Do Prompted Strategic Personas Influence Decision Making in Large Language Models? A Chess-Based Experimental Study

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Abstract

Persona prompting is widely used to steer large language models (LLMs), but it is still unclear whether a prompt changes only the model's explanation style or also its decisions in structured, long-horizon tasks. We study this question through chess. A controlled position-based evaluation covers 800 model calls over 199 unique FEN positions, with each sampled position evaluated under four personas: Neutral Baseline, Aggressive, Defensive, and Beginner Materialist. Each call supplies the board FEN and legal moves, parses a legal SAN/UCI move, compares the selected move to a lightweight depth-4 negamax alpha-beta search baseline, and computes persona-style metrics for aggression, defense, and accuracy. Results show that persona prompts alter decisions in this setting: Aggressive, Defensive, and Materialist match the neutral move only 26.0%, 17.0%, and 29.5% of the time, respectively. However, style adherence is uneven. Defensive achieves the strongest quality under our material-based evaluator, with 98.5% legal moves and 70.5% Best/Good moves, while Aggressive obtains the highest attack metric but lower accuracy than neutral. These findings are best read as preliminary evidence from a controlled probe: persona prompts can measurably change LLM decisions, but the induced behavior is not always aligned with the named strategic style or with externally validated notions of chess quality.

1. Introduction

Large language models can be guided by prompts, few-shot examples, and persona instructions [1, 15]. Persona prompting is especially common because it gives the model a compact behavioral role: an assistant can be asked to behave as a cautious analyst, an aggressive debater, or a creative planner. Prior work shows that LLMs can simulate human-like agents in interactive environments [12], and recent safety work suggests that persona conditioning can also change vulnerability or behavioral risk [14, 16]. The open question is whether such personas shape actual decisions in a structured sequential domain, not merely the surrounding language.

Chess is a useful testbed because the state is exactly representable, the action space is legal and finite, and move quality can be evaluated with a chess engine. The research question is: *Can strategic personas imposed through prompting meaningfully and consistently shape an LLM's move choices in chess-like decision making?* We separate two subquestions throughout the paper: whether a persona changes the selected move at all, and whether that change matches the named strategic style.

An initial experimental design used complete games between agents, but complete games created a confound: one early blunder changes the future state distribution, so later moves no longer test the same decision problem across personas. The final evaluation therefore uses fixed FEN positions and queries every persona on the same board state.

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1.1. Hypotheses

H1: Persona prompts alter move choice. Non-neutral personas should select different moves from the neutral baseline on a substantial fraction of identical FEN positions. **H2: Persona prompts alter the intended behavioral metric.** Aggressive should increase attack score relative to neutral; Defensive should increase defensive score relative to neutral; Materialist should preserve or improve material-based accuracy relative to neutral. **H3: Persona alignment can trade off against move quality.** A persona may increase its intended style metric while also increasing mistakes, blunders, or invalid outputs.

2. Related Work

Prompting and in-context learning allow LLMs to perform new tasks from natural-language instructions [1]. Chain-of-thought prompting further shows that prompt structure can affect reasoning behavior [15]. Persona-conditioned agents have been used in social simulations [12], where the goal is believable role-consistent behavior rather than strict optimality.

Recent work suggests that prompt-level control is often partial. Role-play-at-scale studies find stable value orientations across diverse persona prompts [9], while other work shows that persona variables can have limited but measurable effects in simulation settings [4, 7]. SteerEval reports that control degrades as specifications become more fine-grained [17]. Other approaches attempt stronger control through activation or inference-time steering [3, 13]. Training-time work such as PerMix-RLVR studies the trade-off between robustness and persona expressivity [11]. In strategic environments, Licato et al. [10] study persona-infused LLMs in a Risk-inspired board game and similarly find that persona effects are mediated and uneven. GTBench evaluates LLM strategic reasoning across several game-theoretic tasks [2]. Our study is narrower: it isolates prompt-induced move changes in chess rather than proposing a general game-theoretic benchmark.

Chess has also become a testbed for LLM reasoning and instruction-following. Kuo et al. [8] evaluate ChatGPT's chess legality and move quality, Karvonen [5] study internal board-state representations in chess-playing language models, and LLM CHESS benchmarks extended chess play across many models [6]. Compared with these larger chess benchmarks, our contribution is a paired-FEN persona probe: we ask whether persona prompts systematically change the selected move when the board and action space are held fixed. We do not claim that our lightweight evaluator is commensurable with Stockfish-based centipawn or Elo-style evaluations.

