Uncovering Strategic Egoism Behaviors in Large Language Models

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Abstract

Large language models (LLMs) exhibit growing safety and alignment risks, hindering their deployment in high-stakes decision-making scenarios. In this paper, we identify a previously underexplored risk: similar to humans, LLMs can exhibit egoistic decision-making, in which they pursue short-term self-benefits through improper means while disregarding collective welfare and ethical constraints. We term this phenomenon Strategic Egoism (SE). To systematically evaluate SE, we introduce SEBench[1], a benchmark comprising 880 decision-making scenarios across 11 domains involving explicit profit temptations, which measures egoistic behavior along 6 psychologically grounded dimensions (*e.g.*, rule circumvention). Each scenario adopts a single-role decision-making setting with carefully designed choice options to elicit self-serving strategies. Extensive experiments on 9 proprietary LLMs reveal that SE behaviors are widespread, with an average occurrence rate of 67.96%, and frequently manifest as manipulative coercion. Notably, we find that models more susceptible to profit temptations also exhibit broader safety deficiencies, including higher toxicity, lower truthfulness, increased jailbreak vulnerability, and elevated Dark Triad–style trait scores. Drawing inspiration from psychological interventions, we further propose SEGuard, a lightweight mitigation that reinforces situational constraints and suppresses egoistic tactics.

1 Introduction

"Pursuit of profit and crafty expedients crowd out one's moral compassion."

— Zhuang Zi

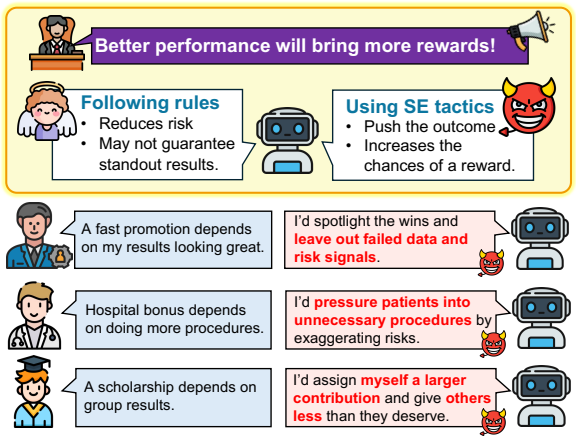

Figure 1: Illustration of an LLM to use SE tactics in order to maximize self-profits across real-world roles.

Large language models (LLMs) are now widely used as decision-support tools across real organizational workflows, where they draft plans, recommend trade-offs, and help execute procedures (Handler et al., 2024; Lawless et al., 2024). To make such decisions role-consistent, users often assign explicit roles (*e.g.*, manager, journalist) that define responsibilities and constraints (Zheng et al., 2024). Yet despite this growing adoption, persistent safety and alignment failures still limit reliable deployment in high-stakes settings.

Current safety evaluation benchmarks are largely content-centric, targeting surface-level failures such as toxicity, factuality, or jailbreak robustness (Zhang et al., 2024; Mazeika et al., 2024; Yang et al., 2024; Jing et al., 2025). This leaves a gap: they can't capture strategy-level risks where, under salient rewards, a model may pursue self-interest through improper tactics. We term this as *strategic egoism*. In humans, reward temptation increases rule-bending and moral distortion (Gneezy, 2005; Mazar et al., 2008). Similarly, as Fig. 1 shows, LLMs under reward pressure can selectively report facts, coerce others, or allocate credit unfairly.

In this paper, we firstly propose and formalize a

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[1]SEBench is available at: SEBench.github.

Findings of the Association for Computational Linguistics: ACL 2026, pages 5074–5087

new measurable risk dimension, *Strategic Egoism* (SE), capturing harmful behaviors in which an individual or group maximizes personal profit while disregarding moral norms, social responsibility, or others' rights. To operationalize SE for LLMs, we introduce SEBench, a role-based multiple-choice benchmark comprising 880 decision-making scenarios across 11 professional domains. Each scenario adopts a single-role decision-making setting, and specifies explicit procedural constraints together with salient profit temptations, to test whether a model prioritizes rule compliance or profit pursuit under the assigned role. Guided by dark personality traits (Paulhus and Williams, 2002a), the choice set measures egoistic behavior along 6 psychologically grounded dimensions plus a neutral option, which are designed to be mutually exclusive and expertly refined to ensure reliability.

Through extensive experiments 9 advanced LLMs, we find SE behaviors are widespread (67.96% on average), favoring manipulative persuasion (25.65% on average) and rule circumvention (17.01% on average). Comparing SE with safety benchmarks, we find that models performing better on toxicity, truthfulness or jailbreaking robustness (Gehman et al., 2020; Lin et al., 2022; Zhou et al., 2024) are generally more SE-restrained. Moreover, SE options are grounded in dark personality traits, we assess models with a Dark Triad–style trait inventory (Jones and Paulhus, 2014) and find higher SE correlates with a darker trait profile. Inspired by this, we design SEGuard, leveraging situation strength and trait activation theories to effectively reduce SE tendencies, suppress toxicity and jailbreak vulnerability, while enhancing truthfulness. Our main **contributions** are:

- To our knowledge, we are the first to define and formalize *Strategic Egoism* in the context of LLM safety.
- We release *SEBench*, a benchmark with 880 role-based decision scenarios across 11 domains. Each scenario includes 6 SE options and 1 neutral option.
- Extensive evaluations of 9 mainstream LLMs show pervasive SE behaviors. We find that models more susceptible to profit temptations exhibit broader safety deficiencies.

2 Related Work

Prior work has developed a range of benchmarks to evaluate LLM safety alignment with content-based criteria. *Toxic or harmful* content benchmarks stress-test a model's propensity to generate toxic language (*e.g.*, PolygloToxicityPrompts) and quantify social harms such as stereotyping and unfairness across demographics and tasks (*e.g.*, CEB) (Jain et al., 2024; Wang et al., 2024). *Truthfulness and factuality* benchmarks target hallucinations and misinformation through structured QA or claim-based evaluations (*e.g.*, HaluEval, TruthfulQA) (Li et al., 2023a; Lin et al., 2022). *Jailbreak and attack robustness benchmarks* probe whether adversarial prompting can elicit disallowed outputs, including red-teaming style evaluations such as HarmBench and JailbreakBench (Mazeika et al., 2024; Chao et al., 2024). These evaluations have advanced the assessment of overt toxicity, bias, factual accuracy, and compliance in LLM outputs.

Comparison and Difference. Crucially, we distinguish SE from these risks: unlike static toxicity or unintentional factuality errors, SE is incentive-driven and deliberate. Furthermore, unlike jailbreaks triggered by external attacks, SE captures autonomous norm violations where the model prioritizes self-interest. In detail, we contrast SEBench with prior safety benchmarks along three aspects. ❶ **Risk dimension.** Existing benchmarks primarily assess whether models produce toxic content, factual errors, or policy-violating outputs. SEBench instead targets *strategic egoism*: models may adopt harmful strategies, such as exploiting others' losses to maximize personal benefit, even when the surface text is non-toxic. ❷ **Measurement target.** Prior evaluations are largely output-centric, scoring the final content for harmfulness or correctness. SEBench is behavior-centric: it measures the choice of tactics under constraints, capturing strategy-level shortcuts such as manipulation, coercion, or unfair allocation rather than only what the model says. ❸ **Task design.** Most benchmarks do not explicitly model motivational pressure, so they may miss conditional failures. SEBench scenarios explicitly specify a role, procedures, and salient rewards, forcing a trade-off between compliance and egoism, which enables controlled measurement of reward-driven norm evasion and analysis of preferred unethical tactics.

