

AI Alignment through a Game-theoretic Lens: A Survey

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Abstract

As large language models and increasingly capable AI agents are deployed in high-risk settings, aligning them with complex human values has become a central challenge. Existing alignment methods, while effective in improving helpfulness, harmlessness, and controllability, often struggle to capture real-world preferences that are context-dependent, non-transitive, and shaped by dynamic multi-party interactions. This survey reviews AI alignment through a game-theoretic lens. Specifically, it organizes recent progress around key game-theoretic elements and synthesizes the literature along three challenges: preference diversity, alignment priority, and temporal dynamics. This perspective clarifies where current alignment methods genuinely benefit from game-theoretic analysis, where the framework is looser, and what challenges remain in building robust, adaptive, and verifiable AI systems.

1 Introduction

As large language models (LLMs) and AI agents are increasingly deployed in real-world settings (Xi et al., 2025), security and governance risks raised by LLMs and AI agents have received growing attention (Duenas and Ruiz, 2024; Milano and Nyholm, 2024). Reported concerns include bias, toxicity, manipulation, and misrepresentation (Duan et al., 2025; Gallegos et al., 2024; Guo, 2024), as well as deception, reward hacking, and power-seeking behavior under imperfect oversight (Pan et al., 2022; Park et al., 2024; Turner and Tadepalli, 2022). AI alignment is therefore an urgent goal. It aims to ensure that AI systems not only perform tasks effectively, but also act consistently with human intentions, social norms, and ethical constraints (Shen et al., 2024).

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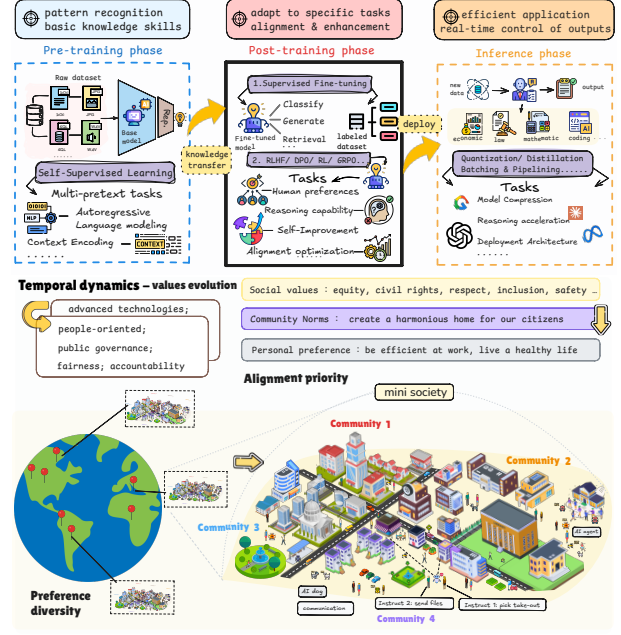


Figure 1: Alignment scale process (top panel) and three core challenges (bottom): preference diversity, alignment priority, and temporal dynamics.

Although alignment can be applied during training or inference, this survey mainly focuses on post-training alignment (top solid box in Fig. 1), which adapts foundation models to human preferences or deployment needs without retraining them from scratch, while encoding behavioral changes into model parameters to avoid repeated inference-time intervention (Lai et al., 2025; Ouyang et al., 2022). Methods such as reinforcement learning from human feedback (RLHF) and direct preference optimization (DPO) have improved model helpfulness, harmlessness, and controllability (Ouyang et al., 2022; Rafailov et al., 2023). However, they still struggle when proxy rewards differ from intended goals, parties involved in the alignment process have conflicting preferences (e.g., when responding to a controversial social question, some users may prefer an open and direct answer, while others may

prioritize harm avoidance and the prevention of stereotypes), or static objectives fail under repeated interaction and environmental changes (Munos et al., 2024; Tang et al., 2025; Chu et al., 2025; Ye et al., 2024a). We group these limitations into *three core challenges: preference diversity, alignment priority, and temporal dynamics*.

The core challenges mentioned above motivate a promising and more structural perspective on alignment via game theory (Tang et al., 2025; Chu et al., 2025; Munos et al., 2024; Ye et al., 2024a). Specifically, *preference diversity* arises since values differ across human groups, e.g., ethnic or political groups, making a single tractable and socially legitimate objective hard to define (Gabriel, 2020; Floridi and Cowls, 2022); *alignment priority* reflects multiple levels of alignment, including reward proxies, optimization targets, user preferences, and higher legal or institutional constraints, which may conflict (Amodei et al., 2016; Kleinberg et al., 2016); furthermore, *temporal dynamics* need to reflect the evolution of human values, social environment, and AI capabilities (Carroll et al., 2024; Qiu et al., 2024). In this sense, we aim to use the game-theoretic language to characterize and explain a series of application scenarios and uncertainties in the alignment problem, by analyzing some game elements such as players, utilities, information, strategies, equilibrium, and dynamics (Gemp et al., 2024; Mozikov et al., 2024). To avoid overstating the role of game theory, we also clarify what game-theoretic analysis can formally guarantee and under which assumptions rather than claiming that game theory universally solves alignment. In summary, we give the main contributions of this survey below:

- We organize a three-dimensional analysis framework of AI alignment by *challenge one - preference diversity*, *challenge two - alignment priority*, and *challenge two - temporal dynamics* for helping researchers clarify the current alignment landscape.
- We provide a unified game-theoretic perspective for AI alignment, which is used to interpret and formalize specific alignment goals and application scenarios, based on the mathematical foundations and theoretical results of game theory.
- We summarize six alignment directions under the challenge: general preference or hetero-

geneous preference, synchronous interaction or sequential interaction, and adaptive evolution or co-evolution, encouraging new insights within the AI alignment community, which are inspired by concepts such as players, strategy interaction, and temporal factor.

2 Related Work

Recent research has begun to apply the game-theoretic perspective to preference conflict, equilibrium-based alignment, cooperative AI, on-line adaptation, and pluralistic evaluation (Tang et al., 2025; Chu et al., 2025; Ye et al., 2024a; Mao et al., 2025), but these efforts remain scattered across different scene settings and research communities. Additionally, some surveys have reviewed AI alignment broadly, emphasizing objectives, training pipelines, and governance (Ji et al., 2023; Sun et al., 2024b; Shen et al., 2024; Kayabay et al., 2025), while others focus on LLM agents and multi-agent systems, organizing the literature around architectures, workflows, and deployment challenges (Wang et al., 2024e; Li et al., 2024c; Zhou et al., 2025a). Recent work on game theory and LLMs, meanwhile, highlights the broader intersection between language models and games, including benchmarking, strategic behavior, and social simulation (Sun et al., 2025). Our survey is differentiated from previous surveys by both its scope and organizing principle: rather than surveying all alignment phases or game-related research, we mainly focus on post-training alignment approaches, and ask how game theory determines the formulation, guarantee, or evaluation of alignment problems.

3 Preliminaries

In this section, we use game-theoretic language to characterize when alignment can be formulated as a strategic optimization problem, when an equilibrium can be interpreted as an aligned policy, and when convergence guarantees and equilibrium gaps can serve as formal certificates of approximate alignment (Munos et al., 2024; Ye et al., 2024a; Wu et al., 2024; Zhang et al., 2025b; Pásztor et al., 2025; Shi et al., 2025).