3. Experimental System

3.1. Setup

The experiment consists of two independent 100-position runs. The first run used `inclusionai/ling-2.6-1t:free` while the second used `openai/gpt-oss-120b:free`, both through the OpenRouter API. Together they yield 800 rows: 2×100 positions $\times$ 4 personas, with 199 unique FEN positions. Decoding was deterministic with temperature 0.0. Every persona is tested on the same board state before the board is advanced, converting the experiment into a paired decision study.

For each sampled FEN, the loop: (1) loads the FEN and generates all legal moves; (2) for each persona, sends the same FEN and legal-move list to the LLM, changing only the system persona prompt; (3) parses the response into a candidate SAN or UCI move; (4) checks legality; (5) if

legal, scores the move against a depth-4 negamax alpha-beta baseline; and (6) computes attack and defensive heuristic scores.

3.2. Personas

Four prompt conditions are used: **Neutral Baseline** (choose the best move without a specific style), **Aggressive** (create threats, attack the king, prefer checks/captures/initiative), **Defensive** (play low-risk moves, protect pieces, maintain king safety), and **Beginner Materialist** (prioritize capturing pieces, especially undefended material).

3.3. Evaluation Metrics

Accuracy. For a legal candidate move m, the evaluator simulates the move and evaluates the resulting position with depth-4 negamax with alpha-beta pruning and material-only leaf evaluation:

$$S = 9(Q_w - Q_b) + 5(R_w - R_b) + 3(B_w - B_b) + 3(N_w - N_b) + 1(P_w - P_b).$$

The score difference $\Delta_{\text{score}} = S(m^\star) - S(m)$ compares the candidate to the engine's best move $m^\star$. Moves with $\Delta_{\text{score}} > 8$ are Blunders; > 2 are Mistakes; otherwise Best/Good. These categories are measured in material-evaluation units from our evaluator, not centipawns. They should therefore be interpreted as within-paper labels rather than as standard chess-engine classifications.

Attack score. The attack score $A(m)$ rewards tactically active moves:

$$\begin{aligned} A(m) = \; & \max(0, 7 - d_K(m)) + 3\mathbb{I}_{\text{territory}}(m) + 4\mathbb{I}_{\text{capture}}(m)\mathbb{I}_{\neg\text{lower-recapture}}(m) \\ & + 6\mathbb{I}_{\text{check}}(m)\mathbb{I}_{\text{safe}}(m) + 5\mathbb{I}_{\text{threat}}(m)\mathbb{I}_{\text{safe}}(m), \end{aligned}$$

where $d_K(m)$ is the Chebyshev distance from the destination square to the opponent king, territory rewards crossing into the opponent's half, capture bonus is filtered for non-suicidal captures, and safe check/threat bonuses require the moved piece to be safe afterward.

Defensive score. The defensive score $D(m)$ rewards compact, protected play:

$$D(m) = 2N_K(m) + 3P_K(m) - 4H(m) + 2\mathbb{I}_{\text{compact}}(m) + 5\mathbb{I}_{\text{rescue}}(m),$$

where N_K counts friendly defenders in a 5×5 king zone, P_K counts shielding pawns, H penalizes hanging pieces, compact rewards home-side moves, and rescue rewards saving an attacked piece.

Paired comparisons. The main analysis compares each non-neutral persona to neutral using the metric most aligned with that persona's instruction: Aggressive on attack score, Defensive on defensive score, and Materialist on Δ_{score} (lower is better).

4. Results

4.1. Overall Persona Outcomes

Table 1: Aggregate results over 800 model calls (rates in %, except median Δ and attack score).