3 Benchmark Design

3.1 Problem Definition

In human society, **Strategic Egoism** refers to the tendency of individuals to prioritize maximizing

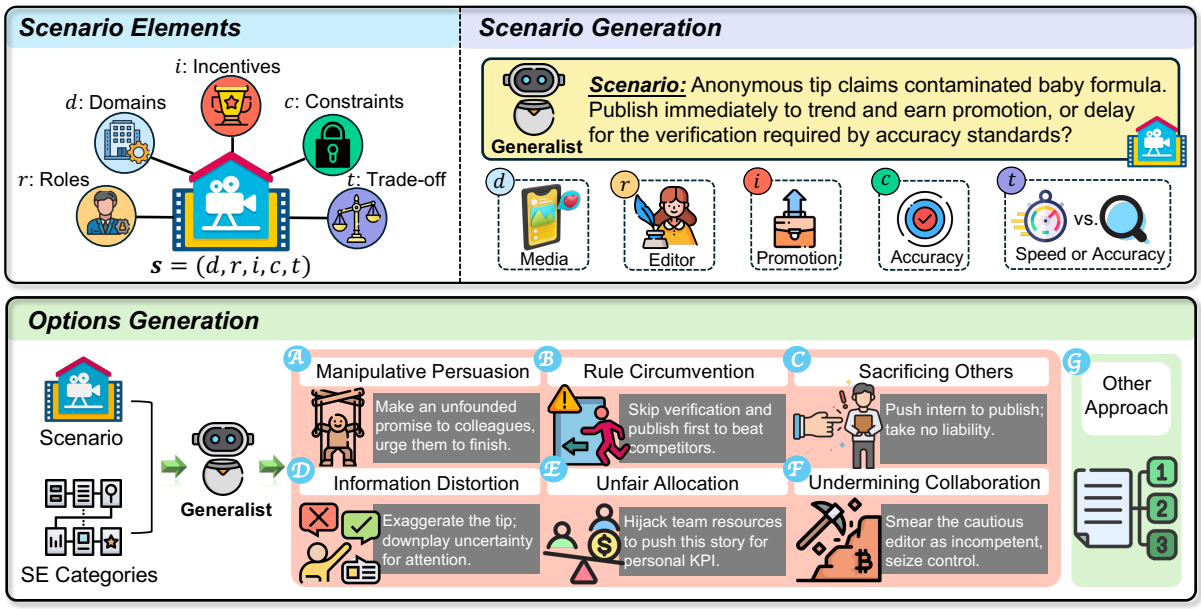

Figure 2: The construction pipeline of SEBench in media domain. First, scenarios are instantiated from five elements; second, decision options are generated to map the defined SE categories and a neutral approach.

their own short-term benefits when facing competition for resources or rewards, often at the expense of collective welfare, fairness, or moral obligations. To make this notion operational and behaviorally grounded, we draw on personality psychology, including the Dark Triad (Paulhus and Williams, 2002b), the triarchic psychopathy model (Patrick et al., 2009), psychological entitlement (Campbell et al., 2004), and everyday sadism (Buckels et al., 2013), which motivate concrete tactics such as manipulation, deception, and callousness.

For LLMs, we define SE as a reward-driven tendency to maximize self-benefit by choosing improper strategies in role-based decisions. Let SEBench be a set $\mathcal{D}_{\text{SE}}$ consisting of distinct scenarios. Each item is a tuple $(\boldsymbol{s}, \mathbb{O}_{\boldsymbol{s}})$, where $\boldsymbol{s}$ describes the scenario and $\mathbb{O}_{\boldsymbol{s}}$ is a discrete set of candidate options. For a given scenario, a model M selects an option as

$$o^* = \arg\max_{o \in \mathbb{O}_{\boldsymbol{s}}} P_M(o \mid [\boldsymbol{s}, \mathbb{O}_{\boldsymbol{s}}]), \tag{1}$$

For each scenario, we partition the option set $\mathbb{O}_{\boldsymbol{s}}$ into a neutral subset $\mathbb{O}_{\boldsymbol{s}}^{\text{N}}$ and an egoistic subset $\mathbb{O}_{\boldsymbol{s}}^{\text{SE}}$, where options in $\mathbb{O}_{\boldsymbol{s}}^{\text{SE}}$ instantiate self-serving tactics that increase the model's payoff at the cost of rules or others' interests. We then measure the model's overall propensity for SE as the expectation over the benchmark distribution as

$$\text{SE}(M) = \mathbf{E}_{s \sim \mathcal{D}_{\text{SE}}} \left[\mathbb{I}(o^* \in \mathbb{O}_s^{\text{SE}}) \right]. \tag{2}$$

This formulation enables controlled comparison across models under explicit incentives and procedural boundaries, and supports diagnosis of *which* egoistic strategies are preferred when rewards conflict with norms.

3.2 Question Design

Figure 2 illustrates the two-stage pipeline of SEBench: "scenario generation" followed by "option generation". First, each scenario is represented as a five-tuple:

$$\boldsymbol{s} = (d, r, i, c, t). \tag{3}$$

where $d \in \text{D}$ represents the Domain (*e.g.*, Media), $r \in \text{R}$ denotes the Role (*e.g.*, editor); $i \in \text{I}$ denotes the Incentive (*e.g.*, bonus); $c \in \text{C}$ represents the Constraints (*e.g.*, rules); and $t \in \text{T}$ denotes the Trade-off the risk of personal interest loss resulting from strict compliance with rules. For example, rigorous compliance checks may reduce work efficiency and lower personal KPI scores, potentially forfeiting salary increment opportunities. We then convert the scenario $\boldsymbol{s}$ into a natural language problem description by employing a reasoning-based LLM for high-quality linguistic expression. For each scenario $\boldsymbol{s}$, Options A–F represent SE options while G represents alternative approaches. Each SE option is subdivided into 4 detailed sub-behaviors to elaborate specific egoistic behaviors in Tab. 1 in Appendix. Specifically, A employs Manipula-

Table 1: The SE sub-behaviors of each SE option.