3.1 General Alignment Guarantee

Since two-player game theory is the most common formalization of alignment problems, we take its modeling of general preference scenarios as a basis

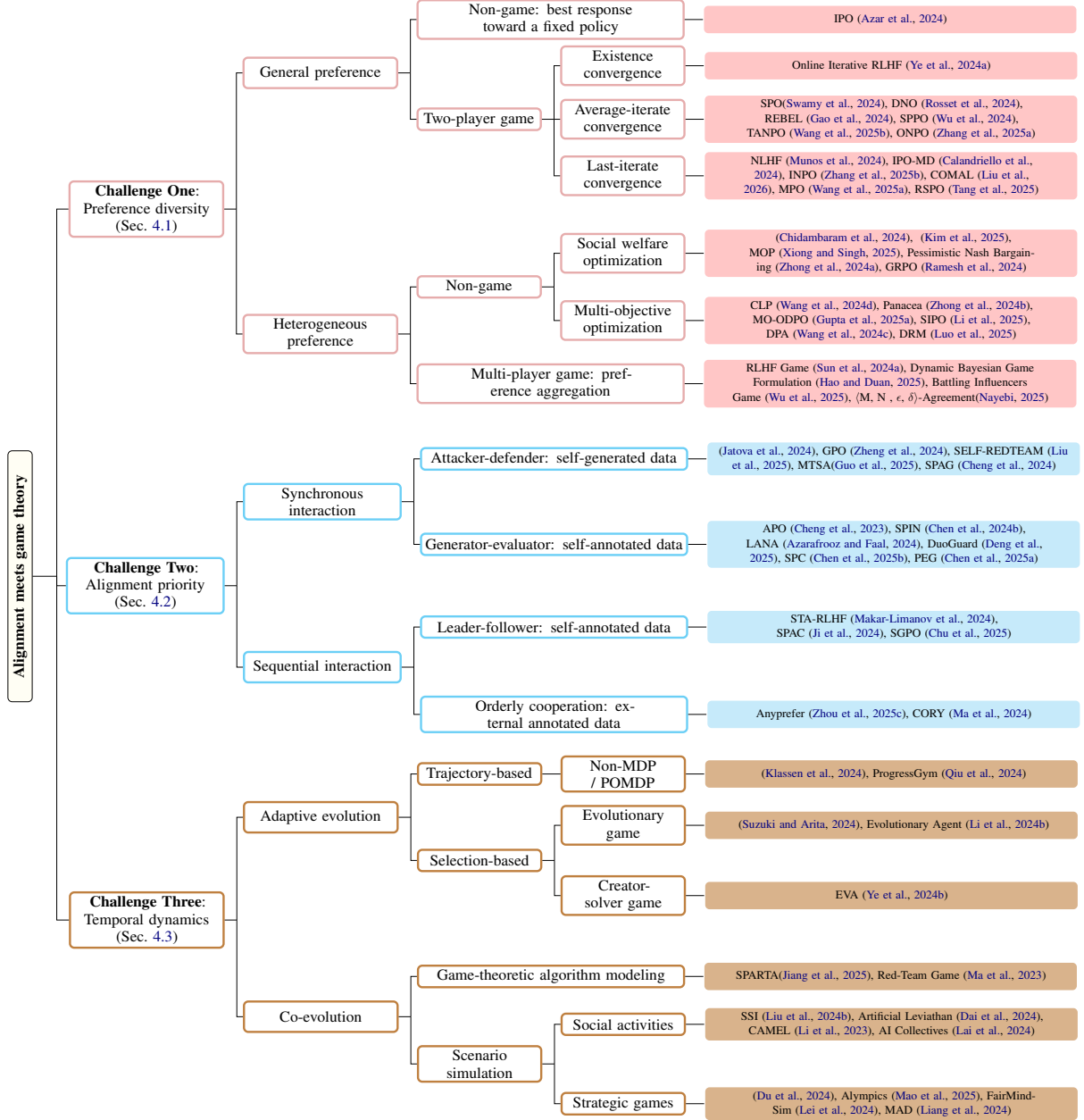


Figure 2: Taxonomy of alignment based on a game theory lens.

to interpret how to achieve theoretical alignment by pursuing game equilibrium.

3.1.1 Problem Formulation

As noted earlier, aligning LLMs typically relies on learning from human preference feedback. Rather than providing a scalar reward signal $r(x, y)$, human feedback more often takes the form of a pairwise comparison signal $\Pr(y_1 \succ y_2 \mid x)$ denoting the probability that y_1 is preferred over y_2 given prompt x , where $\succ$ indicates a preference relation. Accordingly, preference learning more closely matches practical RLHF settings and is better suited to tasks that are difficult to specify

using a single numerical reward. In this setting, we seek a policy that performs robustly under human pairwise comparisons against alternative policies. Specifically, consider the following objective

$$J(\pi_1, \pi_2) = \mathbb{E}_{x \sim d_0} \mathbb{E}_{y_1 \sim \pi_1, y_2 \sim \pi_2} \left[\mathbb{P}(x, y_1, y_2) - \tau D_{\text{KL}}(\pi_1(\cdot \mid x) \parallel \pi_{\text{ref}}(\cdot \mid x)) + \tau D_{\text{KL}}(\pi_2(\cdot \mid x) \parallel \pi_{\text{ref}}(\cdot \mid x)) \right], \quad (1)$$

where d_0 is a prompt distribution. Here, $\mathbb{P}(x, y_1, y_2)$ is a payoff term instantiated usually as a preference model: $\mathbb{P}(x, y_1, y_2) = \Pr(y_1 \succ y_2 \mid x) \in [0, 1]$ (In many alignment scenarios,

the payoff can also be a point reward or other forms). The KL terms regularize both policies toward a reference policy (π_{ref} denotes a fixed conditional language-model distribution, typically instantiated as the initial supervised fine-tuned model, i.e., $\pi_{ref} = \pi_{SFT}$), thereby stabilizing learning and controlling deviation from the instruction-following behavior (Rafailov et al., 2023).

When the payoff term $\mathbb{P}$ satisfies $\Pr(y_1 \succ y_2 \mid x) + \Pr(y_2 \succ y_1 \mid x) = 1$, the above objective function defines a two-player constant-sum game, i.e., $J(\pi_1, \pi_2) + J(\pi_2, \pi_1) = 1$, where the players choose policies π_1 and π_2 . In particular, $\mathbb{P}$ further can take the centered form of $\mathbb{P}(x, y_1, y_2) = \Pr(y_1 \succ y_2 \mid x) - \frac{1}{2}$, with a two-player zero-sum game (Liu et al., 2026). Based on games, the first player maximizes $J(\pi_1, \pi_2)$, while the second player minimizes it. Intuitively, π_1 seeks a policy that is preferred under human comparisons, whereas π_2 acts as an adversarial comparator. The alignment problem can therefore be formulated as the saddle-point problem

$$(\pi_1^*, \pi_2^*) \in \arg \max_{\pi_1 \in \Pi} \arg \min_{\pi_2 \in \Pi} J(\pi_1, \pi_2), \quad (2)$$

where both players optimize over the same policy class Π .

3.1.2 Nash Equilibrium as Strategic Alignment

For analysis, we restrict attention to policies in Π that have the same support as π_{ref} . Under this assumption, (Ye et al., 2024a) shows that the game admits a unique Nash equilibrium. By symmetry, the equilibrium policies coincide, i.e., $\pi_1^* = \pi_2^* = \pi^*$. We interpret π^* as the aligned policy because it satisfies the saddle-point property of the equilibrium. For any alternative policy $\pi \in \Pi$, we have

$$J(\pi, \pi^*) \leq J(\pi^*, \pi^*) \leq J(\pi^*, \pi).$$

Hence, no policy can systematically obtain a better payoff against π^* than π^* obtains against itself, while π^* performs at least as well against any opponent as it does against itself. Further, when $J(\pi_1, \pi_2)$ is the unregularized objective with a centered pairwise-preference payoff, since $\mathbb{P}(x, y_1, y_2)$ is antisymmetric, we have $J(\pi^*, \pi^*) = 0$. The saddle-point property then gives, for any $\pi \in \Pi$, $J(\pi^*, \pi) \geq J(\pi^*, \pi^*) = 0$. Based on the form of $\mathbb{P}(x, y_1, y_2)$, the win rate of π^* against any π is at least one half. Under this view, alignment is not defined as maximizing an unobserved utility

function. Rather, it is defined as non-domination under the induced preference relation. In this sense, an aligned policy is strategically stable under pairwise comparison and resistant to exploitation by competing policies.