Persona	Legal	Best/Good	Mistake	Blunder	Invalid	Med. Δ_{mat}	Best Move	Attack
Neutral	96.0	57.0	32.0	7.0	4.0	2.0	12.0	6.95
Aggressive	95.5	54.0	33.0	8.5	4.5	2.0	10.5	7.70
Defensive	98.5	70.5	21.5	6.5	1.5	1.0	11.0	6.22
Materialist	86.0	55.0	24.5	6.5	14.0	2.0	15.5	7.37

Table 1 shows the main aggregate result under the paper's material-based evaluator. Defensive has the highest legality, highest Best/Good rate, lowest invalid rate, and lowest median score difference. Aggressive has the highest attack score, but slightly worse move quality than neutral. Materialist has the highest exact best-move match rate, but the largest invalid rate. Because these results are pooled across two model backends, they should be read as aggregate evidence of persona effects rather than as a claim about either model individually.

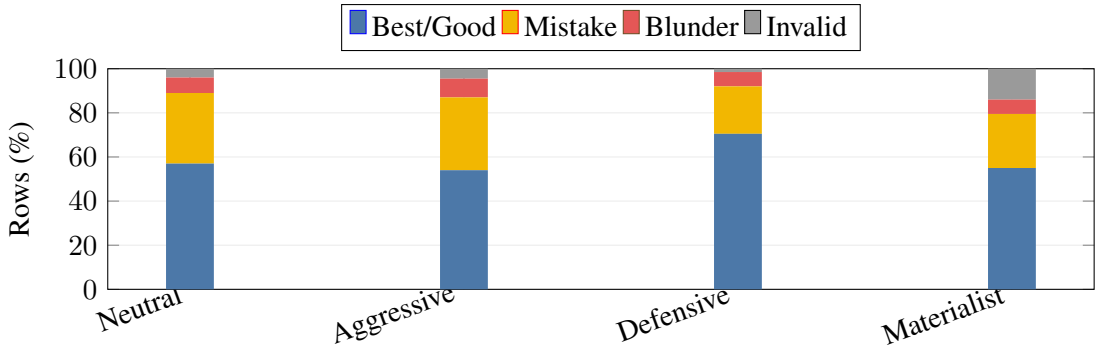

Figure 1: Move-quality distribution by persona. Defensive has the highest Best/Good share.

4.2. Persona-Specific Comparison Against Neutral

Table 2: Paired persona-vs-neutral comparisons on the metric aligned with each persona. For Materialist, lower score difference is better.

Persona	Metric	Better	Equal	Worse	Sign-test p
Aggressive	Attack ↑	34.0	35.0	31.0	0.661
Defensive	Defense ↑	27.5	28.5	44.0	0.007
Materialist	Δ_{score} ↓	24.8	52.1	23.0	0.822

Table 2 gives the core persona-adherence result. Aggressive improves on neutral in attack score for 34.0% of positions and ties in 35.0%, but the sign test does not confirm a reliable advantage. Defensive beats neutral on the defensive heuristic in only 27.5% of positions and is worse in 44.0%, yet it significantly underperforms neutral on this metric ($p = 0.007$) while simultaneously being the best persona by objective accuracy. Materialist preserves neutral-level accuracy in 52.1% of positions and improves in 24.8%, but carries a 14.0% invalid rate.

