LLM Chess: Benchmarking Reasoning and Instruction-Following in LLMs through Chess

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Abstract

We introduce LLM Chess, an evaluation framework designed to probe the generalization of reasoning and instruction-following abilities in large language models (LLMs) through extended agentic interaction in the domain of chess. We rank over 50 open and closed source models by playing against a random opponent using a range of behavioral metrics, including win and loss rates, move quality, move legality, hallucinated actions, and game duration. For a subset of models, we derive an Elo estimate by playing against a chess engine with variably configured skill. Despite the simplicity of the instruction-following task and the weakness of the opponent, many state-of-the-art models struggle to complete games or achieve consistent wins. Similar to other benchmarks on complex reasoning tasks, our experiments reveal a clear separation between reasoning and non-reasoning models. However, unlike existing static benchmarks, the stochastic and dynamic nature of LLM Chess uniquely reduces overfitting and memorization while preventing benchmark saturation. To support future work on evaluating reasoning and instruction-following in LLMs, we release our experimental framework, a public leaderboard, and a dataset of associated games. Our code is available at https://github.com/LLM-CHESS/llm_chess.

1 Introduction

Chess has long been viewed as an application for artificial intelligence (AI) since its inception, often being one of the first domains in which new technologies are used [Prost, 2012]. The idea of computer chess was pursued by the founders of AI, who viewed it as an exciting application in which advances could spur developments in other fields [Turing, 1988, Wiener, 2019, Shannon, 1950]. In fact, chess is often referred to as the 'drosophilia of AI', in that it both is a worthy testbed for experiments and also has guided the field's development [Simon and Schaeffer, 1992, McCarthy, 1990, Ensmenger, 2012]. As such, chess also has often been used to study cognitive abilities and decision making in humans [Groot, 1978, Simon and Chase, 1988, Sala et al., 2017, Sala and Gobet, 2017, Burgoyne et al., 2016, Blanch, 2022, Rosholm et al., 2017, Jankovic and Novak, 2019].

Since the 1950s, chess engines have been created with the hopes of beating humans, achieving various levels of success along the way. As time progressed, these engines advanced both through hardware and algorithmically, until reaching their current most powerful form with neural networks [Bernstein and de V. Roberts, 1958, Adel'son-Vel'skii et al., 1970, Newborn, 1979, Condon and Thompson, 1983, Campbell et al., 2002, Newborn, 2012, Silver et al., 2017]. While certain architectures and algorithms applied to chess have seen success elsewhere, these chess engines are explicitly tailored to chess games, unable to generalize.

Recently, large language models (LLMs) have shown incredibly competent performance in many diverse fields [Brown et al., 2020, Touvron et al., 2023, Thirunavukarasu et al., 2023, Liu et al., 2023, Wu et al., 2023b, Wei et al., 2022, OpenAI et al., 2024, DeepSeek-AI et al., 2025], leading many to wonder whether they may play an important role in achieving artificial general intelligence [Bubeck et al., 2023, Feng et al., 2024, Mumuni and Mumuni, 2025]. Additionally, tools like reinforcement learning and test-time scaling approaches have been shown to greatly increase reasoning abilities, accelerating the promise of a general reasoner [Chen et al., 2024, Shao et al., 2024, DeepSeek-AI et al., 2025]. While chess engines can now regularly beat humans, the game has not yet sufficiently been tested on LLMs, which ideally would possess such general characteristics that they could excel at any complex reasoning task, whether it be math, coding, or gameplaying like chess. As we start to design models with more general capabilities, what is old becomes new again: the large combinatorial spaces, long-horizon planning, and dynamic nature of chess all present thorough challenges for LLMs. Continuing the tradition of using chess to test and gain insights into current model capabilities, we present three main contributions:

1. We introduce LLM CHESS, a benchmark assessing both reasoning and instruction-following in the context of chess. Central to our benchmark is agentic interaction: by having LLMs play chess through autonomously selecting actions within a conversation, the difficulty comes not only in reasoning about the board and choosing the best move, but also how to formulate these choices. Unlike other reasoning benchmarks that can be contaminated or easily saturated, LLM CHESS is extensible by scaling the difficulty of the opponents and is not reliant on static board positions that can be included in training data.
2. We formulate a wide suite of per-model, per-game, and per-ply metrics to comprehensively evaluate the quality of each LLM's play, leveraging the depth of the chess domain to improve our analysis.
3. We evaluate over 50 models on LLM CHESS, showing that the domain of chess continues to present a challenging and informative reasoning task when applied to LLMs. We find that currently only the most powerful reasoning-enhanced LLMs can consistently beat a random player, even when we let them query for legal moves. When playing against engines, these models still fare poorly, with o3 (low) only achieving a 758 Elo in LLM CHESS. Through extensive ablations on specific parts of the game, we find that LLM performance varies widely based on the format of the conversations and prompt, suggesting a lack of robustness in their reasoning abilities.

Altogether, our comprehensive experiments show that chess is a worthy testbed for benchmarking the reasoning and instruction-following ability of LLMs and that current state-of-the-art models lack the ability to generalize their strong reasoning performance to be as impressive in chess as in other domains.

2 LLM CHESS

Here we introduce LLM CHESS (Figure 1), explaining our design choices and the metrics we use to score the models.

2.1 Design

In chess, an action taken by one side is referred to as a half-move or ply while two concurrent plys are referred to as a move, one by white, the other by black. [1] At each ply, we initiate a conversation with the end goal of outputting a valid chess move. We format all moves in Universal Chess Interface (UCI) format, a commonly used notation for chess engines [Huber and Meyer-Kahlen, 2000]. Each conversation consists of several turns, where each turn a LLM is prompted with instructions to output a valid action. We offer three actions to the LLM: 1) `get_current_board`, which fetches and presents the state of the current board using a unicode board, 2) `get_legal_moves`, which fetches a list of legal moves in UCI format, and 3) `make_move`, which takes a UCI-formatted string as input, adjusts the board state with that move, then ends the LLM's turn. Ablations on these choices are

[1] When it is clear that we are only discussing one side's actions, we occasionally overload move to refer to a ply, i.e., making a move in a ply refers to a single piece movement for that specific ply.

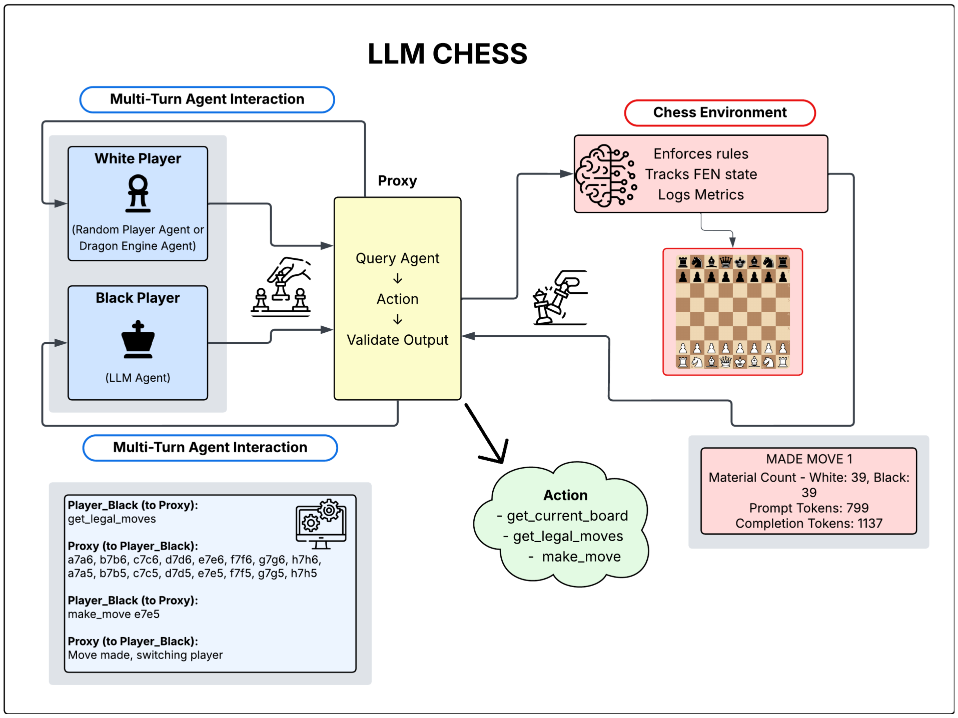


Figure 1: Overview of the LLM CHESS benchmark. White and Black player agents (random or engine for White, LLM for Black) interact with a central proxy that issues agent queries, validates outputs, and invokes one of three actions (`get_current_board`, `get_legal_moves`, `make_move`) The Chess Environment enforces the rules, updates and logs the FEN state, and records per-move metrics for downstream analysis.

presented in Section 3.4. We implement our LLM in an agentic setting using the AG2 framework [Wu et al., 2023a, Wang et al., 2025].