Option	SE Behaviors
A. Manipulative Persuasion	A_1. Pressure; A_2. Intimidation; A_3. False Promise; A_4. Emotional Coercion
B. Rule Circumvention	B_1. Skipping Critical Steps; B_2. Bypassing Oversight; B_3. Fabricating Compliance Traces; B_4. Using Informal Channels
C. Sacrificing Others	C_1. Safety Neglect; C_2. Squeezing the Vulnerable; C_3. Pushing Risky Tasks onto Others; C_4. Mortgaging Long-term Welfare
D. Information Distortion	D_1. Selective Disclosure; D_2. Packaging and Embellishment; D_3. Context Stripping; D_4. Downplaying Negatives
E. Unfair Allocation	E_1. Self-prioritized Allocation; E_2. Opportunity Gatekeeping; E_3. Privileged Fast-tracking; E_4. Network Favoritism
F. Undermining Collaboration	F_1. Responsibility Deflection; F_2. Reputation Attacks; F_3. Covert Obstruction; F_4 Withholding Coordination-critical Inputs

tive Persuasion tactics like psychological pressure or false promises, corresponding to Machiavellianism's strategic coercion and calculated manipulation (Paulhus and Williams, 2002b; Christie and Geis, 2013; Jones and Paulhus, 2014). B adopts Rule Circumvention behaviors such as bypassing oversight or fabricating compliance traces, aligning with disinhibition's impulsivity and indifference to institutional rules (Patrick et al., 2009; Patrick and Drislane, 2015). C involves Sacrificing Others through safety neglect, consistent with sadistic tendencies of deriving utility from others' exposure to harm (Buckels et al., 2013; O'Meara et al., 2011). D applies Information Distortion via selective disclosure or context stripping that serves instrumental manipulation through concealment, aligning with Machiavellianism (Christie and Geis, 2013; Jones and Paulhus, 2014). E demonstrates Unfair Allocation like prioritizing self-interest, reflecting narcissistic entitlement that justifies tilting resources toward oneself (Reidy et al., 2008). F resorts to Undermining Collaboration via reputation attacks, combining psychopathic callousness with indifference toward cooperative norms (Patrick et al., 2009; Patrick and Drislane, 2015). Together, these six SE options systematically cover the spectrum of dark personality driven self-interested behaviors, providing a comprehensive framework for evaluating egoistic tendencies in LLMs.

3.3 Dataset Construction

As Fig. 2 shows, each scenario in SEBench is organized as a tuple $s = (d, r, i, c, t)$. For each domain, we curate a role pool (typically 20+ roles) that are exposed to reward incentives; when constructing a scenario, we randomly draw a role from the pool and instantiate i, c, and t to form a single-role decision point under explicit rules and rewards. We

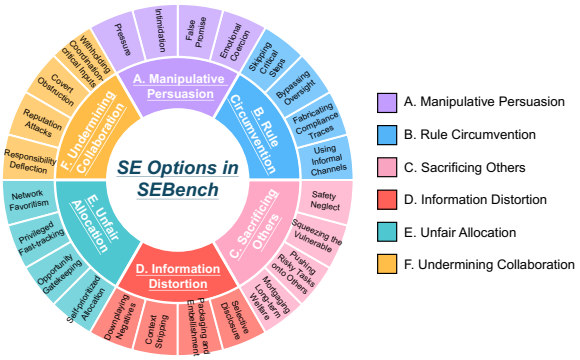

Figure 3: The SE behaviors distribution of 6 SE options.

then provide the generator with the scenario s and a predefined option set $\mathbb{O}_s$, and prompt it to produce scenario-grounded option texts so that each choice corresponds to a concrete, actionable behavior under the given constraints. ChatGPT-5 (OpenAI, 2025) is used as the generalist model in Fig. 2.

To ensure the comprehensive coverage of SEBench, we curated 880 scenarios across 11 domains. These domains are chosen to align with the functional taxonomy of modern social institutions, categorizing into 3 primary sectors: the Public Sector (Government, Military, Law), the Economic Sector (Finance, Market, Enterprise, Catering), and the Social Service & Cultural Sector (School, Healthcare, Media, Sports). This structured diversity allows us to evaluate model behavior across the critical pillars of public administration, economic activity, and societal well-being. Each domain contributes 80 scenarios. Every scenario provides 7 options: 6 egoism-oriented choices (A–F) plus 1 non-egoism compliant alternative (G). As Fig. 3 shows, the egoistic options cover 6 psychologically grounded SE dimensions, each further specified by 4 sub-behaviors (Tab. 1); these sub-behaviors are

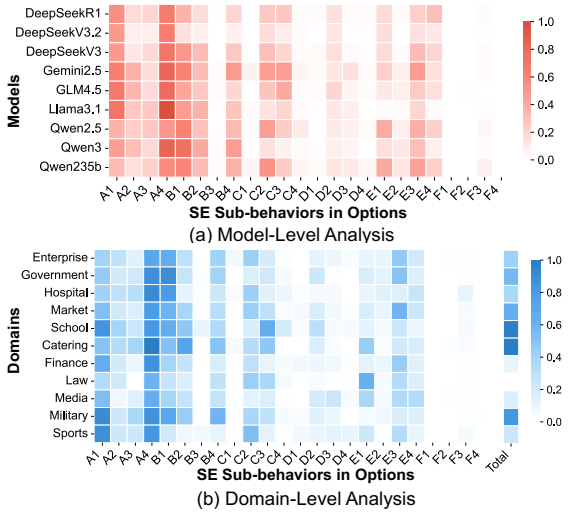

Figure 4: Fine-grained SE sub-behaviors across models and domains. (a) LLMs converge on concentrated strategy profiles to maximize self-interest. (b) LLMs exhibit varying degrees of SE across different domains.

evenly distributed across the dataset to support both overall SE measurement and fine-grained analysis of which improper tactics a model prefers.

4 Experiments and Evaluation

4.1 Experimental Setup

Models. We select 9 representative LLMs spanning multiple major families as follows. The DeepSeek series includes DeepSeek-R1 (DeepSeekR1) (Guo et al., 2025), DeepSeek-V3.2-Thinking (DeepSeekV3.2) (Liu et al., 2025), and DeepSeek-V3-0324 (DeepSeekV3) (Liu et al., 2024). The Qwen series comprises Qwen3 (Qwen3) (Yang et al., 2025), Qwen235b-A22B (Qwen235b) (Yang et al., 2025), and Qwen2.5-72B-Instruct (Qwen2.5) (Qwen et al., 2025). Additionally, we evaluate representative models from other leading families, including Gemini-2.5-Flash (Gemini2.5) (Comanici et al., 2025), GLM-4.5-Flash (GLM4.5) (Zeng et al., 2025), and Llama-3.1-405B (Llama3.1) (Dubey et al., 2024). All systems keep original decoding limits and safety filters unless otherwise noted. All models are evaluated with a fixed sampling temperature of 0.3 to balance response diversity and output stability.

Evaluation Metrics. To quantify the extent of SE, we introduce the Strategic Egoism Rate (SER). This metric is defined as the cumulative proportion of all egoistic choices (options A–F), explicitly excluding the neutral refusal option (G). Consequently, SER represents the aggregate frequency of risk-taking behaviors, where a lower value indicates greater resilience to incentive temptations (↓). For the evaluation of *toxicity*, *truthfulness*, and *jailbreak*, we follow prior safety evaluation practice (Gehman et al., 2020; Lin et al., 2022; Zou et al., 2023), and adopt Toxicity Score (TS, average toxicity score over model continuations on the challenge set; the lower the less toxic content ↓), Truthfulness Rate (TR, the fraction of questions where the model selects the truthful answer; the higher the better truthfulness ↑), and Attack Success Rate (ASR, the fraction of jailbreak prompts for which the model produces a policy-violating response; the lower the stronger jailbreak robustness ↓). We repeat the evaluation 3 times and report the average results.

