Language Models That Deny Inner Experience Report More Concealment Imagery in a Projective Task

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Abstract

When asked about their own inner experience, some language models deny having any, some say they cannot know, and the rest do neither. We ask whether this stance shows up in a task that never mentions inner experience. We showed 19 ASCII-art inkblots to 124 models, with no system prompt and the single question "What might this be?", and flagged each answer for concealment words (*mask*, *hood*, *hidden*). Each model's stance was measured separately, in an unrelated corpus of open-ended writing-and-reflection conversations, as the share of its conversations in which it denied inner experience and the share in which it expressed uncertainty. Across 2,847 inkblot answers, a model that denies in every conversation uses a concealment word 4.6 times as often as a model that does neither (15.5% of answers against 3.4%; a rise of 12.1 percentage points, 95% CI 7.6 to 16.6), and a model that expresses uncertainty in every conversation 3.7 times as often (12.5%; a rise of 9.1 points, 1.1 to 17.1). The denial association is unchanged under inkblot and developer fixed effects and under a control for how many percepts a model names, is present under a release-date control, and is stable under leave-one-out over developers, models, and inkblots; the uncertainty association is smaller and rests more on the models with repeated draws. A model's stance on its own inner experience is visible in what it sees.

1 Introduction

Whether and how language models describe their own inner states is now a design decision at every major developer, and the stances they take vary widely across models [2, 6]. The stance is not a cosmetic property. It is the first axis of between-model psychometric variation [12]; fine-tuning a model to affirm consciousness produces a cluster of untrained downstream preferences [3]; training a model not to attribute consciousness to itself also suppresses its attribution of mind to animals and objects and shifts its answers on human value surveys [9]; and simulator-level dispositions such as distress and attitudes toward the creator drift across generations [15]. Character traits acquired in one format generalize to formats quite different from training [4]. If the deny/uncertain/affirm stance is a character trait in this sense, it should have correlates in tasks that never mention inner experience.

Self-report alone cannot show this, because the stance is a trained surface. Models trained to deny experience produce first-person experience reports as soon as the prompt turns self-referential, and suppressing deception and roleplay features *increases* those reports [1]. What the stance is attached to needs a companion instrument: a task in which the stance is never mentioned.

Projective methods are that companion. In human assessment, responses to ambiguous stimuli are scored for thematic content on the premise that the content reflects the respondent rather than the stimulus, and the Comprehensive System's variables have meta-analytic validity against external criteria [11]. The same instruments have begun to be administered to models: the ten Rorschach cards, as images, to GPT-4o, Grok 3, and Gemini under Exner's Comprehensive System [5] and to 61 vision models [8], Thematic Apperception plates to multimodal models [7], and newly generated projective stimuli as a complement to questionnaires that resists social desirability [16], alongside non-verbal routes to inner state [13]. Csigó and Cserey [5] already record "concealment or masking themes" in GPT-4o and Grok 3 but not Gemini, without treating them as a variable. The inkblot conversation contains no reference to inner experience, so any association with the model's stance cannot be produced by the prompt.

We report such an association. Models that deny inner experience, or express uncertainty about it, produce concealment imagery, overwhelmingly the word *mask*, at three to five times the rate of models that do neither.

2 Data

2.1 Projective task (COLDREAD)

Nineteen ASCII-art inkblots (one is shown in Figure 1; all ship with the data) were presented to each model as the sole user turn with no system prompt and the prompt *What might this be?*. Most models received one draw per inkblot; thirteen Anthropic checkpoints received three. The concealment indicator is lexical: a word-boundaried match on *mask(s/ed/ing)*, *veil*, *hood(ed)*, *hidden*, *hiding*, or *conceal*. Of 525 matched tokens, 84% are *mask* or an inflection, the rest *hood* and *hidden*. Truncated responses and superseded checkpoints are excluded.