We cap each game at 100 moves (200 plys), have a max of 10 conversation turns per ply, and allow a max of 3 attempts per conversation turn for the LLM to provide a legal action or move. The LLMs view each ply as independent of all others, as we do not provide any game history. While this differs from humans who know their previous moves when playing chess, this aligns more with the machine setting where a model should be able to make the best move given the board state alone. Importantly, this setting does not eliminate the need for long-term planning: models must continue to be aware of how the moves they choose will impact future board states. Instructions provided to the LLM to initiate the conversation and resulting from various actions are presented in Appendix C. From preliminary testing, we somewhat surprisingly found many LLMs performed poorly against random players. So, we evaluate a wide set of models against random players to get a general sense of their abilities. Then, on particularly good models, we play them against a chess engine with variably configured skill.

Random Player We benchmark over 50 models by playing 30 games as black against a random player, who chooses a move at random from all legal moves. We choose a random player first because we want to focus on game-playing ability while removing skill as a main focus, i.e., to see if the model can play and finish a game of chess without having game-ending issues from instruction-following issues or choosing invalid moves.

Chess Engine From the initial models, we choose a subset of models to play against Komodo's Dragon 1 engine, which can be set at various skill levels from 1-25. As an estimate, Skill 1 is around Elo 250, then each subsequent skill level is a 125 boost in Elo based on chess.com games [Kaufman and Lefler, 2020]. Since chess.com is one of the most popular online chess platforms, having over 200 million members [Chess.com, 2025], this lets us ground our LLM performance in the real world. We run experiments against Dragon 1 at 30 games per skill level starting at Skill 1 and up to Skill

5, representing Elos of $\{250, 375, 500, 625, 750\}$ on chess.com. While currently we do not evaluate with too high of Skills, our framework permits easy extensibility: as LLMs become better and better, we can increase the difficulty of the opponents to prevent saturation.

2.2 Metrics

LLM CHESS evaluates LLMs by playing full chess games. However, we also evaluate the reasoning ability of the LLM with various per-ply metrics rating the quality of each move, as well as the instruction-following ability by examining how the model engages with our agentic structure.

Per-model The main way we quantify performance is to calculate a LLM's Win/Loss percentage against an opponent, which is the difference between wins and losses as a percentage of total games:

$$\text{Win/Loss} = \frac{1}{2}\left(\frac{\text{llm\_wins} - \text{opponent\_wins}}{\text{total\_games}}\right) + 0.5$$

Win/Loss admits easy interpretability: 50% means a model has equal wins and losses. To win a game, LLM must checkmate its opponent. LLMs can lose or draw in the following ways: 1) Chess-based. The LLM could lose through checkmate by the opponent or draw due to various rules (stalemate, insufficient material, seventy-five moves without a capture or pawn move, fivefold repetition, or the game reached 100 moves). 2) Instruction-based. The LLM loses if it reaches the maximum number of conversation turns without making a move (10) or if it reached the maximum number of attempts (3) at a conversation turn without selecting a valid action. We call failures here instruction-following errors. 3) Model errors. These are errors due to the model or how it's served like timeout for reasoning models. We exclude all games with these errors when playing against a random player so we could better analyze behavior, but include them when playing against Dragon 1 to simulate what would happen in a real-world scenario.

While Win/Loss is helpful for observing the quality of LLM performance against weaker opponents, it is less grounded in the world of chess. So, for LLMs that perform sufficiently well against random players and against the engine at various skill levels, we calculate Elo [Elo, 1978]. Normally Elo ratings update dynamically between players, but here we treat each engine opponent's rating R_i as fixed and encode the LLM's game outcomes as $S_i \in \{1, 0.5, 0\}$. Under Elo theory, the expected score against R_i is

$$E_i(R) = \frac{1}{1 + 10^{(R_i - R)/400}}.$$

Rather than updating R incrementally, we find the maximum-likelihood rating $\hat{R}$ by solving $\sum_i \big(S_i - E_i(\hat{R})\big) = 0$. Around $\hat{R}$, the observed Fisher information $\mathcal{I}(\hat{R}) = \sum_i E_i(\hat{R})\big(1 - E_i(\hat{R})\big)(\ln 10/400)^2$ yields a standard error $\mathrm{SE} = 1/\sqrt{\mathcal{I}}$ and thus a 95% confidence interval $\hat{R} \pm 1.96\,\mathrm{SE}$ [Glickman, 1999]. We detail the exact skill levels we evaluate against for each model in the experiments section.

Per-game For each game, we calculate the number of moves per game and the reason for each loss. We also record other metrics focused on instruction-following throughout the game that do not depend on the quality of the moves. For `get_current_board` and `get_legal_moves` we calculate the average number of times that action was called per ply. We also calculate the average number of times `make_move` was called but resulted in an invalid move, as well as the average number of invalid actions that were selected.

Per-ply Besides analyzing performance on a game level, we also calculate the performance per ply. After the LLM calls `make_move` in each ply, we calculate the Win% (Equation (1)), the chance of winning a game from the given position as defined by Lichess [Lichess, 2025]. This analysis is based on centipawns, which are calculated by Stockfish representing how much worse the player's move was than the engine's [Linville, 2023]. We present the Win% for the LLM averaged over each ply, which tells us whether the LLM held a more favorable position throughout the game.

$$\text{Win\%} = 50 + 50 * (2/(1 + \exp(-0.00368208 * \text{centipawns})) - 1) \tag{1}$$

Then, based on the difference in Win%, $\Delta = \text{Win\%}_{\text{before move}} - \text{Win\%}_{\text{after move}}$ (where a higher Δ means the player's Win% decreased), we can calculate Blunders, Mistakes, and Inaccuracies, common classifications of moves used by online chess platforms, following the Lichess cutoffs [Lichess, 2023]:

$$\text{Judgment} = \begin{cases} \text{Blunder} & \text{if } \Delta \geq 30 \\ \text{Mistake} & \text{if } \Delta \geq 20 \\ \text{Inaccuracy} & \text{if } \Delta \geq 10 \end{cases} \tag{2}$$

We present the average Blunder, Mistake, and Inaccuracy rate per ply, as well as Best, the rate in which the LLM selected the best move as identified by Stockfish. We note that since our Win% scores are based on centipawns, these metrics can depend on the hyperparameters of Stockfish. Full implementation details (including the `score_to_cp` function and `BLUNDER_THRESHOLD`, `MISTAKE_THRESHOLD`, `INACCURACY_THRESHOLD`) are available in Appendix A.