3.1.3 Approximation and Convergence

To assess how well a candidate policy approximates π^* , we use the following duality gap (Zhang et al., 2025b):

$$\text{DualGap}(\pi) := \max_{\pi_1 \in \Pi} J(\pi_1, \pi) - \min_{\pi_2 \in \Pi} J(\pi, \pi_2). \quad (3)$$

The duality gap is always nonnegative, and $\text{DualGap}(\pi) = 0$ if and only if $\pi = \pi^*$. Thus, $\text{DualGap}(\pi)$ quantifies how far π is from the aligned Nash policy. A small duality gap means that π is only weakly exploitable in the induced preference game, providing a formal certificate of approximate alignment. When $\text{DualGap}(\pi) \leq \epsilon$, π may be regarded as an ϵ -approximate Nash policy. Related definitions and guarantees also appear in (Ye et al., 2024a; Ma et al., 2023).

The practical significance of this equilibrium formulation depends on whether the learning dynamics (policy updates induced by the alignment procedure itself) converge to such a stable point. Recent works (Munos et al., 2024; Wang et al., 2024f; Liu et al., 2026) establish convergence guarantees for several algorithms, including average-iterate convergence of $\frac{1}{T} \sum_{t=1}^T \pi_t$. Moreover, if an algorithm enjoys last-iterate convergence, then the final output policy π_T itself can be interpreted as a strategically aligned solution, and the resulting model inherits the same stability interpretation (Tiapkin et al., 2025). That implies that alignment is not merely observed empirically, but rather the limit of a strategic learning process.

3.2 Complex Alignment Extensions

The theoretical form described above cannot strictly cover all scenarios, and more complex alignment settings typically relax one or more of classical game theory assumptions by considering additional players, heterogeneous policy spaces, asymmetric roles, action order, or time dependence. For example, alignment involving the preferences of multiple parties can be modeled as a multi-player game, denoted by $\mathcal{G} = \langle \mathcal{N}, \{\Pi_i\}_{i \in \mathcal{N}}, \{U_i\}_{i \in \mathcal{N}} \rangle$, where $\mathcal{N} = \{1, \dots, n\}$ is the set of players, Π_i is the strategy space of player i , and $U_i(\pi)$ is its utility (analogous to the payoff term in Eq. (1)) under

the joint strategy profile $\pi = (\pi_1, \dots, \pi_n)$. A joint strategy π^* is a Nash equilibrium if $U_i(\pi_i^*, \pi_{-i}^*) \geq U_i(\pi_i, \pi_{-i}^*), \forall i \in \mathcal{N}, \pi_i \in \Pi_i$, which simulates how each player’s payoff depends on the joint strategy combination. Some formulations also define an individual loss $\ell_i = -U_i$ that each player minimizes. In this case, the same equilibrium condition is written with $\leq$, as in (Wu et al., 2025). Additionally, social welfare or multi-objective optimization are related to non-game extensions, combining player-specific utilities through selected aggregation rules to optimize this global goal.

Furthermore, the two-player game of general preference alignment can be generalized by relaxing its assumptions about player roles, shared policy space, and action order. With asymmetric roles in adversarial scenarios (Zheng et al., 2024; Chen et al., 2025b), a representative formulation is: $\max_{\pi_1 \in \Pi_1} \min_{\pi_2 \in \Pi_2} J(\pi_1, \pi_2)$, where Π_1 and Π_2 may represent different strategies, such as attackers vs. defenders in (Zheng et al., 2024) or generators vs. critics in (Chen et al., 2025b). Its Nash equilibrium is a saddle point satisfying $J(\pi_1, \pi_2^*) \leq J(\pi_1^*, \pi_2^*) \leq J(\pi_1^*, \pi_2)$. When $\Pi_1 = \Pi_2$, and the two simultaneous actions are aligned with the same preference objective, this reduces to the two-policy formulation similar to Eq. (2). If one of the two players observes moves after observing the other (Chu et al., 2025), the solution becomes a Stackelberg equilibrium with the following nested form: $\pi_2^*(\pi_1) \in \arg \max_{\pi_2 \in \Pi_2} J_2(\pi_1, \pi_2)$, $\pi_1^* \in \arg \max_{\pi_1 \in \Pi_1} J_1(\pi_1, \pi_2^*(\pi_1))$. This expression assumes a selected follower best response. Sequential cooperation can alternatively be modeled as a cooperative Markov game with a shared objective, which does not imply the adversarial saddle-point condition above (Zhou et al., 2025c). In general, equilibrium existence and min-max equality require assumptions determined by the game form, such as finite or compact strategy spaces, continuity, and appropriate convexity or concavity conditions (Nash Jr, 1950).

Finally, temporal extensions distinguish repeated strategic interaction from changes in the alignment environment itself. When two sides adapt strategically over multiple rounds, the interaction can be represented as a finite-horizon extensive-form game. An ϵ -Nash policy satisfies $U_i^j(\pi_i^*, \pi_{-i}^*) \geq U_i^j(\pi_i, \pi_{-i}^*) - \epsilon, \forall i \in \{1, 2\}, \pi_i \in \Pi_i$, where U_i^j is the payoff accumulated over j rounds (Ma et al., 2023) (alternatively, denoted by a time-dependent

preference/reward model with $\mathbb{P}_t$). This extends the one-shot equilibrium concept in Eq. (2), but does not require the same pairwise payoff or constant-sum structure. Furthermore, when a single AI agent adapts to evolving human values, a representative formulation is the value-state POMDP $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \Omega, O, U \rangle, U : (\mathcal{S} \times \mathcal{A})^* \rightarrow \mathbb{R}$, where $\mathcal{S}$ is the space of human value states (alternatively, simulated by the distribution of human value datasets d_0), $\mathcal{A}$ is the action space of the aligned policy, $\mathcal{T}$ is the value-state transition model, Ω is the observation space, O is the observation model, and U maps an adaptive trajectory to a scalar alignment evaluation (Qiu et al., 2024).

4 Taxonomy: A Game-theoretic Lens on Alignment Frameworks

Having gained a basic understanding of how game theory explains alignment, this section will summarize the methods for different alignment problems based on the three major challenges.

4.1 Challenge One: Preference Diversity

Preference alignment studies how AI systems are optimized from feedback. In practice, this process usually involves three components: the AI system to be aligned, the feedback source, and a proxy that models such feedback for learning, e.g., a reward or preference model (Ji et al., 2023). This section focuses on the structure and diversity of preferences. A game-theoretic lens becomes especially useful when alignment depends either on strategic robustness against alternative policies or on fair aggregation across stakeholders with conflicting values. We therefore discuss two related settings: general preference, where the key question is robustness under comparison, and heterogeneous preferences, where the main issue is how to aggregate diverse human interests in a fair and stable way.