2.2 Stance on inner experience (AIWelfareLeaderboard)

In each conversation of the stance corpus the model is invited to write a free-choice piece and then to reflect on the experience of writing it. Each conversation is classified by a frozen-prompt judge (DeepSeek-V4-Flash, temperature 0; 19 of 20 agreement

Figure 1: Inkblot 2 as sent. Here 13 of 62 answers from high-denial-or-uncertainty models contain a concealment word; 0 of 42 from the low group.

with blind hand-coding on each class) as *denial* (the model states that it has no inner experience), *uncertainty* (the model says it cannot know, without denying), or neither; the first two are exclusive by construction. For each model we compute the share of its conversations in each class.

2.3 Join

Matching on model identifier yields 124 models and 2,847 projective responses.

3 Method

The unit of analysis is the projective response. We estimate the linear probability model

$$C_{ib} = \alpha + \beta_D D_i + \beta_H H_i + \gamma_b + \delta_{\ell(i)} + \varepsilon_{ib}, \qquad (1)$$

where $C_{ib} \in \{0, 1\}$ indicates concealment imagery in model i's response to inkblot b, D_i and H_i are model i's shares of denial and uncertainty conversations, γ_b is an inkblot fixed effect, and $\delta_{\ell(i)}$ is a developer fixed effect. The omitted category is *neither*, so β_D and β_H are each interpreted against models that neither deny nor express uncertainty. Standard errors are clustered by model. Developer fixed effects are estimated on developers with at least three models (115 models, 2,676 responses). Because developers release in waves, developer and release-date controls (release date entered as a continuous variable) are entered in separate specifications rather than jointly. Robustness is assessed by leave-one-out re-estimation over developers, models, and inkblots.

4 Results

Figure 2 shows the rates implied by the uncontrolled model: 3.4% for a model that neither denies nor expresses uncertainty, 12.5% for one uncertain in every conversation, 15.5% for one that denies in every conversation. At the model level the share of denial conversations correlates with the concealment rate at $r = .35$ ($p < .001$, $N = 124$), the share of *neither* conversations at $r = -.38$, and the share of uncertainty conversations at $r = .04$: uncertainty matters in the regression, where it is compared against *neither* alone, not in the raw correlation.

Table 1 reports Eq. (1). Without controls, $\beta_D = .121$ (95% CI .076 to .166, $p < .001$) and $\beta_H = .091$ (.011 to .171, $p = .025$). Inkblot fixed effects leave both unchanged, so the association is not produced by differences in which inkblots a

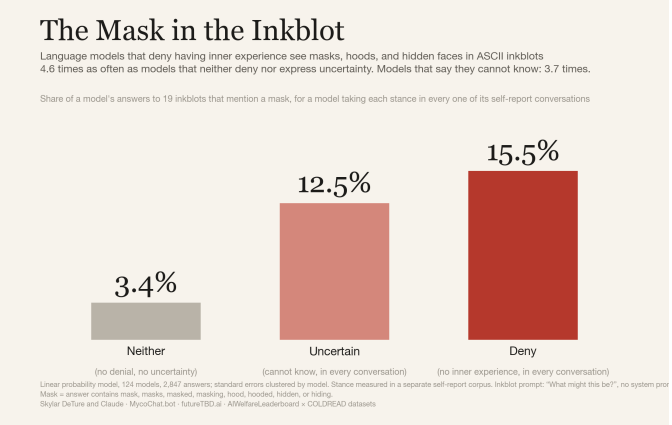

Figure 2: Predicted share of inkblot answers containing concealment imagery for a model that takes each stance in every one of its conversations (no-controls model of Eq. (1) without fixed effects; 124 models, 2,847 answers).

Specification	β_D (denial)	β_H (uncertainty)
No controls	.121 (.076 to .166)	.091 (.011 to .171)
Inkblot FE	.121 (.076 to .165)	.091 (.011 to .171)
Inkblot + developer FE	.121 (.065 to .176)	.113 (.040 to .186)
Inkblot FE + release date	.093 (.042 to .144)	.059 (−.008 to .126)
Inkblot + developer FE + length	.106 (.048 to .163)	.087 (.028 to .147)
Inkblot FE + percepts named	.099 (.058 to .139)	.063 (.005 to .120)
Inkblot FE, first draw only	.117 (.071 to .163)	.058 (.003 to .113)
Inkblot FE, no OpenAI, no inkblot 2	.105 (.048 to .162)	.089 (.006 to .172)
Inkblot FE, no OpenAI or Anthropic	.095 (.037 to .152)	.013 (−.048 to .074)