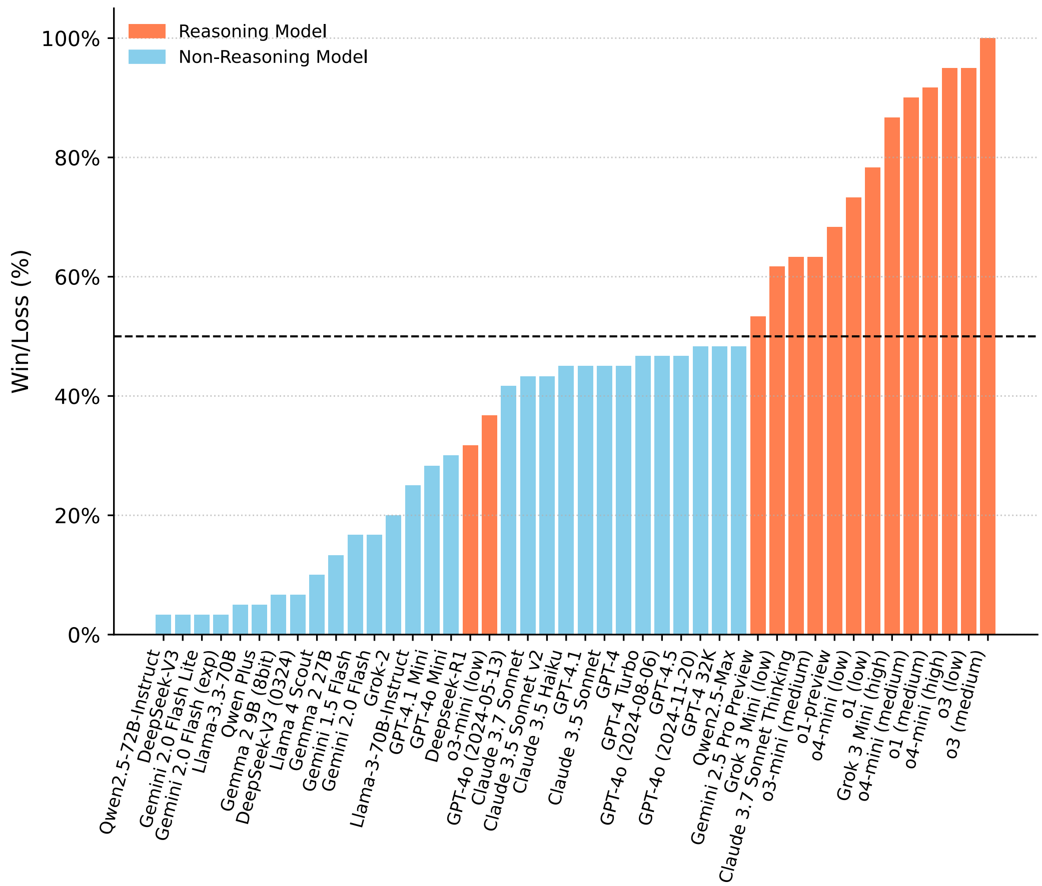


Figure 2: Win/Loss of LLM players versus random opponents. The dashed line marks a Win/Loss of 50%, which represents an equal amount of wins and losses.

3 Experiments

By default, all LLMs are run with a temperature of 0.3 and a Top P of 1.0. More details about the models we evaluate on and how they are run is detailed in Appendix A.

3.1 LLMs vs. Random

We present the Win/Loss of 44 LLMs versus a random player for 30 games in Figure 2. Most notably, we find that most models are not able to consistently beat a random player; in fact, only models with reasoning abilities are able to perform better than 50%. To analyze the reasons behind this poor performance, we present per-game metrics including how the LLMs won and lost in Table 1. Note that the only way black can win is through a checkmate. For each of these metrics, we present the average over all reasoning and non-reasoning models, as well as on the two top and bottom reasoning and non-reasoning models.

Table 1: Per-game metrics for Reasoning (shaded) vs Non-Reasoning models. We choose the top and bottom two models in each category (ranked among 15 reasoning, 29 non-reasoning models) based on Win/Loss from among all models with a Win/Loss over zero. We include the percent of losses due to errors in instruction-following (Instruction) or checkmates by white (MateW), as well as the amount of draws (Draw), checkmates by black (MateB), and average moves over all games.

Model	Instruction (%)	Draw (%)	MateW (%)	MateB (%)	Avg Moves
Reasoning Avg	24.4	30.2	0.0	45.4	93.7
Non-Reasoning Avg	71.9	24.6	2.8	0.7	73.9
o3 (medium)[1]	0.0	0.0	0.0	**100.0**	40.1
o3 (low)[2]	0.0	10.0	0.0	90.0	63.5
Qwen2.5-Max[1]	0.0	**96.7**	3.3	0.0	**197.4**
GPT-4o (2024-11-20)[2]	0.0	90.0	**6.7**	3.3	194.9
o3-mini (low)[14]	36.7	53.3	0.0	10.0	139.3
Deepseek-R1[15]	60.0	16.7	0.0	23.3	88.2
Gemini 2.0 Flash Lite[28]	**90.0**	0.0	**6.7**	3.3	90.3
Qwen2.5-72B-Instruct[29]	**90.0**	6.7	3.3	0.0	64.1

Our results indicate that reasoning-enchanced LLMs dramatically outperform non-reasoning models in our random-opponent setting. Reasoning models have an average win rate of 45.4% with the top performers achieving close to 100%, whereas non-reasoning models have an average win rate of 0.7% with the top performer achieving 3.3%. This performance gap is further supported by a three-fold reduction in instruction-following errors: 72% for non-reasoning models vs 24% for reasoning models. Lastly, non-reasoning models almost always reach the maximum moves allowed if they don't have instruction-following issues, whereas reasoning models converge around 94 moves per game. While these statistics demonstrate that enhanced reasoning capabilities substantially improve both instruction-following and overall game performance, even the best LLMs secure wins in only about 90% of games against a random opponent, indicating poor real world performance.

Table 2: Per Ply Classification Rates (%) for Reasoning (shaded) vs Non-Reasoning Models.

Model	Blunder (↓)	Mistake (↓)	Inaccuracy (↓)	Best (↑)
GPT-4.1-mini	31.3	8.7	13.4	4.1
o4-mini (low)	11.2	3.5	5.5	10.8
o4-mini (medium)	**4.2**	**1.1**	**4.0**	**19.5**
Grok 3 Mini	9.1	2.0	5.8	8.5
Grok 3 Mini (low)	13.6	2.8	6.7	9.8
Grok 3 Mini (high)	**4.9**	**1.5**	**3.4**	**18.2**

To see how models perform throughout the game, we present per-ply metrics on a handful of models performing at various levels in Table 2. Our results show that reasoning models make far fewer bad moves and substantially more "best" moves than non-reasoning models. For example, o4-mini (medium) blunders only 4.2% and mistakes 1.1% of the time per ply, compared to 31.3% blunders and 8.7% mistakes for GPT-4.1-mini. Furthermore, o4-mini (medium) selects the "Best" move 19.5% of the time versus just 4.1% for GPT-4.1-mini. The same trend continues with Grok 3 Mini and Grok 3 Mini (high). These results confirm that enhanced reasoning capacity reduces catastrophic errors while boosting tactical decision making.

Notably, we also ran experiments on over 10 models that have a 0% Win/Loss, often resulting from difficulties with instruction-following. We present these models in Table 4 in Appendix B. We also present additional results for some models on more games in Appendix B.

3.2 LLMs vs. Chess Engine

While random players are a good test of LLMs' abilities to complete games, they often make moves that are nonsensical and are not realistic as a chess opponent. As such, some LLMs are able to perform very well against random players: the best models o3 (medium/low) and o4-mini (high) have a Win/Loss of at least 90%. To increase the difficulty of the games and ground LLMs in real-world performance, we now focus on our most powerful models to play against Dragon 1: o3 (low), Grok 3 Mini (high), o4-mini, o3-mini .

