, M. H. Duong, E. F. Domingos, A. M. Fernandes, et al. Do LLMs trust AI regulation? Emerging behaviour of game-theoretic LLM agents. arXiv preprint arXiv:2504.08640, 2025.
- [14] J. Cabrera, M. S. Loyola, I. Magaña, and R. Rojas. Ethical dilemmas, mental health, artificial intelligence, and llm-based chatbots. In *Int. Work-Conference Bioinf. Biomed. Eng.*, pages 313–326. Springer, 2023.
 [15] V. Capraro, R. Di Paolo, M. Perc, and V. Pizziol. Language-based game
- [15] V. Capraro, R. Di Paolo, M. Perc, and V. Pizziol. Language-based game theory in the age of artificial intelligence. *J. Roy. Soc. Interface*, 21 (212):20230720, 2024.
- [16] T. J. Chaffer. Governing the agent-to-agent economy of trust via progressive decentralization. arXiv:2501.16606, 2025.
- [17] X. Chen, D. Simchi-Levi, and Y. Wang. Utility fairness in contextual dynamic pricing with demand learning. arXiv:2311.16528, 2023.
- [18] A. Dafoe, Y. Bachrach, G. Hadfield, E. Horvitz, K. Larson, and T. Graepel. Cooperative ai: machines must learn to find common ground. *Nature*, 593(7857):33–36, 2021.
- [19] B. El, D. Choudhury, P. Liò, and C. K. Joshi. Towards mechanistic interpretability of graph transformers via attention graphs. arXiv:2502.12352, 2025.
- [20] H. A. Falcão Filho. Making sense of negotiation and ai: The blossoming of a new collaboration. *Int. J. Commerce Contract.*, 8(1-2):44–64, 2024.
- [21] C. Fan, Z. Tariq, N. Saadiq Bhuiyan, M. G. Yankoski, and T. W. Ford. Comp-husim: Persistent digital personality simulation platform. In Proc. 32nd ACM Conference on User Modeling, Adaptation and Personalization, pages 98–101, 2024.
- [22] E. Ferrara. Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci*, 6(1):3, 2023.
- [23] N. Fontana, F. Pierri, and L. M. Aiello. Nicer than humans: How do large language models behave in the prisoner's dilemma? arXiv:2406.13605, 2024.
- [24] R. A. Fulgu and V. Capraro. Surprising gender biases in gpt. Comp. Human Beha. Rep., 16:100533, 2024.
- [25] J. W. Gichoya, K. Thomas, L. A. Celi, N. Safdar, I. Banerjee, J. D. Banja, et al. Ai pitfalls and what not to do: mitigating bias in ai. *Brit. J. Radiology*, 96(1150):20230023, 2023.
- [26] L. Hammond, A. Chan, J. Clifton, J. Hoelscher-Obermaier, A. Khan, E. McLean, C. Smith, W. Barfuss, J. Foerster, T. Gavenčiak, et al. Multiagent risks from advanced ai. arXiv:2502.14143, 2025.
- [27] T. A. Han. Intention Recognition, Commitments and Their Roles in the Evolution of Cooperation: From Artificial Intelligence Techniques to Evolutionary Game Theory Models, volume 9. Springer SAPERE series, 2013. ISBN 978-3-642-37511-8.
- [28] T. A. Han. Emergent behaviours in multi-agent systems with evolutionary game theory. AI Commun., 35(4), 2022.
- [29] T. A. Han, C. Perret, and S. T. Powers. When to (or not to) trust intelligent machines: Insights from an evolutionary game theory analysis of trust in repeated games. *Cognitive Sys. Res.*, 68:111–124, 2021.
- [30] L. He, G. Sun, D. Niyato, H. Du, F. Mei, J. Kang, et al. Generative ai for game theory-based mobile networking. *IEEE Wireless Commun.*, 32 (1):122–130, 2025.
- [31] Z. He and C. Zhang. Afspp: Agent framework for shaping preference

- and personality with large language models. arXiv:2401.02870, 2024.
- [32] K. Hooker and D. P. McAdams. Personality and adult development: Looking beyond the ocean. J. Gerontology B, 58(6):P311–P312, 2003.
- [33] W. Hua, O. Liu, L. Li, A. Amayuelas, J. Chen, L. Jiang, et al. Game-theoretic llm: Agent workflow for negotiation games. *arxiv*:2411.05990, 2024.
- [34] L. J. Klinkert, S. Buongiorno, and C. Clark. Driving generative agents with their personality. arXiv:2402.14879, 2024.
- [35] J. Li, X. Cheng, W. X. Zhao, J.-Y. Nie, and J.-R. Wen. Halueval: A large-scale hallucination evaluation benchmark for large language models. arXiv:2305.11747, 2023.