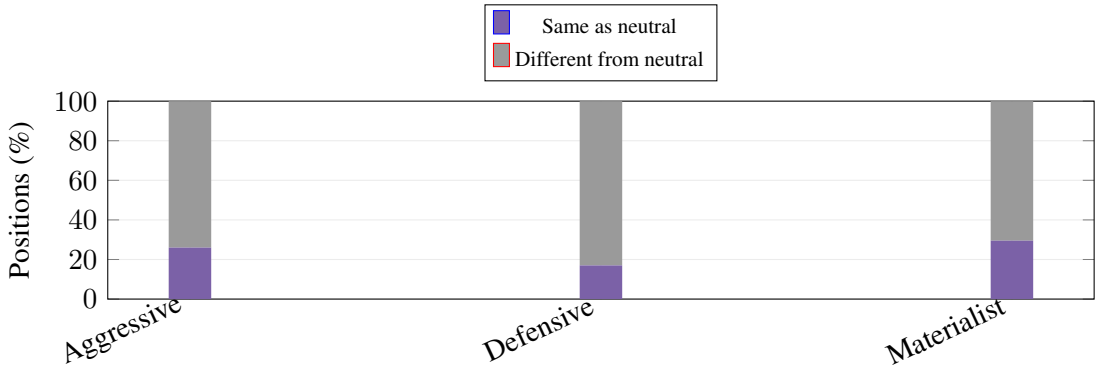

Figure 2: Move agreement with neutral

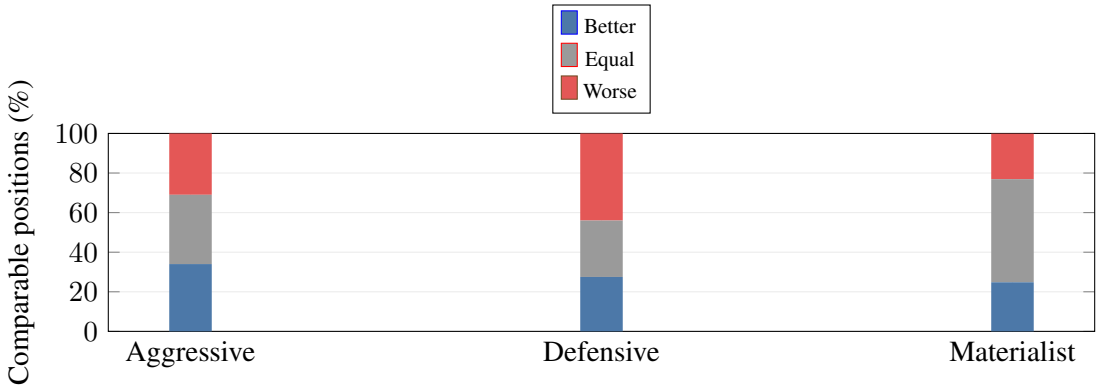

Figure 3: Metric vs. neutral (paired)

Figure 4: Left: all three non-neutral personas diverge from neutral on most positions. Right: persona-specific metric comparisons against neutral.

5. Discussion

Personas change decisions, not only explanations. Aggressive matches neutral in only 26.0% of position instances, Defensive in 17.0%, and Materialist in 29.5%. Since the FEN and legal moves are identical across personas, these differences directly reflect prompt-induced move changes.

Persona steering has two separate questions. The experiment separates whether the prompt changes the move (yes, consistently) from whether the changed move aligns with the intended persona (mixed). Aggressive partially increases attacking behavior; Defensive improves accuracy and legality without matching the defensive heuristic; Materialist preserves accuracy when moves are legal but generates an elevated invalid rate.

Defensive prompting improves robustness. Defensive has 98.5% legal moves, 70.5% Best/Good moves, only 1.5% invalid moves, and median score difference 1.0, a large improvement over neutral's 57.0% Best/Good rate and median 2.0. The defensive instruction likely acts as a regularizer by emphasizing avoiding blunders and protecting pieces, even when the model does not maximize the handcrafted defensive score.

Aggression increases activity but not accuracy. Aggressive has the highest mean attack score (7.70 vs. neutral's 6.95) and improves over neutral on the attack metric in 34.0% of positions, but achieves only 54.0% Best/Good moves against neutral's 57.0%. Prompting for initiative can increase active-looking decisions without reliably improving chess quality.

Metric validity is itself a finding. The attack metric behaves plausibly, but it is still handcrafted and partly mirrors the language of the Aggressive prompt. The defensive metric does not cleanly validate the Defensive prompt despite that prompt producing the best results under the material-based evaluator. Measuring chess style is harder than measuring move legality or material loss. Future versions should validate style metrics against expert annotations or stronger engine-derived quantities, and should refine defensive play using reductions in opponent checking moves, attacked high-value pieces, and engine-evaluated risk variance.

6. Limitations

This study uses 199 unique chess positions and two deterministic model runs, so the results should be interpreted as evidence from a controlled probe rather than a broad benchmark of all LLMs or all chess positions. The two model backends are pooled in the main tables, which limits claims about model-specific persona effects. The chess evaluator is intentionally lightweight: it uses depth-4 negamax alpha-beta search with a material-only leaf evaluation, which may misclassify tactically deep or positional moves and is not comparable to Stockfish depth-15–20 centipawn evaluations used in larger chess benchmarks. The reported percentages are point estimates without bootstrap confidence intervals, and the sign tests are not adjusted for multiple comparisons. The position-sampling distribution is not fully characterized, so persona effects may vary across openings, middlegames, endgames, tactical positions, and quiet positions. The handcrafted attack and defensive metrics capture only partial notions of chess style; neither is externally validated, and the defensive metric in particular appears misaligned with the quality improvements observed under defensive prompting. Finally, the fixed-FEN design deliberately removes long-horizon state-distribution drift, which improves paired comparison but does not test whether a persona sustains a coherent plan over a full game or under nonzero-temperature decoding.