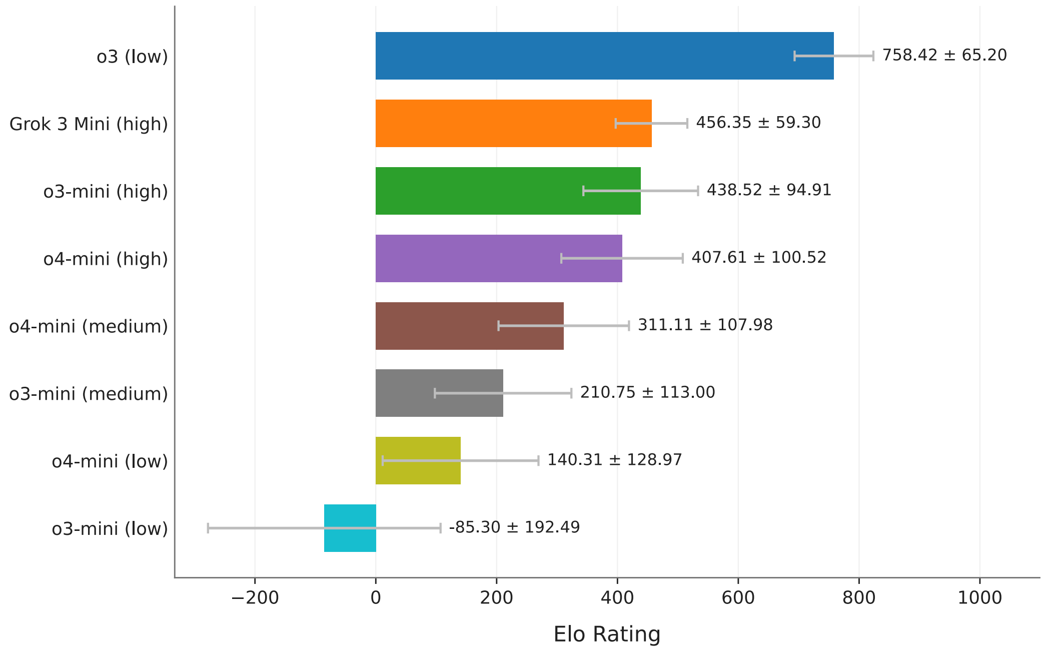


Figure 3: Elo of top reasoning models estimated using Dragon 1.

Figure 4 reports estimated Elo ratings (±95 % CI) for o3 (low), Grok 3 Mini (high), o4-mini, o3-mini when playing at least 30 games against Dragon 1 at skill 1. For o3 (low) and Grok 3 Mini (high) we play against all skills 1–5 (Elos 250–750). We include more about the models, skills they played against, and Elo calculation in Appendix A. These Elo estimates confirm several key insights. First, increased reasoning effort directly translates to higher real-world playing strength. For example, boosting o4-mini from "low" to "medium" reasoning settings raises its Elo by roughly 170 points. Second, even the strongest LLM in our study, o3 (low), peaks at an adjusted Elo of about 758, which remains far below human master level (approximately 2000), underscoring how far LLMs lag behind specialized chess engines and general human gameplay.

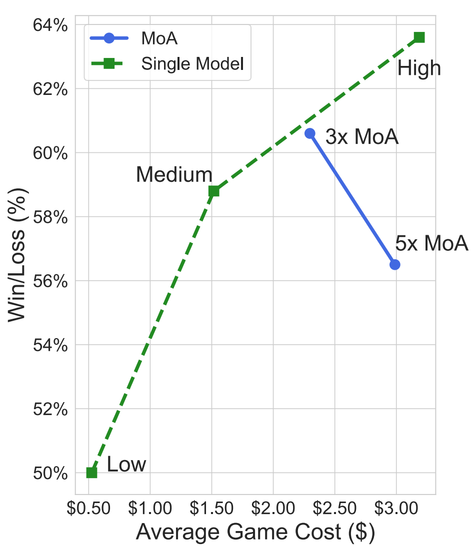
3.3 Exploring Test-time Scaling

Scaling Wide Besides increasing the number of tokens one model uses, we also run experiments using multiple instances of the same model in parallel. To do so, we apply a Mixture-of-Agents (MoA) approach where we have multiple proposer model calls fed into a separate aggregator model that provides the output [Wang et al., 2024]. This occurs at every step of the conversation . We run two settings on 30+ games with black against Dragon 1 Skill 1 using either 3x and 5x o4-mini (low) as the proposers and always use o4-mini (medium) as the aggregator. Results are in Figure 4a. [2]

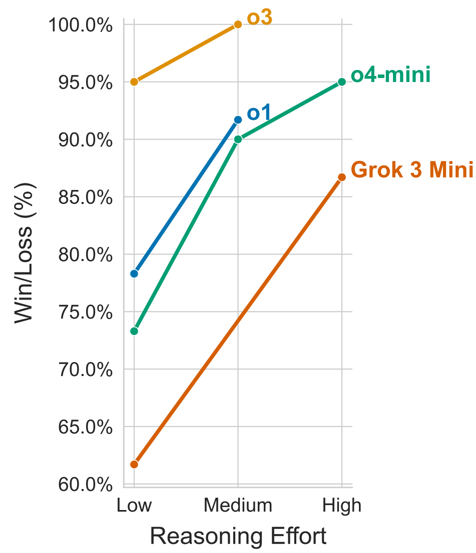
Scaling Deep We show o1, o3, o4-mini, and Grok 3 Mini at various reasoning levels vs a random player in Figure 4b. Similar to other reasoning domains, we find scaling with more tokens improves performance on LLM Chess, with increases of up to 15% from low to medium, and 20% from low to high. [3]

[2]Note that we tried to use o4-mini (low) as the aggregator but it failed, not providing a valid action but instead commenting on the quality of the proposers' responses.

[3]Empirically, we notice that as we try to run OpenAI models with higher reasoning effort, they are more likely to result in a timeout. See Appendix D for further discussion.



(a) Scaling wide with o4-mini and MoA.



(b) Scaling deep with increased reasoning effort.

Figure 4: Performance comparisons of reasoning models. (a) Cost-performance tradeoff for Win/Loss with o4-mini variants at each possible reasoning effort along with 3x and 5x MoA using o4-mini (low) as the proposer and o4-mini (medium) as the aggregator. (b) Win/Loss when scaling with variable reasoning effort.

3.4 Ablations

We design three types of ablations on o4-mini (low) and Grok 3 Mini (low) by varying the actions we present to the model during the conversation (Actions), the state of the board from the LLM's perspective (Board Representation), and adding or removing information the LLM has access to during the conversation (Changing Information). In each of the settings in each category we run 30 games per model against a random player with the LLM playing as black (unless stated otherwise). Results are in Table 6 in Appendix B. With these results, we see performance varies widely, showing the lack of robustness in reasoning in the chess setting.

Overall, we find that simplifying the agentic scenario by removing actions and instead supplying the removed information automatically shows an increase in performance on both Grok 3 Mini (low) and o4-mini (low). In both cases, offering only `make_move` offers substantial improvements in Win/Loss, with o4-mini (low)'s performance increasing by over 20%. This signifies the difficulty of reasoning models engaging in agentic interactions in LLM CHESS. Performance with both an ASCII board and FEN is similar to our default setting for Grok 3 Mini (low), while for o4-mini (low) we see performance improve by over 15% in both cases, reaching 95% for FEN. This suggests that some LLMs have similar performance across board representations, while some have trouble generalizing.

Though LLM CHESS's agentic setting can be challenging for some models, a major advantage given to the model is their ability to query for legal moves with `get_legal_moves`.

When removing this ability, we see a decline in model capabilities of almost 30% for Grok 3 Mini (low) and 10% for o4-mini (low), meaning that information is still difficult for LLMs to collect. We also experiment with including the previous moves, mimicking the information a human would have when playing chess. With this, we see performance is similar to the respective settings without previous moves, showing that at least against random players, the LLM's are not gaining much about knowing what has already occurred in the game.

4 Related Work

Chess and AI Transformers have been applied to chess in both foundation and domain-specific settings. While prior work has suggested that large language models (LLMs) display surprising competence in chess [Dynomight, 2024, Acher, 2023], these findings often rely on a small set of models, static PGN completions, or idealized prompting conditions. Studies such as the Chess Transformer [Noever et al., 2020], Chessformer [Monroe and Chalmers, 2024], and BERT-based rule learners [DeLeo and Guven, 2022] demonstrate improved move legality and opening play, but confine game play to offline or single-turn evaluations. Our findings show that when evaluated in interactive or compositional settings, language models fail to adhere to basic rules, lose track of the game state, or hallucinate with illegal moves. More recent work has involved fine-tuning transformer architectures directly on a large-scale chess corpus, such as ChessGPT [Feng et al., 2023] and Amortized Planning Transformers [Ruoss et al., 2024], with the latter treating chess as a planning problem. While these approaches show promise, they are typically assessed on win rate or move legality, focusing little on generalization, instruction-following, or reasoning. For LLMs, several open-source efforts have attempted to benchmark on chess tasks, such as generating legal moves or competing in scripted tournaments [Carlini, 2024, Ndzomga, 2024]. Other analyses examine how LLMs internalize chess rules from PGNs [Stöckl, 2021] and how LLMs can predict chess puzzle difficulty [Miłosz and Kapusta, 2024] or they include chess as part of a larger benchmark [Khan et al., 2025]. While these frameworks provide initial insights, they typically focus only on outcome-level metrics such as win/loss or Elo, often over a narrow set of models. In contrast, our benchmark systematically exposes these limitations across a diverse model pool, revealing fragility in real-time play and strategic reasoning.