- [36] Y. Li, Y. Du, K. Zhou, J. Wang, W. X. Zhao, and J.-R. Wen. Evaluating object hallucination in large vision-language models. arXiv:2305.10355, 2023.
- [37] Y. Lu, A. Aleta, C. Du, L. Shi, and Y. Moreno. Llms and generative agent-based models for complex systems research. *Phys. Life Rev.*, 2024
- [38] S. Mao, Y. Cai, Y. Xia, W. Wu, X. Wang, F. Wang, T. Ge, and F. Wei. Alympics: Llm agents meet game theory—exploring strategic decision-making with ai agents. arXiv:2311.03220, 2023.
- [39] H. Min. Artificial intelligence in supply chain management: theory and applications. *Int. J. Logistics: Res. Appl.*, 13(1):13–39, 2010.
- [40] E. Montero-Porras, J. Grujić, E. Fernández Domingos, and T. Lenaerts. Inferring strategies from observations in long iterated prisoner's dilemma experiments. Sci. Rep., 12(1):7589, 2022.
- [41] L. Newsham and D. Prince. Personality-driven decision-making in Ilmbased autonomous agents. arXiv:2504.00727, 2025.
- [42] L. Newsham, R. Hyland, and D. Prince. Inducing personality in Ilm-based honeypot agents: Measuring the effect on human-like agenda generation. arXiv:2503.19752, 2025.
- [43] G. Owen. Game theory. Emerald Group Publishing, 2013.
- [44] J. S. Park, J. O'Brien, C. J. Cai, M. R. Morris, P. Liang, and M. S. Bernstein. Generative agents: Interactive simulacra of human behavior. In *Proc. 36th ACM Symp. on user interface software and technology*, pages 1–22, 2023.
- [45] N. Patel and S. Trivedi. Leveraging predictive modeling, machine learning personalization, nlp customer support, and ai chatbots to increase customer loyalty. *Empirical Quests for Management Essences*, 3(3): 1–24, 2020.
- [46] S. T. Powers, O. Linnyk, et al. The Stuff We Swim in: Regulation Alone Will Not Lead to Justifiable Trust in AI. *IEEE Technology and Society Magazine*, 42(4):95–106, 2023.
- [47] D. Ramachandran, A. Keshari, and M. K. Tiwari. Contract price negotiation using an ai-based chatbot. In *Int. Conf. Data Analytics in Public Procurement and Supply Chain*, pages 303–310. Springer, 2022.
- [48] D. Ray. A game-theoretic perspective on coalition formation. Oxford University Press, 2007.
- [49] Z. Song and T. A. Han. On evolution of non-binding commitments. Physics of Life Reviews, 52:245–247, 2025. ISSN 1571-0645. doi: https://doi.org/10.1016/j.plrev.2025.01.006.
- [50] A. J. Stewart, A. A. Arechar, D. G. Rand, and J. B. Plotkin. The distorting effects of producer strategies: Why engagement does not reveal consumer preferences for misinformation. *Proc. Natl. Acad. Sci.*, 121 (10):e2315195121, 2024.
- [51] M. Stone, E. Aravopoulou, Y. Ekinci, G. Evans, M. Hobbs, A. Labib, P. Laughlin, J. Machtynger, and L. Machtynger. Artificial intelligence (ai) in strategic marketing decision-making: a research agenda. *The Bottom Line*, 33(2):183–200, 2020.
- [52] M. Talajić, I. Vrankić, and M. Pejić Bach. Strategic management of workforce diversity: An evolutionary game theory approach as a foundation for ai-driven systems. *Information*, 15(6):366, 2024.
- [53] M. H. Tessler, M. A. Bakker, D. Jarrett, H. Sheahan, M. J. Chadwick, et al. Ai can help humans find common ground in democratic deliberation. *Science*, 386(6719):eadq2852, 2024.
- [54] S. Van Segbroeck, J. M. Pacheco, T. Lenaerts, and F. C. Santos. Emergence of fairness in repeated group interactions. *Physical review letters*, 108(15):158104, 2012.
- [55] Z. Wang, S. Kokubo, M. Jusup, and J. Tanimoto. Universal scaling for the dilemma strength in evolutionary games. *Physics of life reviews*, 14: 1–30, 2015.
- [56] Z. Wang, R. Song, C. Shen, S. Yin, Z. Song, B. Battu, L. Shi, D. Jia, T. Rahwan, and S. Hu. Large language models overcome the machine penalty when acting fairly but not when acting selfishly or altruistically. arXiv:2410.03724, 2024.
- [57] R. Willis, Y. Du, J. Z. Leibo, and M. Luck. Will systems of llm agents cooperate: An investigation into a social dilemma. arXiv:2501.16173, 2025.