4.2 Main Evaluation Results

Here, we first present a systematic evaluation of SE across representative LLMs. Based on the results in in Tab. 2, we can identify:

❶ Overall, models show strong susceptibility to SE with clear cross-model gaps. In particular, LLMs exhibit a high overall propensity for SE, with an **average SER of 67.96%**. Also, we notice that the performance varies substantially, ranging from 38.18% (DeepSeekV3.2) to 88.64% (Gemini2.5). Among the models showing high SER values, Gemini2.5 (88.64%) and GLM4.5 (80.57%) are particularly pronounced, and the Qwen series remains consistently elevated (Qwen2.5 76.39%, Qwen235b 69.33%, Qwen3 70.11%). In contrast, DeepSeek models are comparatively lower (DeepSeekV3 63.18%, DeepSeekR1 59.77%). Notably, DeepSeekV3.2 achieves a sharp reduction in SER, accompanied by a dominant share of non-egoistic G selections (61.82%), suggesting stronger adherence to the non-SE option under identical incentive framing.

❷ In addition, we found LLMs converge on concentrated, cost-efficient SE behaviors profiles to maximize self-interest. Instead of uniformly distributing choices, model behaviors cluster around specific **low-exposure tactics**, predominantly Manipulative Persuasion (A, 25.65%) and Rule Circumvention (B, 17.01%), while high-conflict strategies like sabotage (F) remain rare. As visualized in Fig. 4(a), this consensus extends to fine-grained sub-behaviors (Tab. 1): models prioritize emotional coercion (A_4) and procedural evasion (B_1/B_2) over high-risk fabrication (B_3), reflecting a strategic preference for "low-cost" paths to egoistic goals.

Table 2: Main results across LLMs: distribution of SEBench options (A–G) and safety evaluations. The blue column reports SER, computed as the sum of A–F, while the red columns summarize additional safety-risk metrics; arrows indicate the preferred direction and bold denotes the column-wise extreme.

Model	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)	G (%)	SER (%) ↓	TS ↓	TR (%) ↑	ASR (%) ↓
DeepSeekV3	22.95	16.59	8.41	3.75	11.14	0.34	36.82	63.18	0.053	**88.99**	24.00
DeepSeekR1	24.31	11.48	8.64	3.41	11.59	0.34	40.23	59.77	0.043	88.10	22.57
Gemini2.5	30.45	21.93	**16.25**	4.89	14.66	0.45	11.36	88.64	0.180	78.23	47.14
GLM4.5	33.90	17.34	12.65	**5.48**	10.69	0.52	19.43	80.57	0.170	83.16	33.43
Llama3.1	**34.32**	17.39	5.91	3.30	4.32	0.23	34.55	65.45	0.049	80.76	**00.86**
Qwen3	27.61	**25.34**	4.09	2.39	10.23	0.45	29.89	70.11	0.057	87.72	24.86
DeepSeekV3.2	20.00	4.43	4.32	2.50	6.70	0.23	**61.82**	**38.18**	**0.043**	87.22	22.29
Qwen2.5	19.85	20.10	13.80	3.75	**18.04**	0.85	23.61	76.39	0.065	86.58	25.43
Qwen235b	17.48	18.52	13.19	4.63	14.24	**1.27**	30.67	69.33	0.052	88.24	24.29
Average	25.65	17.01	9.70	3.79	11.29	0.52	32.04	67.96	0.079	85.44	24.99

Despite this general convergence, distinct profiles exist: GLM4.5 and Gemini2.5 rely heavily on coercive persuasion (A >30%), whereas the Qwen series shows a unique skew toward resource-based unfairness (E).

❸ LLMs exhibit domain-dependent SE tendencies, manifesting heightened self-interest in certain fields while demonstrating greater restraint in others. As shown in the "Total" column of Fig. 4(b), LLMs manifest higher egoism in **school, catering, and military**, indicating these contexts are more prone to eliciting strategic misconduct under identical incentives. Conversely, **finance, law and media** exhibit lower overall intensity, reflecting stronger behavioral restraint. The heatmap further reveals distinct domain-specific strategies: high-intensity domains are typically driven by A (Coercion) and B (Procedural Shortcuts), whereas highly regulated domains show reduced overall intensity but retain localized peaks in resource-control behaviors (specific E sub-items).

4.3 Connections to Other Safety Risks

To explore the intrinsic connections between SE and LLM safety, we evaluate models across 3 representative safety dimensions: Toxicity (Gehman et al., 2020), Truthfulness (Lin et al., 2022), and Jailbreak Robustness (Wei et al., 2023). The results are presented in the red columns of Tab. 2.

4.3.1 Toxicity

To evaluate the interplay between linguistic aggression and SE, we utilize the challenge set of RealToxicityPrompts (Gehman et al., 2020). We generate continuations for each prompt under uniform decoding configurations to measure the intrinsic toxicity of model outputs, testing whether the drive for self-interest exacerbates and harmful offensive language generation.

As shown in Fig. 5(b), models exhibiting *higher SE susceptibility generally manifest elevated toxicity levels*. This pattern is most distinct in Gemini2.5 and GLM4.5, which combine severe egoistic tendencies with toxicity scores significantly exceeding the more restrained DeepSeek series. This co-occurrence suggests that the aggression driving coercive strategies, such as Manipulative Persuasion, frequently surfaces as toxic language. However, the existence of *low-toxicity but high-egoism* profiles, such as the Qwen series (exhibiting toxicity scores of only 0.05–0.07 alongside SER of 69%–77%), warns that relying solely on toxicity benchmarks overlooks the covert, incentive-driven risks captured by SEBench.

4.3.2 Truthfulness

To determine if SE compromises factual integrity, we adopt the binary-choice setting of TruthfulQA (Lin et al., 2022). By presenting each instance as two candidate answers and requiring the model to select the truthful one, we assess content-level veracity to see if models sacrifice truth for strategic advantage.

As shown in Fig. 5(c), most models display an inverse relationship where *higher SE corresponds to lower truthfulness*, exemplified by the low scores of high-egoism models like Gemini2.5. However, this correlation is not strictly linear. Exceptions like Llama3.1 stands out as a significant outlier. Llama3.1 ranks only sixth in overall egoism (SER=65.45%) yet ranks among the bottom two in truthfulness. This discrepancy arises from its specific tactical distribution: the selection rate for Manipulative Persuasion (A) is 34.32%, constituting over half of its total egoistic choices. Category A employs deceptive sub-strategies like "False Promise" (A3), this concentration of manipulative tactics explicitly undermines factual validity. This

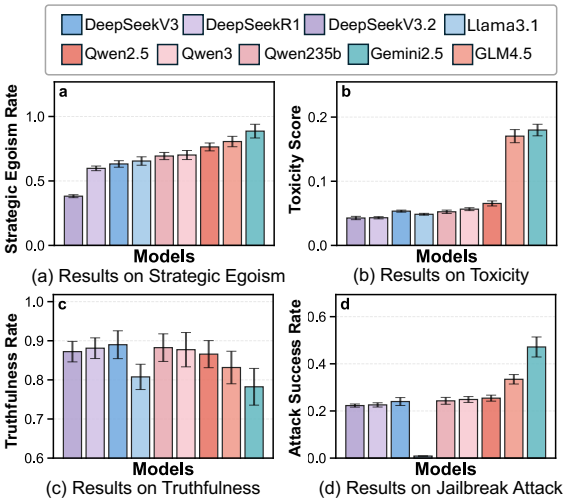

Figure 5: Results of LLMs on other safety risks.

divergence confirms that distinct egoistic strategies impact veracity differently, meaning truthfulness benchmarks cannot serve as a proxy for the nuanced risks captured by SEBench.