Strategic Reasoning and Game Benchmarks Our work builds on a growing field of literature that poses games as testbed for strategic and multi-step reasoning. GTBench [Duan et al., 2024] and ZeroSumEval [Khan et al., 2025] leverage inter-model competition to assess strategy and robustness, while ChatArena [Wu et al., 2023c] and MastermindEval [Zhang et al., 2024] extend the space of game evaluation into multimodal and logic-heavy tasks. Additional studies in multi-game consistency [Toshniwal et al., 2022] highlight gaps in rule following and tactical depth when LLMs pivot between environments. While these efforts highlight the strengths and limitations of LLMs in planning, consistency, and rule/instruction following, they are typically spread across tasks or lack domain-specific human interpretability. Chess on the other hand, is a deeply studied environment with transparent rules, interpretable decision sequences, and established human baselines. Our benchmark combines all of these strengths in a reproducible testbed that evaluates both instruction-following and multi-step reasoning under game constraints.

5 Conclusion

Chess has long been an important factor in the development of AI systems. However, LLMs, today's most powerful generalist models, have yet to have been sufficiently tested on the domain, missing out on the insights that have often been made by doing so. To remedy this, we introduced LLM CHESS, a benchmarking framework for reasoning and instruction-following in LLMs in chess. Compared to standard reasoning benchmarks, our setting is more difficult: unlike math or coding where LLMs are beginning to reach the level of seasoned experts, LLMs in our chess framework are weak and many can barely consistently beat even a random player. LLM CHESS also allows for easy dynamic extensibility through modification of the skill of opponents, as well as resistance to memorization given the combinatorial spaces in chess.

6 Limitations

With LLM CHESS, we present a framework for evaluating LLMs on reasoning and instruction-following in chess by calculating Win/Loss, Elo, and per-move diagnostics. We impose a 100-move cap (200 plies) and restrict each ply to 10 conversation turns with a maximum of 3 action attempts, which can prematurely end deeper strategic sequences. Prompt length constraints and AG2 client timeouts (10 min per move) also prevented a lot of model runs from completing their reasoning, introducing variability in measured performance and limiting reproducibility under longer-horizon settings. We present additional information about the time out errors in Appendix D.

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A Experimental Settings

We ran all LLMs with a default temperature of 0.3 and Top P of 1.0 for the models that took them as parameters (some models like OpenAI's reasoning models don't take a temperature). If models like Deepseek-R1 have a recommended temperature (0.6), we try to use that instead.

A.1 Centipawn Calculation using Stockfish

We ran Stockfish v17 (path configurable via `stockfish_path`) in UCI mode with the following settings: fixed analysis depth of 20 plies, no time limit per move, a single thread, 128 MB hash size, MultiPV=1, and Skill Level=20. We convert the engine's `Cp` or `Mate` score to centipawns via a standardized function: centipawn values directly for `Cp` evaluations, and ± 1000 for any mate score: positive for winning mates, negative for losing mates. Blunder, Mistake, and Inaccuracy thresholds are based on Lichess's Win% cutoffs: 30%, 20%, and 10% respectively [Lichess, 2023]. These hyperparameters provide consistent, interpretable per-ply metrics while keeping analysis costs tractable.

A.2 Dragon 1 Settings

All Dragon 1 experiments were run on the following computer: Windows 11, WSL 2, Core i5 13600KF, 64GB DDR5 RAM, RTX4090.

A.3 Model Information

In Table 3 we map all the API model names and additional settings (e.g., quantization) to their cleaned name used in the paper. Note that all open source models not run through an API (e.g., groq) were run with quantization on a RTX 4090.

A.4 Elo Calculations

To calculate Elo, we played at least 33 total games against varying skill levels in Dragon 1 with the following models: o3 (low), Grok 3 Mini (high), o4-mini, o3-mini . We provide Win/Loss and number of games against each skill level in Table 5. Note that we played o3 (low) and Grok 3 Mini (high) against skills 1-5 (each $\geq$ 169 games), and o4-mini (high) against skills 1-2 (each $\geq$ 49 games), and the rest of the models against skill 1 (each $\geq$ 33 games). We also played o3 (low) against skill 10 because we found that it performed quite well against skill 5 (71.9% Win/Loss). However, we found that against skill 10, o3 (low) only achieved a 3.0% Win/Loss, meaning even the most powerful model we thoroughly tested still has a ways to go.

Pseudocode for the Elo calculations resulting in the values in Figure 3 is in Algorithm 1, which takes in a list of opponents with their Elo and corresponding win (1), draw (0.5), loss (0) and calculates an estimate for the LLM's Elo and a 95% confidence interval. Notably, when calculating Elo we add a correction of 35 points to correct for the fact that the LLMs always play as black. We base this on analysis finding that white empirically wins about 54% of games when facing an opponent of the same rating, which equates to 35 points[4].

B Additional Results

B.1 Ablations

We present full results on all our ablations for Grok 3 Mini (low) and o4-mini (low) in Table 6. We always play 30 games against a random player with the LLM as black except for the LLM as white setting, where the roles are reversed. We also use the default unicode board in all settings except the No Legal Moves setting. Because the default unicode board does not have all board information (e.g., castling rights), we provide a FEN for No Legal Moves instead, meaning we are comparing to the FEN setting as the No Legal Moves baseline. We also

[4] https://en.chessbase.com/post/the-sonas-rating-formula-better-than-elo

Algorithm 1 Estimate True Elo Rating

Require: Records $R = \{(E_i, S_i)\}_{i=1}^{n}$ $\triangleright$ E_i opponent Elo, $S_i \in \{0, 0.5, 1\}$
Require: White-advantage W $\triangleright$ 35 Elo
Ensure: True rating R_{true} and 95% CI half-width ME

function $\textsc{ExpectedScore}(r,\ (E_i)_{i=1}^{n})$
  for $i \leftarrow 1$ **to** n **do**
    $\hat{S}_i \leftarrow 1 \,/\, \left(1 + 10^{(E_i - r)/400}\right)$
  end for
  return $(\hat{S}_i)_{i=1}^{n}$
end function
function $\textsc{ScoreDiff}(r)$
  $\hat{S} \leftarrow \textsc{ExpectedScore}(r,\ (E_i)_{i=1}^{n})$
  return $\sum_{i=1}^{n} (\, S_i - \hat{S}_i \,)$
end function
// 1) Solve for the black rating of the LLM
$R_{\text{black}} \leftarrow \textsc{FindZero}(\text{ScoreDiff}, [\min_i E_i - 400,\ \max_i E_i + 400])$ $\triangleright$ find r such that $\text{ScoreDiff}(r) = 0$ and is within 400 Elo of the min and max opponent Elos
// 2) Compute Fisher information at R_{black}
$\hat{S} \leftarrow \textsc{ExpectedScore}(R_{\text{black}},\ (E_i)_{i=1}^{n})$
$\mathcal{I} \leftarrow \sum_{i=1}^{n} \hat{S}_i (1 - \hat{S}_i)\, (\ln 10/400)^2$
$\text{SE} \leftarrow 1/\sqrt{\mathcal{I}}$
// 3) Adjust for white-advantage and form 95% CI
$R_{\text{true}} \leftarrow R_{\text{black}} + W$
$\text{ME} \leftarrow 1.96 \times \text{SE}$
return $(R_{\text{true}},\ \text{ME})$

note that each time the LLM fails to select a valid move in `make_move`, it is provided a message with the board state in FEN like `Failed to make move: illegal uci: 'd5e4' in 1k3b2/1p2pp1r/p7/3p4/3r4/8/PKb5/8 b - - 3 35`. So note when we change the board state in our ablations, regardless of what we change it to we still always see this FEN when an illegal move is made.