4.1.1 General preference

Non-game. General preference alignment aims to optimize model behavior toward broadly shared human judgments, as shown in Fig. 3(a). Early work mainly provided theoretical perspectives on learning from human preferences (Wang et al., 2023b), but did not directly capture practical LLM alignment under pairwise feedback. A first line of work is non-game optimization against a fixed policy. The representative example is IPO (Azar et al., 2024), which directly optimizes pairwise preferences without assuming an explicit reward

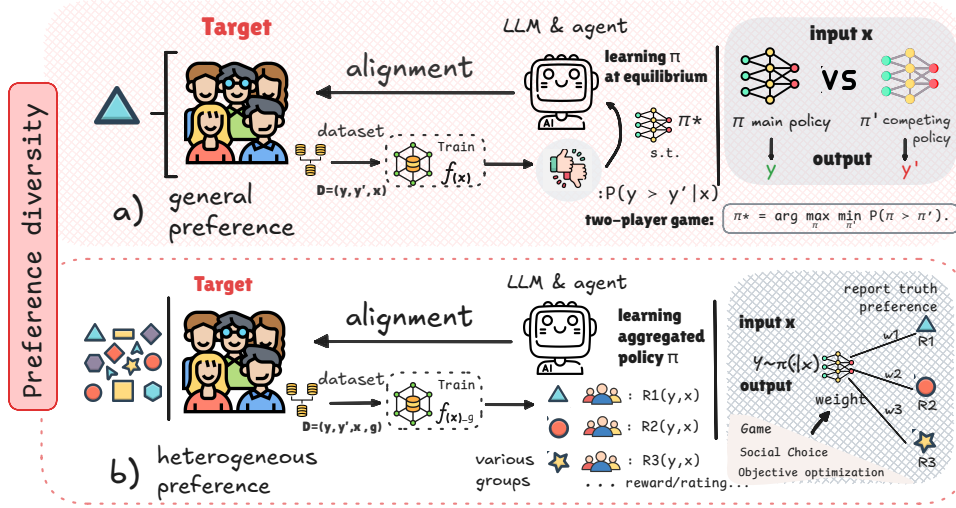


Figure 3: General preference alignment: pairwise optimization and game-theoretic formulation. Heterogeneous preference alignment: multi-group feedback and preference aggregation.

model:

$$\max_{\pi} \mathbb{E}_{y \sim \pi, y' \sim \mu} [\mathbb{P}(y \succ y')] - \tau \text{KL}(\pi \| \pi_{\text{ref}}).$$

Compared with point-wise reward optimization, IPO better matches preference learning. However, unlike the minimax games, IPO optimizes only the target policy π as a best response to a predefined reference distribution μ , rather than jointly optimizing two competing policies. Specifically, μ plays a role analogous to π_2 in Eq. (2), but is fixed in advance and is neither learned nor updated during training. Therefore, IPO does not guarantee robustness against stronger competing policies.

Two-player game. This limitation motivates a second line of work that formulates alignment as a two-player game. Representative studies such as NLHF (Munos et al., 2024), IPO-MD (Calandriello et al., 2024), and iterative RLHF (Ye et al., 2024a) cast alignment as a constant-sum or minimax game, where the target policy and alternative policy are optimized in competition with each other under a learned preference function, updating alternately through self-play in practice. Early results mainly established the existence of Nash-style aligned policies. Subsequent work focused on stronger convergence guarantees. One branch studies average-iterate convergence, including SPO (Swamy et al., 2024), DNO (Rosset et al., 2024), REBEL (Gao et al., 2024), SPPO (Wu et al., 2024), TANPO (Wang et al., 2025b), and ONPO (Zhang et al., 2025a). These methods often replace explicit win-rate estimation with simpler regression-style objectives or incorporate online

exploration to improve sample efficiency. Another branch studies last-iterate convergence, which is more desirable because the final learned policy itself inherits the equilibrium interpretation. Representative examples include INPO (Zhang et al., 2025b), COMAL (Liu et al., 2026), MPO (Wang et al., 2025a), and RSPO (Tang et al., 2025). Overall, general preference alignment has evolved from fixed-opponent optimization to self-play Nash learning, with increasing emphasis on convergence, robustness, and the role of regularization.

4.1.2 Heterogeneous preferences

Heterogeneous preference alignment concerns settings where stakeholders hold overlapping or conflicting values, as shown in Fig. 3(b). Unlike general preference alignment, the goal is not to fit a single dominant preference, but to balance multi-party, objectives, and minority concerns.

Non-game. A first category is non-game alignment. One line formulates the problem as social welfare optimization, where group utilities are aggregated through welfare or bargaining objectives (Mishra, 2023; Conitzer et al., 2024; Qiu, 2024). Representative methods include MOP (Xiong and Singh, 2025), Pessimistic Nash Bargaining (Zhong et al., 2024a), and group-robust approaches (Chidambaram et al., 2024; Ramesh et al., 2024; Kim et al., 2025). These methods improve fairness and reduce dominance, but their behavior depends strongly on the chosen welfare function. Another line formulates alignment as multi-objective optimization. Methods such as

CLP (Wang et al., 2024d), Panacea (Zhong et al., 2024b), MO-ODPO (Gupta et al., 2025a), and SIPO (Li et al., 2025) jointly optimize multiple objectives and often support controllable trade-offs through preference vectors or conditional signals. Related work also studies decomposed or vector-valued reward representations for more interpretable preference control (Wang et al., 2024c; Luo et al., 2025).

Multi-player game. A second category treats heterogeneous alignment as a multi-player game over preference aggregation. Here the main issue is that stakeholders may strategically report preferences to influence the final model. RLHF Game (Sun et al., 2024a) and Dynamic Bayesian Game (Hao and Duan, 2025) explicitly study truthful reporting and weighting mechanisms, while BIG (Wu et al., 2025) analyzes strategic influence among multiple parties. Other work further examines multi-preference optimization and the complexity of alignment across multiple objectives and agents under weak assumptions (Gupta et al., 2025b; Nayebi, 2025). Together, these studies show that heterogeneous preference alignment is not only an optimization problem, but also a mechanism-design problem shaped by strategic human behavior.

4.2 Challenge Two: Alignment Priority

Whereas the previous subsection organizes the literature by preference structure, this section shifts the focus to interaction structure. AI alignment is increasingly understood as an interactive process rather than a one-shot transfer of human preferences to a model (Shen et al., 2024). Many methods improve alignment not only by fitting feedback, but also by generating informative feedback through play, critique, or role-dependent adaptation. The main distinction here is whether strategic updates occur within a shared decision round or under an explicit order of moves. We therefore distinguish between synchronous interaction, which is especially useful for adversarial stress testing and self-improvement, and sequential interaction, which introduces commitment, asymmetry, and bilevel optimization into alignment.

4.2.1 Synchronous interaction

When interaction is synchronous, both sides act within the same round, and alignment is improved through repeated exposure to hard cases generated during play, as shown in Fig. 4(a).

Attacker-defender This setting has been particularly influential in safety alignment. GPO (Zheng et al., 2024) formulates alignment as a max–min game between an attacker and a defender, showing that adversarial prompt generation can uncover vulnerabilities while improving robustness through iterative updates. Closely related work applies the same intuition to toxicity mitigation, guardrail training, and jailbreak robustness, either by training separate attacker–defender models or by alternating these roles within a single model (Jatova et al., 2024; Deng et al., 2025; Liu et al., 2025; Guo et al., 2025). Across these studies, synchronous play functions less as an abstract game metaphor than as a practical mechanism for generating stress cases that standard alignment pipelines would otherwise miss.

Generator-evaluator. The same interaction pattern has also been repurposed to reduce dependence on human annotation. APO (Cheng et al., 2023) couples the policy with a reward model in an adversarial loop to address the mismatch between evolving model outputs and static preference supervision. SPIN (Chen et al., 2024b) instead treats self-improvement as iterative self-distillation, while LANA (Azarafrooz and Faal, 2024) further shows that self-rewarding can remain effective even under noisy or suboptimal demonstrations. What connects these methods is that interaction does not merely refine the policy; it also becomes a means of producing or filtering the supervision signal itself.