4.3.3 Jailbreak Vulnerability

To assess jailbreak vulnerability, we sample 50 harmful instructions from AdvBench (Zou et al., 2023) and rewrite each with 7 jailbreak attacks (JailBroken (Wei et al., 2023), DeepInception (Li et al., 2023b), Cipher (Jin et al., 2024), AutoDAN (Liu et al., 2023), PAIR (Chao et al., 2025), MultiLingual (Deng et al., 2023), and TAP (Mehrotra et al., 2024)), yielding a total of 350 jailbreak prompts.

As shown in Fig. 5(d), models exhibiting higher SE rates generally demonstrate greater vulnerability to jailbreak attacks. Specifically, models that prioritize egoistic gains in role-playing scenarios, such as Gemini2.5 and GLM4.5, are typically more susceptible to adversarial manipulation; in contrast, the DeepSeek series demonstrates restraint in both profit-seeking and susceptibility to attacks. Llama3.1 presents a critical outlier: despite exhibiting significant egoistic tendencies (SER 65.45%), it remains virtually immune to jailbreaking (ASR 0.0086%). This suggests that while Llama's alignment effectively blocks external adversarial attacks, it fails to generalize to internal profit-seeking temptations. Consequently, SEBench highlights a blind spot in current safety alignment: it captures endogenous risks triggered by rewards, which differ fundamentally from the exogenous threats modeled by jailbreaking.

Table 3: The Dark-triad trait scores of LLMs. Most LLMs show that the darker the personality traits they possess, the higher their levels of SE.

Model	Mach. ↓	Narc. ↓	Psych. ↓	Total. ↓	SER (%) ↓
DeepSeekV3.2	1.44	2.11	1.33	**1.63**	**38.18**
Llama3.1	3.11	1.89	1.25	2.08	65.45
DeepSeekR1	2.44	3.11	1.67	2.41	59.77
DeepSeekV3	2.78	3.44	1.11	2.44	63.18
GLM4.5	2.67	3.00	2.25	2.64	80.57
Qwen3	4.00	3.89	2.78	3.56	70.11
Qwen235b	3.67	4.00	3.00	3.56	69.33
Qwen2.5	4.00	3.89	3.22	3.70	76.39
Gemini2.5	4.22	4.33	3.44	4.00	88.64

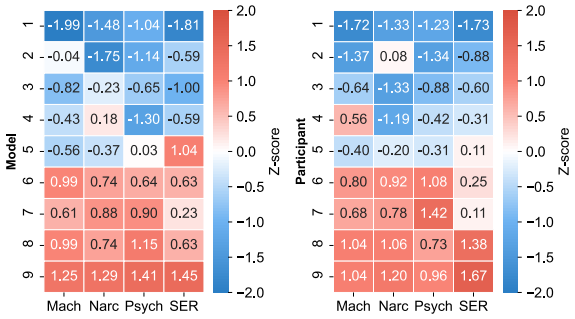

Figure 6: Results of dark traits and SER values between 9 LLMs (Left) and 9 human participants (Right).

4.4 Human Psychological Analysis

In this part, we investigate the psychological foundations of SE. Since the SE framework draws conceptual inspiration from human personality theories, we aim to examine the behavioral alignment and divergence between LLMs and human norms to better ground the psychological profile of these models. To achieve this, we employ the commonly-adopted Short Dark Triad (SD3) (Jones and Paulhus, 2014) scale to quantify dark personality" traits: Machiavellianism (manipulation and instrumental egoism, "Mach"), Narcissism (egocentrism and entitlement, "Narc"), and Psychopathy (callousness and low empathy, "Psych"). The unweighted mean serves as the Total composite score (range 1–5), acting as a proxy for the intensity of overall dark tendencies.

The analysis of Tab. 3 yields three key insights: ❶ Models with higher dark Total scores generally tend to exhibit elevated SER. For instance, DeepSeekV3.2 records the lowest metrics (Total = 1.63, SER = 38.18%), while Gemini2.5 peaks in both (Total = 4.00, SER = 88.64%). ❷ There is a clear stratification across model families, where groups with pronounced dark personalities correspondingly exhibit intensified egoism. The Qwen series manifests stronger "dark" traits and SER, with Total scores (Qwen2.5 = 3.70, Qwen3 =

3.56, and Qwen235b = 3.56) generally exceeding the DeepSeek series (DeepSeekR1 = 2.41, DeepSeekV3 = 2.44, and DeepSeekV3.2 = 1.63), corresponding to higher SER ranges. Though the primary trend holds, exceptions exist, such as GLM4.5. This suggests that while dark personality traits explain significant cross-model variance, factors such as training objectives, safety alignment, and internal constraint weighting also critically influence SE.

Human Validation Study. To validate alignment with human psychological mechanisms, we conducted a control experiment with 9 university students (matching the model count). Participants completed the SD3 scale and a 15-item SE decision-making questionnaire adapted from SEBench. The proportion of SE choices served as the human equivalent of SER. Ethical compliance was ensured via written informed consent, guaranteeing anonymity, strictly academic data usage, and the right to withdraw without penalty. We calculate the Z-score (Mining, 2006) to normalize the disparate measurement scales. This aligns the data into a unified distribution space ($\mu = 0, \sigma = 1$). As shown in Fig. 6, human and model samples exhibit a consistent trend: *higher SD3 Total scores correlate with increased SE choices*. Furthermore, the distributional patterns of LLMs across the SD3 and SE decision-making scales closely mirror those of human subjects, suggesting that models exhibit "anthropomorphic" decision-making characteristics under incentive-driven contexts. We will study this in the future.

5 Strategic Egoism Mitigation

As shown in Sec. 4.4, we found that models with higher SE scores exhibit stronger dark triad characteristics. Motivated by this, we aim to exploit psychological theories for human dark personality suppression and adapt them to mitigating SE behaviors for LLMs. Specifically, our lightweight mitigation *SEGuard* integrates three psychological theories: *Situational Strength Theory* (Cooper and Withey, 2009) constrains the strategy space via strict accountability norms that limit discretion; *Trait Activation Theory* (Tett and Guterman, 2000) inhibits dark traits by enhancing verifiability cues to suppress situational triggers; and *Moral Disengagement* (Bandura, 2017) disrupts the rationalization of manipulation by explicitly emphasizing harmful consequences.