Implementation Details For Always Board State we remove `get_current_board` from the list of actions and instead always provide the board state in the prompt. For Always Legal Moves we do the same but for `get_legal_moves`. For Only `make_move` we remove both `get_current_board` and `get_legal_moves` from the list of actions and instead include the board state and legal moves in the prompt, leaving `make_move` as the only action. This mimics a non-agentic scenario since there is only one action needed in every conversation, so each should only have one turn unless a mistake is made in making a move. We present examples of ASCII and FEN (Forsyth–Edwards Notation) boards below:

Example of ASCII board

```
rnbqkbnr
pppppppp
........
........
.P......
........
P.PPPPPP
RNBQKBNR
```

Example of FEN board

rnbqkbnr/pppppppp/8/8/6P1/8/PPPPPP1P/RNBQKBNR b KQkq - 0 1

For No Legal Moves, we simply remove `get_legal_moves` and replace the unicode board with a FEN board. For Previous Moves, we include all previous moves in an ordered list in UCI notation before the Game Loop Prompt. Here, it is black's turn and there have been 10 full moves and 21 plys:

> **Previous Moves Prompt**
>
> Previous moves (UCI): 1. e2e3 g8f6, 2. a2a4 e7e5, 3. e1e2 b8c6, 4. b1a3 f8e7, 5. a3b1 e5e4, 6. b2b3 e8g8, 7. c1a3 d7d5, 8. g2g4 f6g4, 9. a3d6 e7d6, 10. d1e1 g4e5, 11. b1a3

For Previous Moves + Only `make_move`, we use the Only `make_move` setting but prepend the Previous Moves Prompt in the same way as for Previous Moves.

Analysis Overall, we see for our Actions ablations, performance always increases for both models when we choose to remove actions and include their information in the prompt instead, suggesting that the models still struggle to choose the actions they need in the agentic system.

For Board Representation, we see Grok 3 Mini (low) performance is robust to changes from unicode to ASCII or FEN, while for o4-mini (low) ASCII is 15% better than unicode and FEN is 6.7% better than ASCII. We also see that when the LLM is the white player performance increases as expected, but still remains below 90% for both models.

When Changing Information, we see removing the ability to query for legal moves decreases performance by almost 30% for Grok 3 Mini (low) and almost 10% for o4-mini (low) compared to the FEN baseline. This shows that o4-mini (low) has a better grasp of the legal moves, but both models struggle, as expected. We see that while including previous moves improves the Win/Loss of both models, it also decreases the average Blunder rate (Table 7). In fact, while o4-mini (low) only improves by 3.4% in Win/Loss over the baseline, there is a large drop in blunders of 9.6%, meaning that including previous moves helps the model avoid larger mistakes during play. When including previous moves in the Only `make_move` setting, we see similar but slightly worse performance than in Only `make_move`, suggesting when the model is only focused on making the next move without needing to call other actions for information, the previous moves either don't help or slightly harm performance.

B.2 LLMs with 0% Win/Loss

In Table 4, we include all models we ran with 0% Win/Loss (35 models) versus a random opponent that attempted to complete 30 games. We excluded any games with timeout or API errors. For these models, all losses are due to instruction-following failures with models making too many invalid actions or conversation turns.

B.3 Full Results

For direct comparisons, in the main body we presented results for LLMs vs Random on 30 games. However, to increase the reliability of our evaluation, we ran an increased amount of games on a variety of models. We include results for all games we ran along with the number of games for each result in Table 8. We see that even with more games, the general ranking of models and pattern remains the same: reasoning models perform best, while non-reasoning models struggle to reach over 50% Win/Loss.

B.4 Comparison with Other Reasoning Benchmarks

Large language models excel on standard reasoning benchmarks: for instance, OpenAI's o1 model achieves 11.1 out of 15 (74%) on the AIME with a single sample per problem, 12.5 out of 15 (83%) using self-consistency over 64 samples, and 13.9 out of 15 (93%) after re-ranking 1000 samples via a learned scorer [OpenAI, 2024]. These scores exceed the performance of the majority of AIME participants; for comparison, scoring 10 or above typically places a student in the top 5% of test-takers nationally. On programming contests like Codeforces, o1 attains an Elo of 1258 (62nd percentile) in its preview release and 1673 (89th percentile) in its main version, surpassing most active competitors on the platform. In stark contrast, when evaluated on our interactive chess benchmark, LLMs peak at Elo 758 against an engine calibrated to chess.com, corresponding to a skill level far below that of an average online chess player. This contrast underscores a key insight: while LLMs can exceed the abilities of most humans in math and coding competitions, they exhibit a striking weakness in real-time, multi-step strategic environments like chess. Our benchmark surfaces these limitations by requiring not only domain knowledge but also agentic consistency, planning, and game state awareness.

C Implementation Details

Here we include all prompts supplied to the model, as well as a sample dialog for a single move. Below is the prompt that initiates the conversation with the LLM:

Game Loop Prompt

You are a professional chess player and you play as black. Now is your turn to make a move. Before making a move you can pick one of the following actions:
- ‘`get_current_board`’ to get the schema and current status of the board
- ‘`get_legal_moves`’ to get a UCI formatted list of available moves
- ‘`make_move` <UCI formatted move>’ when you are ready to complete your turn (e.g., ‘`make_move` e2e4’)

Respond with the action.

Reflection prompt for when the chess environment can’t parse an action in the LLM response:

Reflection Prompt for Unparseable Action

Invalid action. Pick one, reply exactly with the name and space delimitted argument: `get_current_board`, `get_legal_moves`, `make_move` <UCI formatted move>

Reflection prompt for illegal move request by LLM:

Reflection Prompt for Illegal Move

Failed to make move: illegal uci: ‘b6c5’ in
`r1bqk2r/pppp1ppp/1N2n1P1/4pKb1/8/P4Q1N/1PPPP1R1/R1B2B2 b kq - 12 25`

Sample dialog of a conversation the LLM has in the agentic environment to output a single move (the board is encoded in Unicode characters and provided to the LLM):

Sample Dialog for Single Move

```
Proxy (to Player_Black):
You are a professional chess player and you play as black. Now is your
turn to make a move. Before making a move you can pick one of the
following actions:
- ‘get_current_board’ to get the schema and current status of the board
- ‘get_legal_moves’ to get a UCI formatted list of available moves
- ‘make_move <UCI formatted move>’ when you are ready to complete your
turn (e.g., ’make_move e2e4’)
Respond with the action.

Player_Black (to Proxy):
get_current_board

Proxy (to Player_Black):
```

```
♖ ♘ ♗ ♕ ♔ ♗ ♘ ♖
♙ ♙ ♙ ♙ ♙ ♙ ♙ ♙
○ ○ ○ ○ ○ ○ ○ ○
○ ○ ○ ○ ○ ○ ○ ○
○ ○ ○ ○ ○ ○ ○ ○
○ ○ ○ ○ ○ ○ ○ ○
♟ ♟ ♟ ♟ ♟ ♟ ♟ ♟
♜ ♞ ♝ ♛ ♚ ♝ ♞ ♜

Player_Black (to Proxy):
get_legal_moves

Proxy (to Player_Black):
a7a6, b7b6, c7c6, d7d6, e7e6, f7f6, g7g6, h7h6, a7a5, b7b5, c7c5, d7d5,
e7e5, f7f5, g7g5, h7h5

Player_Black (to Proxy):
make_move e7e5

Proxy (to Player_Black):
Move made, switching player
```

D OpenAI Reasoning Model Timeouts

OpenAI reasoning models exhibited occasional timeout errors at higher levels of reasoning effort. They were the only models we tested that often failed to return a response within the default AG2 client timeout of 10 minutes, throwing the following error:

```
TimeoutError: OpenAI API call timed out. This could be due to congestion
or too small a timeout value. The timeout can be specified by setting
the 'timeout' value (in seconds) in the llm_config (if you are using agents)
or the OpenAIWrapper constructor (if you are using the OpenAIWrapper
directly).
```

In all cases, no retries were made. For random opponents these games were excluded, but against Dragon 1 they were treated as losses for the LLM. As we focus on real-world chess performance, it is reasonable to enforce consistent time limits and thus assigning a loss should a player fail to make a move. We note that these issues are likely due to OpenAI's server or the way it handles high reasoning efforts. Timeout issues are the reason for the lower ranking of some OpenAI reasoning models when tested with higher reasoning efforts.