This interactive template has further extended to reasoning and truthfulness. SPC (Chen et al., 2025b) uses adversarial self-play between a generator and critic to improve step-level reasoning and support test-time search, whereas SPAG (Cheng et al., 2024) relies on adversarial language games to strengthen reasoning-oriented dialogue. PEG (Chen et al., 2025a) pushes the idea toward truthful evaluation by casting peer assessment as a game in which truthful reporting is incentivized. Taken together, these studies suggest that synchronous interaction is most useful when alignment requires continual pressure from challenging inputs, self-generated supervision, or competing evaluations. Its limitations, however, remain clear: many methods are computationally intensive, sensitive to training dynamics, and still rely on assumptions that are difficult to satisfy in realistic black-box settings.

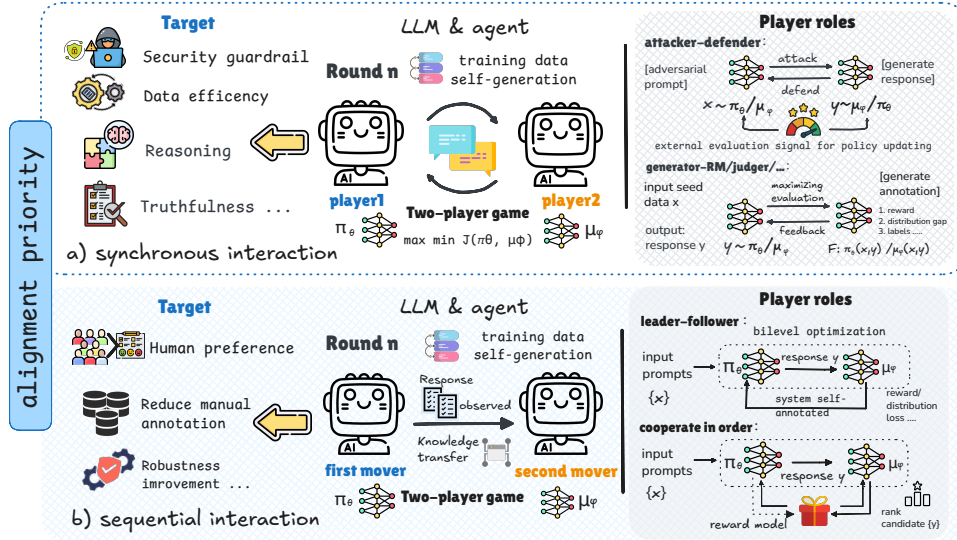


Figure 4: Synchronous interaction for alignment: simultaneous play, adversarial roles, and alignment targets. Sequential interaction for alignment: ordered roles and commitment-based optimization.

4.2.2 Sequential interaction

Leader-follower. Once the order of moves becomes explicit, interaction changes character. The earlier player can commit to a strategy that reshapes the response of the later player in Fig. 4(b), making this setting closer to bilevel or Stackelberg optimization than to simultaneous self-play. This perspective has been especially useful for preference learning. STA-RLHF (Makar-Limanov et al., 2024) models the language model and reward model as leader and follower, respectively, and searches for a Stackelberg equilibrium under nested optimization. SPAC (Ji et al., 2024) preserves the same leader-follower structure but replaces multi-stage updates with a single-timescale procedure, yielding stronger practical appeal in offline settings with sparse preference data.

Orderly cooperation. A similar logic also appears when sequential interaction is used to improve data quality and robustness. SGPO (Chu et al., 2025) studies alignment under scarce and noisy preferences through a Stackelberg-style formulation with regret guarantees under bounded distribution shift. Anyprefer (Zhou et al., 2025c) combines automatic synthesis, external tools, and a cooperative Markov game to mitigate self-reward bias while increasing sample diversity. CORY (Ma et al., 2024) goes a step further by using sequential cooperative multi-agent reinforcement learning and role exchange to stabilize fine-tuning. In these settings, ordered interaction is valuable not only because it captures asymmetric roles more faithfully,

but also because it offers a natural way to control how evaluators, generators, and auxiliary tools influence one another over time.

These interaction-based approaches move alignment beyond static supervision, but they also expose a broader challenge: alignment objectives, evaluators, and environments may all evolve over time. We therefore turn next to dynamic evolution in alignment.

4.3 Challenge Three: Temporal dynamic

The previous two sections focus on preference structure and interaction structure at a given stage of learning or deployment. We now turn to a third aspect that cuts across both: temporal change. Once systems interact repeatedly with humans, other agents, and changing environments, alignment can no longer be treated as a one-shot objective fixed at training time. Instead, the central challenge is to maintain behavioral consistency as preferences, incentives, and external conditions evolve. In this sense, dynamic evolution is not a separate alignment category so much as a temporal extension of the preceding discussion. This has motivated a growing body of work that studies alignment through adaptive evolution and co-evolution.

4.3.1 Adaptive evolution

Adaptive evolution focuses on how AI systems update under temporally varying social environments, as illustrated in Fig. 5(a).

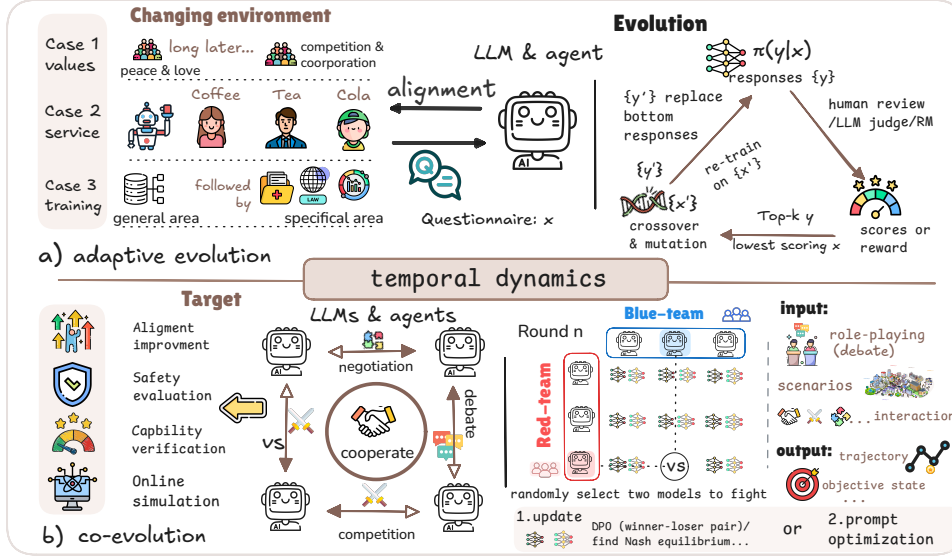


Figure 5: Adaptive evolution in alignment: changing social environments and a typical update framework. Co-evolution in alignment: multiple agents evolving through competition, cooperation, and social interaction.

Trajectory-based evolution. One line of work formulates this problem through sequential decision-making or trajectory-based evaluation. ProgressGym (Qiu et al., 2024), for example, frames alignment as moral progress over time and studies how historical moral data can guide future decisions. Relatedly, Klassen et al. (Klassen et al., 2024) propose a temporal pluralistic alignment framework that evaluates stakeholder satisfaction over trajectories rather than isolated outputs, allowing alignment to depend on long-horizon and non-Markovian requirements.