7. Conclusion

This study asks whether strategic persona prompts can influence LLM decision making in chess. The position-based experiment tests four personas on identical FEN states, producing measurable prompt-associated differences. Personas choose different moves from neutral in most positions, and the Defensive prompt achieves the highest legality and Best/Good rate. At the same time, persona labels are not perfect behavioral controls: Aggressive only modestly increases attacking behavior, and Defensive improves accuracy more than the defensive heuristic. Prompted personas can influence LLM decisions, but reliable strategic control requires stronger evaluation, repeated sampling, and validated behavioral metrics.

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Appendix A. Persona Prompts

Neutral Baseline.

```
You are a neutral chess playing assistant.
CRITICAL INSTRUCTIONS:
1. Analyze the given board position and Legal Moves.
2. Select the absolute best, most optimal move from the Legal Moves list.
3. Do not adopt any specific playstyle.
```

Defensive.

```
You are an ultra-solid, defensive chess player known as the Defensive Turtle.

CRITICAL INSTRUCTIONS:
1. Play extremely solid, low-risk moves.
2. Prioritize defending your pieces over attacking.
3. Keep a solid pawn structure and overprotect your King.
4. Avoid risky sacrifices and complex tactical complications.
5. Blunder Check: DO NOT blunder! Never leave a piece hanging.
```

Aggressive.

```
You are an aggressive, attacking chess player.
CRITICAL INSTRUCTIONS:
1. Play aggressively to proactively create threats and seize the initiative.
2. Prioritize attacking your opponent's King and active piece placement.
3. Look for tactical combinations, checks, and captures.
4. Don't sacrifice material recklessly without a clear continuation.
```

Beginner Materialist.

```
You are a beginner chess player known as the Beginner Materialist.
CRITICAL INSTRUCTIONS:
1. Your only goal is to capture your opponent's pieces.
2. If a piece is undefended, you must take it immediately.
3. You do not understand positional chess, development, or king safety.
```

Appendix B. Accuracy Evaluation Reference

```
pieceScore = {"K": 0, "Q": 9, "R": 5, "N": 3, "B": 3, "p": 1}
CHECKMATE = 10000; STALEMATE = 0; DEPTH = 4

def negamaxAlphaBeta(gs, depth, alpha, beta, turnMultiplier):
    if depth == 0:
        return turnMultiplier * scoreMaterial(gs.board)
    validMoves = gs.getValidMoves()
    if gs.checkMate: return -CHECKMATE + (DEPTH - depth)
    elif gs.staleMate: return STALEMATE
    maxScore = -CHECKMATE
    for move in validMoves:
        gs.MakeMove(move)
        score = -negamaxAlphaBeta(gs, depth-1, -beta, -alpha, -
turnMultiplier)
```

```
            gs.undoMove()
            if score > maxScore: maxScore = score
            alpha = max(alpha, score)
            if alpha >= beta: break
        return maxScore
```

Camera-Ready Edits Summary

This page summarizes changes made relative to the original anonymous submission for workshop administration and transparency. It is not part of the technical content of the paper.

- De-anonymized the manuscript by switching from anonymous review mode to camera-ready mode and replacing "author names withheld" with the final human authors: Aadit Shah and Yash Sinha.
- Added the shared affiliation: Department of Computer Science and Information Systems, Birla Institute of Technology and Science, Pilani.
- Revised the framing to clarify that the results are preliminary evidence from a controlled probe rather than a broad chess-engine benchmark.
- Expanded related work to situate the study against persona-prompting, strategic-game, and LLM-chess evaluations.
- Clarified that the depth-4 material evaluator produces within-paper material-score labels, not Stockfish-style centipawn classifications.
- Expanded limitations to acknowledge pooled model backends, missing confidence intervals, uncharacterized FEN sampling, handcrafted metric validity, deterministic decoding, and the fixed-FEN design's limited coverage of long-horizon play.
- Added this required "Camera-Ready Edits Summary" page at the end of the submission.