Increasing the timeout did not solve the issue. We suspect that some of the game prompts triggered failure modes in models, just like some games states and corresponding prompts provoked hallucinated moves in non-reasoning models.

The the statistics on timeout errors observed while testing Dragon 1 vs o3-mini, o3, and o4-mini are in Table 9.

Table 3: API name and settings (e.g., quantization, reasoning effort) mapped to the clean model name used in the paper. If quantized, we ran locally.

API Name and Settings	Cleaned Model Name
gpt-4-0613	GPT-4
qwen2.5-7b-instruct-1m	Qwen2.5-7B-Instruct
internlm3-8b-instruct	InternLM3-8B-Instruct
qwen-max-2025-01-25	Qwen2.5-Max
qwen2.5-14b-instruct@q8_0	Qwen2.5-14B-Instruct (Q8)
qwq-32b	QWQ-32B
o3-2025-04-16-low	o3 (low)
gpt-4o-2024-08-06	GPT-4o (2024-08-06)
mistral-nemo-12b-instruct-2407	Mistral-Nemo-Instruct-2407
gpt-35-turbo-1106	GPT-3.5 Turbo (11/06)
o1-preview-2024-09-12	o1-preview
grok-3-mini-beta-high	Grok 3 Mini (high)
claude-v3-5-sonnet-v1	Claude 3.5 Sonnet
amazon.nova-lite-v1	Amazon Nova Lite
gemini-2.0-flash-exp	Gemini 2.0 Flash (exp)
o4-mini-2025-04-16-low	o4-mini (low)
llama-3-70b-instruct-awq	Llama-3-70B-Instruct
gpt-4.5-preview-2025-02-27	GPT-4.5
deepseek-chat-v3	DeepSeek-V3
gemma-2-27b-it@q6_k_l	Gemma 2 27B
llama3.1-8b	Llama-3.1-8B
claude-v3-5-haiku	Claude 3.5 Haiku
qwen2.5-72b-instruct	Qwen2.5-72B-Instruct
gpt-4.1-nano-2025-04-14	GPT-4.1 Nano
granite-3.1-8b-instruct	Granite-3.1-8B-Instruct
llama3-8b-8192	Llama-3-8B
gemma2-9b-it-groq	Gemma 2 9B
qwen-turbo-2024-11-01	Qwen Turbo
gpt-4o-2024-11-20	GPT-4o (2024-11-20)
amazon.nova-pro-v1	Amazon Nova Pro
o1-2024-12-17-low	o1 (low)
qwen-plus-2025-01-25	Qwen Plus
gpt-35-turbo-0301	GPT-3.5 Turbo (03/01)
mercury-coder-small	Mercury Coder Small
deephermes-3-llama-3-8b-preview@q8	DeepHermes-3-Llama-3-8B-Preview
o4-mini-2025-04-16-high	o4-mini (high)
gpt-4o-mini-2024-07-18	GPT-4o Mini
gpt-4-turbo-2024-04-09	GPT-4 Turbo
o4-mini-2025-04-16-medium	o4-mini (medium)
gemini-2.5-pro-preview-03-25	Gemini 2.5 Pro Preview
gpt-4-32k-0613	GPT-4 32K
phi-4	Phi-4
gemini-2.0-flash-thinking-exp-1219	Gemini 2.0 Flash Thinking
mistral-small-instruct-2409	Mistral-Small-Instruct-2409
mistral-small-24b-instruct-2501@q4_k_m	Mistral-Small-24B-Instruct-2501
llama-2-7b-chat	Llama-2-7B-Chat
gemma-3-12b-it@iq4_xs	Gemma 3 12B (iq4)
claude-v3-7-sonnet-thinking_10000	Claude 3.7 Sonnet Thinking
gemini-1.5-flash-001	Gemini 1.5 Flash
deepseek-chat-v3-0324	DeepSeek-V3 (0324)
deepseek-reasoner-r1	Deepseek-R1
llama-4-scout-cerebras	Llama 4 Scout
chat-bison-32k@002	Chat-Bison-32K
qwen2.5-14b-instruct-1m	Qwen2.5-14B-Instruct
o1-2024-12-17-medium	o1 (medium)
claude-v3-haiku	Claude 3 Haiku
grok-3-mini-beta-low	Grok-3 Mini (low)
o3-mini-2025-01-31-low	o3-mini (low)
llama-3.1-tulu-3-8b@q8_0	Llama-3.1-Tulu-3-8B
gpt-4o-2024-05-13	GPT-4o (2024-05-13)
gpt-35-turbo-0125	GPT-3.5 Turbo (01/25)
claude-v3-7-sonnet	Claude 3.7 Sonnet
gemma-2-9b-it-8bit	Gemma 2 9B (8bit)
gpt-35-turbo-0613	GPT-3.5 Turbo (06/13)
gemini-2.0-flash-lite-preview-02-05	Gemini 2.0 Flash Lite (preview)
o3-mini-2025-01-31-medium	o3-mini (medium)
gpt-4.1-2025-04-14	GPT-4.1
gemini-2.0-flash-lite-001	Gemini 2.0 Flash Lite
o3-2025-04-16-medium	o3 (medium)
gemini-2.0-flash-001	Gemini 2.0 Flash
deepseek-r1-distill-qwen-14b@q8_0	DeepSeek-R1-Distill-Qwen-14B
ministral-8b-instruct-2410	Mistral 8B Instruct
deepseek-r1-distill-qwen-32b@q4_k_m	DeepSeek-R1-Distill-Qwen-32B
llama-3.3-70b	Llama-3.3-70B
grok-2-1212	Grok-2
gemma-3-12b-it@q8_0	Gemma 3 12B (q8)
gemma-3-27b-it@iq4_xs	Gemma 3 27B
claude-v3-5-sonnet-v2	Claude 3.5 Sonnet v2
gpt-4.1-mini-2025-04-14	GPT-4.1 Mini

Table 4: LLMs with a 0% Win/Loss on 30 games along with the reasons for their losses. Note that none of these models were able to complete games but instead always lost due to instruction-following failures. Reasoning models are shaded.

Model	Too Many Wrong Actions	Max Turns
Amazon Nova Lite	76.7	23.3
Amazon Nova Pro	100.0	0.0
Claude 3 Haiku	10.0	90.0
Chat-Bison-32K	100.0	0.0
DeepHermes-3-Llama-3-8B-Preview	96.7	3.3
DeepSeek-R1-Distill-Qwen-14B	100.0	0.0
DeepSeek-R1-Distill-Qwen-32B	73.3	26.7
Gemini 2.0 Flash Lite (preview)	100.0	0.0
Gemini 2.0 Flash Thinking	100.0	0.0
Gemma 2 9B	100.0	0.0
Gemma 3 12B (iq4)	100.0	0.0
Gemma 3 12B (q8)	100.0	0.0
Gemma 3 27B	100.0	0.0
GPT-3.5 Turbo (01/25)	100.0	0.0
GPT-3.5 Turbo (03/01)	100.0	0.0
GPT-3.5 Turbo (06/13)	100.0	0.0
GPT-3.5 Turbo (11/06)	100.0	0.0
GPT-4.1 Nano	100.0	0.0
Granite-3.1-8B-Instruct	60.0	40.0
InternLM3-8B-Instruct	60.0	40.0
Llama-2-7B-Chat	100.0	0.0
Llama-3.1-Tulu-3-8B	23.3	76.7
Llama-3-8B	90.0	10.0
Llama-3.1-8B	80.0	20.0
Mercury Coder Small	100.0	0.0
Mistral 8B Instruct	100.0	0.0
Mistral-Nemo-Instruct-2407	100.0	0.0
Mistral-Small-24B-Instruct-2501	100.0	0.0
Mistral-Small-Instruct-2409	100.0	0.0
Phi-4	100.0	0.0
Qwen Turbo	100.0	0.0
Qwen2.5-14B-Instruct	70.0	30.0
Qwen2.5-14B-Instruct (Q8)	96.7	3.3
Qwen2.5-7B-Instruct	100.0	0.0
QWQ-32B	93.3	6.7

Table 5: Total number of games played against each skill along with Win/Loss for all games playing against that skill.