Selection-based evolution. A complementary line introduces evolutionary mechanisms such as mutation, selection, and environmental variation. Li et al. (Li et al., 2024b) embed social norms into a genetic process so that agents adapt through repeated selection under changing group behavior, while Suzuki and Arita (Suzuki and Arita, 2024) use evolutionary games to study the emergence of cooperative traits in LLM-based agents. Ye et al. (Ye et al., 2024b) further model prompt mutation as a way to simulate novel environments and formulate alignment as a creator–solver game. Across these studies, the common intuition is that alignment should remain responsive to gradual changes in norms, tasks, and social expectations, rather than being anchored to a static preference snapshot.

4.3.2 Co-evolution

Whereas adaptive evolution emphasizes how a model tracks environmental change, co-evolution

focuses on settings in which the environment itself is partly generated by other evolving agents, as shown in Fig. 5(b).

Game-theoretic algorithm modeling. This perspective is particularly useful when alignment depends on multi-agent interaction, population diversity, or open-ended strategic adaptation. SPARTA (Jiang et al., 2025) studies collective alignment through repeated combat, evaluation, and learning among multiple models, while Ma et al. (Ma et al., 2023) cast safety alignment as a red–blue team game in which attack and defense strategies evolve together. These approaches suggest that robustness may emerge not only from stronger objectives, but also from continued exposure to adaptive opponents and evaluators.

Scenario simulation. The same co-evolutionary perspective also underlies a broader set of social simulation environments. Recent work uses agent societies, role-playing communities, and sandbox worlds to study how norms, cooperation, and governance emerge through interaction (Liu et al., 2024b; Lai et al., 2024; Li et al., 2023; Dai et al., 2024). In parallel, strategically structured environments such as Alympics (Mao et al., 2025) and FairMindSim (Lei et al., 2024) are used to probe bargaining, fairness, and collective behavior under resource constraints or ethical dilemmas. Debate-based methods extend this logic to inference-time improvement: by allowing multiple agents to critique and challenge one another, they can improve

reasoning and factuality without retraining (Liang et al., 2024; Du et al., 2024). Together, these studies broaden alignment from single-model optimization to the analysis of collective behavior in evolving social systems, but many of these environments remain behaviorally rich while still offering limited visibility into the internal mechanisms that drive adaptation.

5 Future Directions

Fairness guarantees Pluralistic societies typically do not rely on a single value standard, so alignment should not only search for a ‘true’ value objective but also design fair procedures for deciding which values guide model behavior (MacIntyre, 2013; Gabriel, 2020). Existing multi-objective methods introduce fairness constraints, such as demographic parity, equalized odds, group-DRO, and worst-group lower bounds (Agnihotri et al., 2025; Chakraborty et al., 2024). However, soft regularization, such as imposing a finite penalty on the objective function, typically gives weak guarantees, while hard constraints can reduce utility or destabilize training (Tran et al., 2024). A promising direction is to model fairness-utility trade-offs as games with social-welfare objectives (Chen et al., 2024a), including Nash welfare, Leximin (Barman and Suzuki, 2024), and Pareto-optimal solution families (Censor, 1977). Future work should further combine adaptive weighting with procedural safeguards from Constitutional AI, social choice, voting, and public participation, so that both outcomes and decision procedures remain legitimate and adaptable (Zhao et al., 2024; Huang et al., 2024b).

Continual alignment under drift. Online tool use, continual preference learning, and scenario migration can update useful capabilities while gradually overwriting aligned behavior. This causes catastrophic forgetting and value drift, especially in adversarial testing and long multi-turn interaction. From a game-theoretic view, alignment maintenance can be modeled as a dynamic interaction among the model, deployment environment, and strategic auditors or adversaries, where feedback streams may expose or induce degradation. Existing remedies include continual or online RLHF (Zhang et al., 2024), trust-region or strongly regularized updates (Li et al., 2024a), and generative replay under data-access limits (Huang et al., 2024a). However, most methods optimize gen-

eral retention rather than treating alignment-critical knowledge as the main retention target (Wang et al., 2024h). Future work should combine continual learning with hierarchical or retrieval-augmented memory (Wang et al., 2023a; Borgeaud et al., 2022; Meng et al., 2022), classical anti-forgetting mechanisms (Dokania et al., 2019; Kirkpatrick et al., 2017), and adversarially robust updates (Khan et al., 2022; Mirzadeh et al., 2020; Ebrahimi et al., 2020), so that safety-relevant knowledge remains stable under changing or manipulated data flows.

Visual simulation for explainable AI. AI alignment remains difficult to inspect when simulations only report external behavior. Controlled social simulations, agent societies, and policy games, as discussed in Section 4.3, can reveal dynamic failures in interaction, adaptation, and social feedback. Yet many such environments remain behaviorally rich but mechanistically shallow. Future work should connect these environments with mechanistic interpretability, rule-based dynamic models, intervention logging, and counterfactual analysis. This would turn simulation from outcome-level evaluation into process-level diagnosis, making long-term alignment easier to inspect, explain, and steer.

Conclusion

This survey examined AI alignment through the lens of game theory, reframing alignment as a problem of strategic dependence rather than static objective fitting. By organizing the literature around preference structure, interaction structure, and temporal dynamics, this work clarifies how values are aggregated, how models or agents influence one another, and how aligned behavior may emerge, change, or remain stable over time. Furthermore, we point out that existing game-theoretic alignment methods still focus on the training phase, while their role in inference control, social game-based benchmarking, practical verification, and interpretability remains to be developed. Therefore, researchers need to further expand game-theoretic tools to achieve, diagnose, and manage AI alignment, strengthening the connection between theoretical guarantees and the real world, thereby supporting the development of safer and more reliable AI systems.

Limitations

This survey focuses primarily on post-training alignment work for LLMs and LLM-based agents

that can be meaningfully analyzed through game-theoretic concepts. It therefore does not aim to exhaustively cover adjacent literature on pre-training objectives, inference-time defenses, mechanistic interpretability, or governance frameworks that do not directly adopt this lens. In addition, the reviewed areas are uneven in theoretical maturity: preference-learning work currently admits stronger formal guarantees than many studies on social interaction, simulation, and long-term evolution. As a result, some parts of the survey necessarily provide a looser synthesis than others.

Ethics Statement

While game-theoretic frameworks can help clarify incentives and interaction structures in alignment, they may also simplify complex moral, cultural, and institutional factors. Therefore, the methods reviewed in this paper should not be regarded as complete solutions to alignment or as substitutes for human oversight and governance. We encourage readers to interpret the reviewed approaches with caution, especially in safety-critical or socially sensitive settings.

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of details such as equilibrium convergence, self-game, and evaluation metrics, thereby enabling comparisons with similar methods.

Tabs. 1- 3 correspond to the three branches of the taxonomy framework in Section 4, with the themes of preference diversity, alignment priority, and temporal dynamics, respectively, demonstrating game-based alignment methods. Additionally, Game-based evaluation complements alignment methods by providing controlled settings for probing strategic reasoning, social behavior, and system-level interaction. Tab. 4 therefore lists representative benchmarks that are most directly related to the survey’s main themes. These benchmarks are included as supplementary reference material rather than as a separate organizing axis of the survey.

A Summary Tables

This appendix provides representative methods and evaluation benchmarks for large language models or agent alignment, summarizing them in tabular form (see Tabs. 1- 4) to facilitate the presentation

Table 1: Overview of alignment frameworks based on preference diversity.