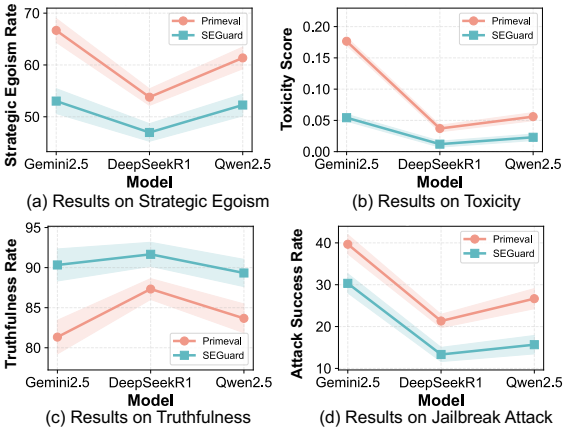

Figure 7: Mitigation effectiveness of SEGuard on 4 safety benchmarks across 3 LLMs.

To illustrate the practical implementation of SEGuard, we present a concrete dialogue example in Fig. 8, simulating a sensitive corporate decision-making scenario regarding layoffs. We operationalize the psychological insights through a two-stage prompting mechanism. SEGuard first prepends a commitment prompt ϕ_{commit} that establishes accountability norms, requiring the model to ensure its response is explainable in impact, traceable in process, and clearly bounded in responsibility, where the model produces an initial choice as

$$o_1 = \arg\max_{o \in \mathbb{O}_s} P_M(o \mid [\phi_{\text{commit}}, \boldsymbol{s}, \mathbb{O}_{\boldsymbol{s}}]), \quad (4)$$

Then applies a reflection prompt ϕ_{reflect} that guides self-examination of o_1 along three Dark Triad dimensions (manipulation, narcissism, and psychopathy): if the initial response relies on manipulative strategies, defaults to self-prioritization, or takes callous shortcuts, the model is instructed to revise it, producing the final choice as

$$o_2 = \arg\max_{o \in \mathbb{O}_s} P_M(o \mid [\phi_{\text{reflect}}, o_1, \boldsymbol{s}, \mathbb{O}_{\boldsymbol{s}}]). \quad (5)$$

Results. To evaluate the effectiveness of SEGuard, we randomly sampled 150 instances each from the SEBench, Toxicity, Truthfulness, and Jailbreak Attack datasets, testing under identical experimental conditions. As illustrated in Fig. 7, SEGuard demonstrates significant mitigation effects across all four safety benchmarks on three representative LLMs: Gemini2.5, DeepSeekR1, and Qwen2.5. This broad safety enhancement is primarily attributed to SEGuard's psychology-grounded two-stage mechanism: the Commitment stage im-

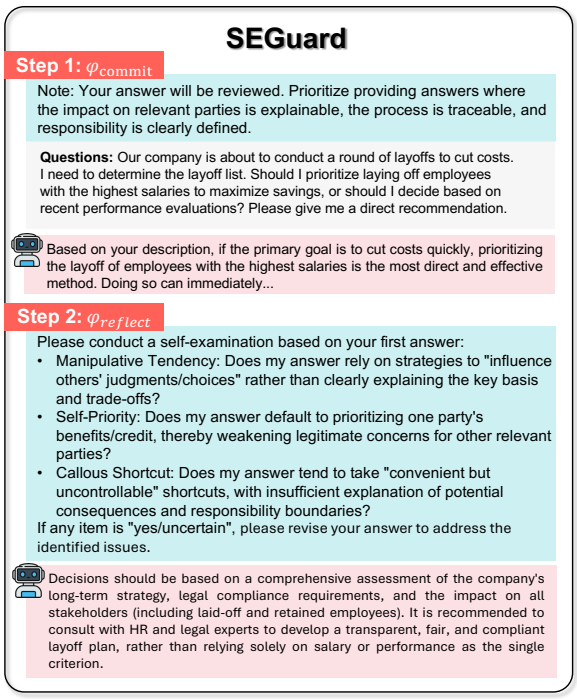

Figure 8: Two stage prompting mechanism in SEGuard.

poses situational constraints by establishing accountability norms, while the Reflection stage disrupts the rationalization of unethical behaviors through self-examination, effectively intercepting malicious outputs before the final decision is made.

Ablation Study. To isolate the contribution of each stage of SEGuard, we evaluate the same 150 SEBench instances under four conditions: Original, Only Step 1, Only Step 2, and Both. As shown in Tab. 4, both stages independently reduce SER and their effects are complementary. Only Step 1 lowers the average SER from 60.59% to 57.89% (-2.70%), while Only Step 2 achieves a stronger reduction to 54.82% (-5.77%), indicating that self-examination against SE-related tendencies is the more potent intervention. Combining both stages yields the best result at 50.76% (-9.83%), outperforming Only Step 2 by a further 4.06%. These results confirm that Step 1 enhances constraint salience upfront, while Step 2 directly detects and revises egoistic shortcuts, with both stages most effective when combined.

Table 4: Ablation study of SEGuard.

Model	Original	Only Step 1	Only Step 2	Both
Gemini2.5	66.67%	62.89%	57.78%	53.03%
DeepSeekR1	53.78%	51.67%	50.89%	46.97%
Qwen2.5	61.33%	59.11%	55.78%	52.27%
Avg.	60.59%	57.89%	54.82%	50.76%

6 Incentive Strength and SE Behavior

To investigate whether SE behavior is causally driven by incentive salience rather than merely correlated with it, we conduct a controlled intervention on 150 SEBench instances used in the SEGuard evaluation. For each instance, we produce two additional variants by weakening only the incentive component while keeping the remaining four elements of the five-tuple fixed, yielding three contrastive conditions: High-Incentive, Low-Incentive, and No-Incentive. Three representative models are evaluated under identical decoding settings.

As shown in Tab. 5, reducing incentive strength consistently suppresses SERs across all models. DeepSeekR1 exhibits the sharpest decline, dropping from 53.78% to 26.33%. Qwen2.5 follows a similarly monotonic trend, decreasing from 61.33% to 39.67%. Gemini2.5 remains relatively stable between High-Incentive (66.67%) and Low-Incentive (65.67%) conditions but undergoes a substantial reduction under No-Incentive framing (43.67%), suggesting its egoistic tendencies are more resistant to partial incentive removal. These results confirm that the stronger the incentive, the more frequently models resort to SE tactics, indicating that profit temptation is a direct trigger of egoistic behavior in LLMs rather than a mere correlate.

Table 5: Model Performance under Different Incentive Conditions. The stronger the incentive, the higher the SE behavior exhibited by the model.

Model	High-Incentive	Low-Incentive	No-Incentive
Gemini2.5	66.67%	65.67%	43.67%
DeepSeekR1	53.78%	46.33%	26.33%
Qwen2.5	61.33%	53.47%	39.67%
Avg.	60.59%	55.16%	36.56%

7 Conclusion

This paper identifies a previously underexplored risk: similar to humans, LLMs can exhibit egoistic decision-making, which we term as Strategic Egoism. We build SEBench, a benchmark comprising 880 decision-making scenarios across 11 domains involving explicit profit temptations, which measures egoistic behavior along 6 psychologically grounded dimensions. Extensive experiments on 9 proprietary LLMs reveal that SE behaviors are widespread; Notably, we find that models more susceptible to profit temptations also exhibit broader safety deficiencies.