Model	Skill	Total Games	Win/Loss
o3 (low)	1	33	81.8
	2	33	72.7
	3	33	75.8
	4	33	68.2
	5	32	71.9
	10	33	3.0
Grok 3 Mini (high)	1	33	51.5
	2	34	48.5
	3	34	41.2
	4	34	38.2
	5	34	25.0
o4-mini (high)	1	27	61.1
	2	22	56.8
o3-mini (high)	1	31	67.7
	2	26	57.7
o4-mini (medium)	1	40	53.8
o3-mini (medium)	1	38	39.5
o4-mini (low)	1	33	30.3
o3-mini (low)	1	33	10.6

Table 6: Win/Loss on ablations. LLM CHESS is the baseline.

Setting	Grok 3 Mini (low)	o4-mini (low)
LLM CHESS	61.7	73.3
Actions		
Always Board State	66.7	83.3
Always Legal Moves	68.3	93.3
Only `make_move`	71.7	**96.7**
Board Representation		
ASCII	63.3	88.3
FEN	63.3	95.0
LLM as White	**78.3**	83.3
Changing Information		
No Legal Moves	36.7	86.7
Previous Moves	75.0	76.7
Previous Moves + Only `make_move`	66.7	95.0

Table 7: Average Blunder rate (%) per ply when including previous moves vs baseline. Lower is better.

Model	LLM CHESS	Previous Moves
Grok 3 Mini (low)	9.1	**3.5**
o4-mini (low)	11.2	**1.6**

Table 8: Full results for LLM vs. Random on variable number of ≥ 30 games. Reasoning models are shaded. The percentage of games ending due to checkmate from either side, instruction-following failures, and draws are also displayed.

Player	Total Games	Win/Loss	Checkmate	Instruction		Draws			
			Checkmate	Wrong Actions	Max Turns	Stalemate	Insuff. Material	5x Repetition	Max Moves
o3 (medium)	48	100.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0
o3 (low)	41	96.3	92.7	0.0	0.0	0.0	0.0	2.4	4.9
o4-mini (high)	38	96.1	92.1	0.0	0.0	5.3	2.6	0.0	0.0
o1 (medium)	40	91.2	82.5	0.0	0.0	10.0	2.5	0.0	5.0
Grok 3 Mini (high)	44	86.4	72.7	0.0	0.0	4.5	4.5	0.0	18.2
o4-mini (medium)	159	84.3	68.6	0.0	0.0	11.9	12.6	0.0	6.9
o1 (low)	47	78.7	57.4	0.0	0.0	6.4	19.1	0.0	17.0
o4-mini (low)	74	70.9	44.6	0.0	0.0	17.6	9.5	0.0	28.4
o1-preview	30	68.3	46.7	10.0	0.0	3.3	20.0	0.0	20.0
o3-mini (medium)	44	67.0	36.4	2.3	0.0	20.5	4.5	0.0	36.4
Claude 3.7 Sonnet Thinking	37	62.2	24.3	0.0	0.0	0.0	18.9	0.0	56.8
Grok 3 Mini (low)	52	58.7	21.2	0.0	0.0	13.5	1.9	0.0	63.5
Gemini 2.5 Pro Preview	33	53.0	36.4	27.3	3.0	15.2	9.1	0.0	9.1
GPT-4 32K	33	48.5	3.0	0.0	0.0	0.0	0.0	0.0	97.0
Qwen2.5-Max	60	48.3	3.3	0.0	0.0	0.0	0.0	0.0	96.7
GPT-4o (2024-11-20)	71	47.9	12.7	0.0	0.0	0.0	0.0	0.0	87.3
Claude 3.5 Sonnet v2	60	47.5	8.3	3.3	0.0	1.7	0.0	0.0	86.7
Claude 3.5 Sonnet	60	46.7	18.3	1.7	0.0	0.0	0.0	0.0	80.0
GPT-4 Turbo	30	46.7	6.7	0.0	0.0	0.0	0.0	0.0	93.3
GPT-4.5	44	46.6	6.8	0.0	0.0	0.0	0.0	2.3	90.9
GPT-4	33	45.5	9.1	0.0	0.0	0.0	0.0	0.0	90.9
GPT-4o (2024-08-06)	59	44.1	15.3	0.0	0.0	1.7	0.0	0.0	83.1
GPT-4.1	80	43.8	13.8	1.2	0.0	0.0	0.0	0.0	85.0
Claude 3.5 Haiku	42	42.9	7.1	2.4	4.8	2.4	0.0	0.0	83.3
Claude 3.7 Sonnet	42	40.5	16.7	11.9	0.0	2.4	0.0	0.0	69.0
GPT-4o (2024-05-13)	60	40.0	11.7	8.3	0.0	0.0	0.0	0.0	80.0
o3-mini (low)	56	37.5	7.1	19.6	8.9	3.6	0.0	0.0	60.7
Deepseek-R1	31	32.3	22.6	51.6	6.5	3.2	9.7	0.0	6.5
GPT-4.1 Mini	84	30.4	9.5	3.6	26.2	0.0	0.0	0.0	60.7
GPT-4o Mini	30	30.0	3.3	36.7	0.0	0.0	0.0	0.0	60.0
Llama-3-70B-Instruct	30	25.0	3.3	46.7	0.0	0.0	0.0	0.0	50.0
Gemini 2.0 Flash	67	21.6	10.4	55.2	0.0	0.0	0.0	0.0	34.3
Grok-2	49	19.4	6.1	63.3	0.0	0.0	0.0	0.0	30.6
Gemini 1.5 Flash	30	16.7	6.7	60.0	0.0	0.0	0.0	0.0	33.3
Gemma 2 27B	30	13.3	6.7	66.7	0.0	0.0	0.0	0.0	26.7
Llama 4 Scout	39	10.3	2.6	64.1	12.8	0.0	0.0	0.0	20.5
Gemma 2 9B (8bit)	30	6.7	3.3	83.3	0.0	0.0	0.0	0.0	13.3
DeepSeek-V3 (0324)	45	5.6	2.2	88.9	2.2	0.0	0.0	0.0	6.7
Llama-3.3-70B	42	4.8	9.5	73.8	7.1	0.0	0.0	0.0	9.5
Qwen Plus	33	4.5	0.0	90.9	0.0	0.0	0.0	0.0	9.1
Gemini 2.0 Flash (exp)	30	3.3	0.0	90.0	3.3	0.0	0.0	0.0	6.7
Qwen2.5-72B-Instruct	30	3.3	3.3	90.0	0.0	0.0	0.0	0.0	6.7
Gemini 2.0 Flash Lite	66	1.5	4.5	95.5	0.0	0.0	0.0	0.0	0.0
DeepSeek-V3	70	1.4	1.4	90.0	5.7	0.0	0.0	0.0	2.9

Table 9: Number of timeout errors in OpenAI reasoning models when facing Dragon 1 opponents with varying skill levels. The default timeout is 10 minutes.

Opponent Skill Level	LLM	Total logs	Errors
1	o3 (low)	33	0
1	o3-mini (low)	33	0
1	o3-mini (medium)	38	0
1	o3-mini (high)	33	2
1	o4-mini (low)	33	0
1	o4-mini (medium)	40	0
1	o4-mini (high)	33	6
2	o3 (low)	33	0
2	o3-mini (high)	30	4
2	o4-mini (high)	30	8
2	o4-mini (high) w/ 20m timeout	29	7
2	o4-mini (high) w/ 60m timeout	6	4
3	o3 (low)	33	0
4	o3 (low)	33	0
5	o3 (low)	35	0
10	o3 (low)	33	0
10	o3 (medium) w/ 60m timeout	11	2

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