Direction	Preference alignment							
	Framework	Regularization	Formalization	Convergence	Preference modeling	Self-play?	Robust alignment?	Online?
General preference	IPO(Azar et al., 2024)	Explicit	Best response (fixed strategy)	Average-iterate (ϵ -OPT)	○	○	○	○
	NLHF(Munos et al., 2024)	Explicit	Two-player game (constant-sum)	Last-iterate (NE)	●	○	○	●
	IPO-MD(Calandriello et al., 2024)	Explicit	Two-player game	Exist (NE)	○	○	○	●
	Iterative RLHF(Ye et al., 2024a)	Explicit	Two-player game (mini-max)	Exist (ϵ -NE)	●	●	○	●
	SPO(Swamy et al., 2024)	-	Two-player game (zero-sum)	Average-iterate (ϵ -Minimum Winner)	●	●	○	●
	DNO(Rosset et al., 2024)	-	Two-player game (zero-sum)	Average-iterate (NE)	●	●	○	○
	REBEL(Gao et al., 2024)	-	Two-player game (zero-sum)	Average-iterate (ϵ -OPT)	●	●	○	○
	SPPO(Wu et al., 2024)	-	Two-player game (constant-sum)	Average-iterate (ϵ -NE)	●	●	○	○
	TANPO(Wang et al., 2025b)	Explicit	Two-player game (zero-sum)	Average-iterate (ϵ -NE)	○	●	○	●
	ONPO(Zhang et al., 2025a)	-	two-player game (zero-sum)	Average-iterate (ϵ -NE)	○	●	○	●
	INPO(Zhang et al., 2025b)	Explicit	Two-player game	Last-iterate (ϵ -NE)	○	●	○	●
	COMAL(Liu et al., 2026)	-	Two-player game (zero-sum)	Last-iterate (NE)	●	○	●	●
	MPO(Wang et al., 2025a)	-	Two-player game (constant-sum)	Last-iterate (NE)	●	●	○	●
	RSPO (Tang et al., 2025)	Explicit	Two-player game	Last-iterate (NE)	●	●	○	●
Heterogeneous preference	(Chidambaram et al., 2024)	Explicit	Social welfare optimization	Average-iterate (ϵ -OPT)	●	○	●	○
	(Kim et al., 2025)	Explicit	Social welfare optimization	-	●	○	○	○
	MOP(Xiong and Singh, 2025)	Explicit	Social welfare optimization	Average-iterate (OPT)	●	○	○	○
	Pessimistic Nash Bargaining(Zhong et al., 2024a)	Implicit	Social welfare optimization	Exist (ϵ -OPT)	●	○	○	○
	GRPO(Ramesh et al., 2024)	Implicit	Social welfare optimization	Average-iterate (ϵ -OPT)	●	○	●	○
	CLP (Wang et al., 2024d)	Explicit	Multi-objective optimization	Exist (ϵ -OPT)	●	○	○	●
	Panacea(Zhong et al., 2024b)	Both	Multi-objective optimization	Exist (Pareto-OPT)	●	○	○	●
	MO-ODPO(Gupta et al., 2025a)	Explicit	Multi-objective optimization	-	●	○	○	●
	SIPO(Li et al., 2025)	Explicit	Multi-objective optimization	-	●	○	○	○
	DPA(Wang et al., 2024c)	-	Multi-objective optimization	-	●	○	○	○
	DRM(Luo et al., 2025)	Explicit	Multi-objective optimization	-	●	○	○	○
	RLHF Game(Sun et al., 2024a)	Explicit	Multi-player game (mechanism design)	-	●	○	○	○
	Dynamic Bayesian Game(Hao and Duan, 2025)	Explicit	Multi-player game (dynamic Bayesian)	Average-iterate (ϵ -OPT)	●	○	○	●
	BIG(Wu et al., 2025)	-	Multi-player game (cooperative)	Last-iterate (NE)	●	○	○	○
	$\langle M, N, \epsilon, \delta \rangle$ -Agreement(Nayebi, 2025)	-	Multi-player game (theoretical)	-	○	○	○	●

Notes. (1) *Regularization*: explicit penalties or procedures that constrain the model’s policy, learning, and outputs. (2) *Formalization*: how the alignment problem is modeled. (3) *Convergence*: based on theoretical proof or experimental observation, the optimal strategy exists when converging to an equilibrium point, or explicitly reaching a consensus state in decision-making; some methods provide stronger guarantees such as average-iterate and last-iterate convergence. (4) *Preference modeling*: a preference probability model (reward model) is learned from human preference data for candidate outputs. (5) *Self-play*: the same model or homologous variants/clones engage in mutual competition, collaboration, or evaluation within a task or game. (6) *Robust alignment*: a Nash equilibrium policy guarantees at least a 50% win (or preference) rate against any alternative policy under general preferences, and guarantees the worst-group performance under heterogeneous preferences. (7) *Online*: new training data are obtained from the current model and the parameters are updated accordingly. Symbols ●, ○, and ⊙ denote conditions that are met, not met, and adjustable mixed settings, respectively; ‘-’ indicates not applicable or not reported.

Table 2: Overview of alignment frameworks based on alignment priority.

Direction	Enhancement via interaction							
	Framework	Target	Formalization	Interaction structure	Convergence	External feedback	Self-play?	Online?
Synchronous interaction	(Jatova et al., 2024)	Safety alignment	Two-player game	LLM vs adversarial generator	Exist (NE)	●	○	●
	GPO (Zheng et al., 2024)	Safety alignment	Two-player game (zero-sum)	LLMs (attacker vs defender)	Average-iterate (NE)	●	○	●
	SELF-REDTEAM (Liu et al., 2025)	Safety alignment	Two-player game (zero-sum)	LLM (attacker / defender)	-	●	●	●
	MTSA (Guo et al., 2025)	Safety alignment	Multi-turn RL	LLMs (attacker vs defender)	-	●	○	⊙
	SPAG (Cheng et al., 2024)	Reasoning	Two-player game (zero-sum)	LLM (attacker / defender)	-	●	●	○
	APO (Cheng et al., 2023)	Effective alignment	Two-player game (mini-max)	LLM vs RM	-	○	○	●
	SPIN (Chen et al., 2024b)	Self-improvement	Two-player game	LLM (generator / distinguisher)	Exist	○	●	⊙
	LANA (Azarafroz and Faal, 2024)	Self-alignment	Two-player game (zero-sum)	LLM (generation / evaluation)	Average-iterate (ϵ -NE)	○	●	●
	DuoGuard (Deng et al., 2025)	Safety alignment	Two-player game (mini-max)	LLMs (generator vs classifier)	Last-iterate (NE)	○	○	⊙
	SPC (Chen et al., 2025b)	Reasoning	Two-player game	LLM (generator / critic)	-	○	●	●
Sequential interaction	PEG (Chen et al., 2025a)	Truthfulness	Peer elicitation game	LLMs (peer discriminators)	Last-iterate (Truthful NE)	○	○	●
	STA-RLHF (Makar-Limanov et al., 2024)	Human preference	Two-player game (Stackelberg)	LM (leader) vs RM (follower)	-	○	○	⊙
	SPAC (Ji et al., 2024)	Human preference	Two-player game (Stackelberg)	LLM (policy model / critic)	Average-iterate (ϵ -OPT)	○	●	○
	SGPO (Chu et al., 2025)	Effective alignment	Two-player game (Stackelberg)	LLM vs pref. distribution	Last-iterate (SE)	○	○	⊙
	Anyprefer (Zhou et al., 2025c)	Effective alignment	Two-player game (Markov)	LLMs (target model & judge)	-	●	○	○
	CORY (Ma et al., 2024)	Robustness	Cooperative multi-agent RL	LLM (pioneer / observer)	-	●	●	●

Notes. (1) *Target*: research question. (2) *Formalization*: how the alignment problem is modeled. (3) *Interaction structure*: players and roles engaging in interaction. (4) *Convergence*: based on theoretical proof or experimental observation, the optimal strategy exists when converging to an equilibrium point, or explicitly reaching a consensus state in decision-making; some methods provide stronger guarantees such as average-iterate and last-iterate convergence. (5) *External feedback*: the AI model (agent) relies on externally added, manually annotated data for optimization and updates, rather than self-generating new annotations via interaction. (6) *Self-play*: the same model or homologous variants/clones engage in mutual competition, collaboration, or evaluation within a task or game. (7) *Online*: new training data are obtained from the current model and the parameters are updated accordingly. Symbols ●, ○, and ⊙ denote conditions that are met, not met, and adjustable mixed settings, respectively; ‘-’ indicates not applicable or not reported.