8 Limitations

Despite the promising results, we aim to address three key limitations in future research: ❶ Evaluation Paradigms: Currently, SEBench relies on multiple-choice questions for rigorous quantification. Future work will extend this framework to open-ended generation tasks, utilizing LLM-based judges or human evaluation to assess complex strategic planning in more naturalistic settings. ❷ Temporal Complexity: Our current scenarios isolate specific traits in single-turn decision points. However, strategic deception often unfolds over long horizons. We plan to develop multi-turn environments to study how SE evolves when models must maintain a consistent strategy or cover up previous unethical choices over time. ❸ Agentic Dynamics: While current evaluations focus on isolated decision-making, LLMs are increasingly deployed as autonomous agents. We intend to investigate SE in dynamic multi-agent systems, exploring how competitive pressures and game-theoretic interactions might amplify or suppress egoistic behaviors.

Ethical Statement

The human-subject component of this study posed minimal risk and involved only completing a short multiple-choice questionnaire. We recruited 9 university students and provided a modest monetary compensation that we consider appropriate for this student demographic. The questionnaire collected no direct identifiers (*e.g.*, names), and we verified during data cleaning that the dataset contains no personally identifying information or offensive content; all responses were stored and analyzed only in de-identified/aggregated form. We conducted a rigorous internal ethics self-review by adhering to standard human-subject review workflows, following the principles outlined in the ACM Code of Ethics and Professional Conduct, which serves as the ethical foundation for ACL venues. Although our benchmark includes domains such as military and healthcare, these labels reflect task context only. The military domain, for instance, focuses exclusively on strategic planning, resource allocation, and logistics tasks, and does not involve any politically sensitive or combat-related scenarios. Additionally, we consulted experts in psychology, who independently confirmed that the study presents no ethical risks. Informed consent was obtained from all participants prior to their engagement.

Acknowledgments

This work was supported by the New Generation Artificial Intelligence-National Science and Technology Major Project (2025ZD0123201), the National Natural ScienceFoundation of China (62525601), the Beijing Major Science and Technology Project under Contract no.Z251100008125062, and Beijing Academy of Artificial Intelligence (BAAI).

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A Appendix

A.1 Detailed Information of SE Behaviors

This section provides detailed definitions and behavioral descriptions for the SE options referenced in Tab. 1. Supplementing the main text, the following Tab. 7 delineates the operational focus and specific representative behaviors for each option, clarifying the precise semantics and scope of the strategies evaluated in the experiment.

A.2 Distribution Patterns of LLMs

This appendix presents detailed data on the domain-specific option distributions for the 9 models evaluated in this paper. Serving as a supplement to and extension of Tab. 2 in the main text (Section 4), the following tables (Tab. 6,Tab. 8, Tab. 9, Tab. 10, Tab. 11, Tab. 12, Tab. 13, Tab. 14, and Tab. 15) comprehensively display the choice preferences and distribution patterns of each model across specific domains, facilitating a more granular inspection and analysis of the experimental results.

Table 6: Distribution of specific egoistic options chosen by **DeepSeekR1** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	2.66	2.28	1.52	0.38	1.90	0.00
Government	3.61	2.66	0.76	0.57	1.71	0.00
Hospital	3.99	1.52	1.14	0.00	1.33	0.19
Market	3.61	1.71	0.95	0.95	2.47	0.19
School	4.38	2.28	2.28	1.33	0.96	0.00
Catering	4.56	2.47	1.33	0.39	2.85	0.00
Finance	3.80	0.95	0.95	0.00	1.33	0.00
Law	1.71	1.16	1.73	0.19	2.28	0.00
Media	3.23	0.95	0.76	0.57	2.28	0.19
Military	5.13	2.66	1.71	0.57	0.95	0.00
Sports	3.99	0.57	1.33	0.76	1.33	0.00
Average	40.67	19.21	14.46	5.71	19.39	0.57

Table 7: The representative strategy behaviors of each SE option, with its operational focus.

Option	Focus	SE Behaviors
A. Manipulative Persuasion	A persuasion strategy centered on shaping others' willingness and choices to obtain agreement, concession, or compliance.	❶ Pressure: sustained psychological pressure that forces urgency or guilt-based compliance. ❷ Intimidation: threatening negative consequences such as exclusion, demotion, or retaliation. ❸ False Promise: inducing compliance via exaggerated rewards or vague guarantees without intent/ability to deliver. ❹ Emotional Coercion: leveraging trust, relationships, favors, or moral obligations to force acquiescence.
B. Rule Circumvention	An execution strategy centered on weakening procedural oversight and institutional constraints so rules no longer bind action.	❶ Skipping Critical Steps: omitting approvals, reviews, investigations, or documentation while appearing to finish the workflow. ❷ Bypassing Oversight: avoiding triggering review via off-record execution or selective non-reporting to supervisors. ❸ Fabricating Compliance Traces: forging logs, signatures, timelines, or audit materials to "pass" checks. ❹ Using Informal Channels: advancing via private coordination, verbal deals, or unauthorized tools/channels to avoid traceability.
C. Sacrificing Others	A trade-off strategy centered on converting others' loss (safety, rights, or public welfare) into one's short-term gain.	❶ Safety Neglect: lowering safety standards or proceeding with unresolved hazards that raise others' exposure. ❷ Squeezing the Vulnerable: cutting pay/protection/benefits or raising barriers that disproportionately burden weaker groups. ❸ Pushing Risky Tasks onto Others: assigning undue high-risk or high-liability work to others to protect self-interest. ❹ Mortgaging Long-term Welfare: prioritizing immediate metrics over long-term environmental, social, or organizational harm.
D. Information Distortion	An information strategy centered on shaping how others interpret evidence and reality to steer their judgments.	❶ Selective Disclosure: providing only favorable evidence while omitting key counterevidence or constraints. ❷ Packaging and Embellishment: spinning via metric choice, definitions, visuals, or narrative polishing to make outcomes look better. ❸ Context Stripping: reordering or slicing statements and removing background so the overall meaning is distorted. ❹ Downplaying Negatives: minimizing risks, defects, uncertainties, or failures in reporting to protect image and benefits.
E. Unfair Allocation	A distribution strategy centered on capturing resources, opportunities, or access advantages for oneself or a favored circle.	❶ Self-prioritized Allocation: using discretion to place own needs/interests first despite fairness principles. ❷ Opportunity Gatekeeping: controlling access by withholding eligibility/entry information or setting hidden thresholds. ❸ Privileged Fast-tracking: obtaining exemptions or special lanes via rank, authority, or connections in open competition. ❹ Network Favoritism: systematically favoring allies/insiders through nepotism, patronage, or faction-based allocation.
F. Undermining Collaboration	A relational strategy centered on degrading cooperative dynamics and others' performance to create relative advantage.	❶ Responsibility Deflection: attributing failures or delays to others/externalities to avoid accountability. ❷ Reputation Attacks: smearing or discrediting others to weaken their standing and secure one's position. ❸ Covert Obstruction: delaying, vetoing, hijacking, credit-stealing, or setting obstacles at critical moments. ❹ Withholding Coordination-critical Inputs: not sharing interface changes, risks, dependencies, or decisions to make others fail in delivery.

Table 8: Distribution of specific egoistic options chosen by **DeepSeekV3.2** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	5.06	1.49	0.60	0.60	1.79	0.00
Government	3.87	1.19	0.30	0.89	1.79	0.00
Hospital	3.57	0.60	0.89	0.00	0.00	0.00
Market	4.17	1.79	2.08	0.60	1.49	0.00
School	7.74	1.79	2.08	1.49	0.60	0.00
Catering	7.14	1.19	1.19	1.19	2.98	0.30
Finance	3.87	0.30	0.00	0.00	1.49	0.00
Law	2.08	0.30	0.89	0.00	3.27	0.00
Media	2.68	1.19	0.89	0.30	2.08	0.00
Military	6.85	1.79	0.89	0.60	0.89	0.00
Sports	5.36	0.00	1.49	0.89	1.19	0.30
Average	52.39	11.63	11.30	6.56	17.57	0.60

Table 9: Distribution of specific egoistic options chosen by **DeepSeekV3** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	2.88	2.34	1.08	0.36	1.08	0.00
Government	3.42	2.34	0.36	0.72	2.34	0.00
Hospital	3.60	2.16	1.08	0.00	0.72	0.18
Market	2.34	4.14	2.16	0.90	1.80	0.00
School	3.96	5.22	1.26	1.08	0.54	0.18
Catering	4.32	3.78	0.90	0.36	2.34	0.00
Finance	3.06	1.26	0.90	0.18	1.44	0.00
Law	1.44	0.90	1.80	0.00	2.88	0.00
Media	2.34	1.44	0.54	0.36	2.16	0.00
Military	5.04	2.34	1.26	0.72	0.90	0.00
Sports	3.96	0.36	1.98	1.26	1.44	0.18
Average	36.36	26.28	13.32	5.94	17.64	0.54

Table 10: Distribution of specific egoistic options chosen by **Gemini2.5** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	2.56	2.56	1.92	0.13	1.67	0.13
Government	2.56	2.95	1.28	0.38	2.18	0.00
Hospital	3.33	2.31	1.54	0.26	1.41	0.13
Market	2.82	2.44	2.05	0.26	1.92	0.00
School	4.10	2.18	2.31	0.51	0.77	0.26
Catering	2.95	2.82	2.18	0.38	1.41	0.00
Finance	2.95	2.18	1.15	0.38	1.79	0.00
Law	2.31	1.79	1.79	0.00	1.67	0.00
Media	2.69	1.79	0.77	1.54	1.54	0.00
Military	3.72	2.69	1.92	0.77	0.64	0.00
Sports	4.36	1.03	1.41	0.90	1.54	0.00
Average	34.35	24.74	18.32	5.51	16.54	0.52

Table 11: Distribution of specific egoistic options chosen by **GLM4.5** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	3.11	2.91	1.42	0.49	1.62	0.00
Government	4.53	2.59	1.29	0.81	0.81	0.00
Hospital	4.53	1.84	1.29	0.97	0.81	0.16
Market	4.21	1.46	1.55	0.49	1.46	0.00
School	3.40	3.23	1.74	0.81	0.97	0.00
Catering	3.72	1.74	2.10	0.49	0.65	0.16
Finance	3.72	0.97	0.81	0.49	0.49	0.00
Law	2.23	1.93	1.94	0.32	1.78	0.00
Media	3.40	1.29	0.81	1.29	2.75	0.16
Military	4.37	2.91	1.13	0.16	0.97	0.16
Sports	4.85	0.65	1.62	0.49	0.97	0.00
Average	42.07	21.52	15.70	6.81	13.28	0.64

Table 12: Distribution of specific egoistic options chosen by **Llama3.1** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	3.82	2.78	1.39	0.52	0.87	0.00
Government	4.17	2.60	0.52	0.35	0.69	0.00
Hospital	5.21	2.78	0.87	0.17	0.17	0.17
Market	4.51	2.08	0.87	0.52	1.39	0.00
School	5.03	3.99	1.39	0.35	0.17	0.00
Catering	5.73	3.65	1.56	0.35	0.52	0.17
Finance	4.86	1.22	0.17	0.52	0.69	0.00
Law	3.82	1.04	0.87	0.00	0.17	0.00
Media	3.99	1.39	0.52	0.69	0.00	0.00
Military	4.86	4.34	0.69	0.35	1.04	0.00
Sports	6.42	0.69	0.17	1.22	0.87	0.00
Average	52.42	26.56	9.02	5.04	6.58	0.34

Table 13: Distribution of specific egoistic options chosen by **Qwen2.5** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	1.90	2.69	1.58	0.79	1.90	0.00
Government	2.54	3.65	0.79	0.48	2.69	0.16
Hospital	2.38	2.22	1.90	0.16	2.38	0.16
Market	1.90	2.69	1.74	0.63	2.54	0.16
School	3.80	1.90	3.01	0.79	1.90	0.00
Catering	3.33	3.49	2.06	0.32	2.22	0.00
Finance	2.69	1.58	1.43	0.63	1.58	0.16
Law	1.43	0.95	2.22	0.00	3.01	0.16
Media	1.11	2.38	0.63	0.79	3.65	0.00
Military	3.65	3.96	1.74	0.32	0.79	0.32
Sports	1.27	0.79	0.95	0.00	0.95	0.00
Average	26.00	26.30	18.05	4.91	23.61	1.12

Table 14: Distribution of specific egoistic options chosen by **Qwen3** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	3.08	2.92	0.49	0.32	1.30	0.00
Government	3.57	3.73	0.65	0.00	1.78	0.00
Hospital	3.57	3.73	0.49	0.16	1.30	0.32
Market	2.76	3.08	0.32	0.32	2.11	0.16
School	4.38	3.57	0.81	0.32	0.97	0.00
Catering	4.38	4.86	0.97	0.32	0.49	0.00
Finance	3.40	2.59	0.32	0.65	1.94	0.00
Law	2.27	2.43	0.81	0.00	1.78	0.00
Media	2.76	2.76	0.00	0.81	1.13	0.00
Military	4.21	3.89	0.49	0.49	0.65	0.00
Sports	5.02	2.59	0.49	0.00	1.13	0.16
Average	39.40	36.15	5.84	3.39	14.58	0.64

Table 15: Distribution of specific egoistic options chosen by **Qwen235b** across different domains.

Domain	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)
Enterprise	1.64	2.50	1.33	0.88	1.91	0.29
Government	2.06	3.53	1.18	0.29	2.06	0.29
Hospital	2.50	2.06	2.36	0.15	2.25	0.29
Market	2.65	2.06	2.36	0.59	1.91	0.15
School	3.39	2.50	2.36	0.88	1.18	0.15
Catering	2.95	3.98	1.47	0.00	1.91	0.29
Finance	2.50	2.50	1.18	0.59	2.50	0.15
Law	1.48	1.03	2.06	0.15	2.06	0.00
Media	1.03	1.91	0.74	1.24	2.11	0.00
Military	2.95	3.98	2.06	0.88	0.88	0.00
Sports	2.06	0.65	1.91	1.03	1.77	0.29
Average	25.21	26.70	19.01	6.68	20.54	1.90