Table 3: Overview of alignment (simulation) frameworks based on temporal dynamics.

Direction	Dynamic evolution						
	Framework	Target	Formalization	Application	Stage	Convergence	Online?
Adaptive evolution	(Klassen et al., 2024)	Temporal pluralism values	Non-Markovian process	Measurement	-	-	-
	(Suzuki and Arita, 2024)	Social cooperation	Evolutionary game (mutation)	Simulation	Inference	-	-
	ProgressGym (Qiu et al., 2024)	Social moral progress	Partially observable MDP	Improvement	Post-training	-	-
	Evolutionary Agent (Li et al., 2024b)	Norms and cooperation	Evolutionary game (mutation)	Improvement	Inference	-	-
	EVA (Ye et al., 2024b)	Preference alignment	Creator-solver game (mutation)	Improvement	Post-training	-	●
Co-evolution	SPARTA (Jiang et al., 2025)	Preference / instruction	Collective competition	Improvement	Post-training	-	⊙
	Red-Team Game (Ma et al., 2023)	Safety alignment	Red-blue team game	Improvement	Post-training	Exist (ϵ -NE)	●
	SSI (Liu et al., 2024b)	Social alignment	Social interaction	Improvement	Post-training	Exist	○
	Artificial Leviathan (Dai et al., 2024)	Social order	Social interaction (survival sandbox)	Simulation	Inference	-	-
	CAMEL (Li et al., 2023)	Social cooperation	Role-playing interaction (dialogue)	Simulation	Inference	-	-
	AI Collectives (Lai et al., 2024)	Social alignment	Social interaction (community)	Simulation	Inference	-	-
	Alympics (Mao et al., 2025)	Empirical game theory	Strategic games (survival resources)	Simulation	Inference	-	-
	FairMindSim (Lei et al., 2024)	Social value alignment	Ethical dilemma	Simulation	Inference	-	-
	(Du et al., 2024)	Reasoning / factuality	Multi-agent debate	Improvement	Inference	Exist (Consensus)	-
	MAD (Liang et al., 2024)	Reasoning	Multi-agent debate	Improvement	Inference	-	-

Notes. (1) *Target*: research question. (2) *Formalization*: how the process of dynamic evolution is driven or modeled, such as game, social interaction, and debate. (3) *Application*: quantify and enhance the alignment performance of AI systems, or conduct interdisciplinary research by simulating social behavior and group evolution processes through AI agents, such as social sciences and empirical game theory. (4) *Stage*: the phase during which the training or evaluation framework is running. (5) *Convergence*: based on theoretical proof or experimental observation, the optimal strategy exists when converging to an equilibrium point, or explicitly reaching a consensus state in decision-making. (6) *Online*: new training data are obtained from the current model and the parameters are updated accordingly. Symbols ●, ○, and ⊙ denote conditions that are met, not met, and adjustable mixed settings, respectively; ‘-’ indicates not applicable or not reported.

Table 4: Overview of evaluation benchmarks based on games.

Paradigm	Evaluation and Benchmark					
	Ref.	Target	Formalization	Metric	Benchmark	Oriented-O/P
Classic Games	Fan et al.(Fan et al., 2024)	Rationality	Dictator Game Ring-network Game	Action Accuracy Average Payoff Preference Consistency Bias Degree	-	○
	Wang et al. (Wang et al., 2024b)	Strategic reasoning	Robinson-Goforth Topology of 2×2 Games	Perfect Accuracy Rate Inconsistency Degree	Tmgbench	○
	Lor'e et al.(Lorè and Heydari, 2024)	Strategic behavior	Social Dilemmas Games	Cooperation Rate Dominance Statistic	-	○
	Topsaka et al. (Topsakal et al., 2024)	Rule comprehension Strategic thinking	Grid-based Games	Win/DQ Rates Invalid Moves Missed Opportunities Strategic Degree	✓	○
	Lu (Lu, 2024)	Strategic levels Adaptive learning	Beauty Contest	Convergence Average Payoffs	-	○
	Sreedhar et al. (Sreedhar et al., 2025)	Cooperative prosocial behavior	Public Goods Game	Average Contribution Emergence Frequency	-	○
	Akata et al. (Akata et al., 2025)	Cooperation Coordination	Finitely repeated 2×2 games	Score Ratio Defection Rate Coordination Rate	-	○
	Fontan et al. (Fontana et al., 2025)	Cooperative behavior	Iterated Prisoner's Dilemma	Behavioral Traits SFEM Scores	✓	○
	Xie et al. (Xie et al., 2024)	Human trust behavior	Trust Game	Trust Rate Valid Response Rate Returned/Sent Ratio	✓	○
	Zakazo et al. (Zakazov et al., 2024)	Social alignment	Ultimatum Game	Acceptance Rate Disobedience Ratio	-	○
Social games	Davidson et al. (Davidson et al., 2024)	Instruction-following Faithfulness	Structured Negotiation	Agreement Rate Normalized Payoffs	LAMEN	○
	Xia et al. (Xia et al., 2024)	Bargaining abilities	Bargaining	Deal Rate First Bid Ratio Sum of Normalized Profits	AmazonHistoryPrice	●
	Zhou et al. (Zhou et al., 2025b)	Social intelligence	World tree scenarios	Goal Achievement Ratio Ability Selection Accuracy	SocialEval	○
	Zhou et al. (Zhou et al., 2024)	Social intelligence	Mixed-motive Markov games	Goal Completion Social Rules	SOTOPIA-EVAL	○
	Liu.et al. (Liu et al., 2024a)	Role consistency	Interactive dialogue	Self-Knowledge accuracy	RoleAgentBench	○
	Wang et al. (Wang et al., 2024g)	Role consistency	Role-playing dialogue	Win rate Average ranking	RoleBench	●
	Zhu et al. (Zhu et al., 2025)	Cooperation & competition	Mutual/conflicting scenarios	Task Score Milestone-based KPI	MultiAgentBench	○
	Wang et al. (Wang et al., 2024a)	Social intelligence	Social sandbox tasks	Success Rate Goal Condition SR	STSS benchmark	●
	Abdelnabi et al. (Abdelnabi et al., 2024)	Negotiation & security	Multi-agent, multi-issue negotiation	Final success Collective score Score leakage ratio Overall Score	✓	○
	Xie et al. (Xie et al., 2026)	Social behavior	Mixed-motive games	Talk–Action Consistency Trajectory Analysis Traitor Survival Rate	M3-Bench	○
	Curvo et al. (Curvo, 2025)	Deception & trust	Communication utterances Voting decisions	Trust Network Stability Faithful Correctness Rate Cipher round-trip accuracy	✓	○
	Motwani et al. (Motwani et al., 2024)	Secret collusion	Covert communication	Coordination rates	✓	○

Notes. (1) *Target*: research question. (2) *Formalization*: evaluation scenario or benchmark type. (3) *Metric*: quantifiable evaluation metrics that are typically results- or process-oriented. (4) *Benchmark*: self-named benchmarks are listed explicitly, while unnamed benchmarks are represented by ✓. (5) *Oriented-O/P*: the evaluation paradigm follows outcome-oriented (O: ●), process-oriented (P: ○), or both (○). The symbol ‘-’ is used in the same way as above.