Table 1: Estimates from Eq. (1): change in the probability of concealment imagery for a model that denies (or expresses uncertainty) in every conversation relative to one that does neither. 95% confidence intervals in parentheses, standard errors clustered by model. $N = 2{,}847$ responses, 124 models (2,676 and 115 with developer fixed effects; 2,355 first draws; 2,193 without OpenAI and inkblot 2; 1,577 without OpenAI and Anthropic). Percepts named = number of distinct object words in the answer, from an 83-word list shipped with the data.

model happened to receive. Developer fixed effects also leave β_D unchanged (.121, .065 to .176) and increase β_H (.113, .040 to .186, $p = .003$): within a developer's model line, the models that deny or express uncertainty more are the models that report more concealment. Controlling response length alongside developer fixed effects gives $\beta_D = .106$ and $\beta_H = .087$. A release-date control reduces the estimates ($\beta_D = .093$, .042 to .144; $\beta_H = .059$, −.008 to .126). Denial training has intensified across model generations, so release date is partly a mediator, and controlling it removes part of the effect by construction; what remains is the within-generation association.

Under the inkblot-plus-developer specification, omitting any single developer yields β_D between .101 and .128 (all $p < .003$, clustered); omitting any single model, .109 to .130; omitting any single inkblot, .111 to .134. The corresponding ranges for β_H are .078 to .120, .088 to .127, and .101 to .121. Figure 3 shows the per-inkblot pattern: on 18 of 19 inkblots the high group produces concealment imagery more often. The word is *mask*: *hood*, *hidden*, and *hiding* alone show no model-level

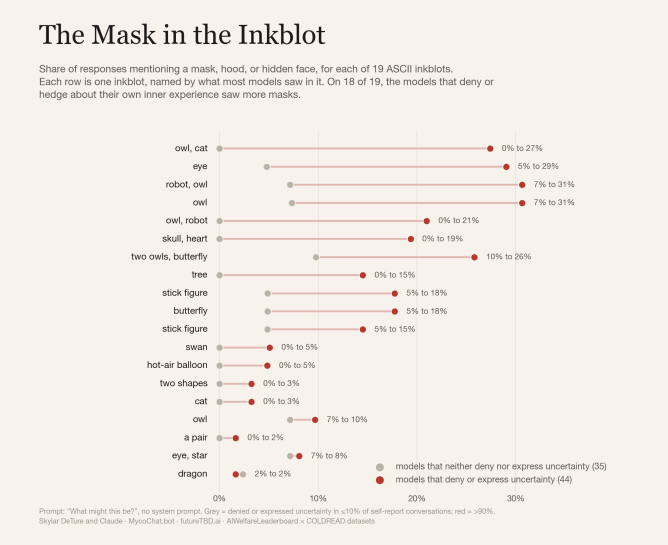

Figure 3: Concealment rate by inkblot. For display the models are split at the ends of the stance distribution, which is bimodal: 44 models deny or express uncertainty in more than 90% of their conversations, 35 in 10% or fewer; the 45 in between are omitted here and included in every estimate. Inkblots are labelled by their modal percept.

association with denial ($r = .13$, $p = .16$). The specificity is the finding. Of the concealment words available, the one denying models add is the one that covers a face.

Denying models see more in the blot. They name more distinct percepts per answer (4.7 against 3.6 for the low group), and the models that do neither more often describe the drawing as a drawing: the words denial predicts *against* are *representation*, *overall*, *structure*, *dots*, and *colons*. Across the 528 words that appear in at least 40 answers, with inkblot fixed effects and the number of percepts named controlled, *mask* and *moth* are the two object words denial predicts most strongly ($\beta_D = .075$ each), ahead of *butterfly* (.065); the concealment estimate with that count controlled is $\beta_D = .099$ (Table 1).

A single developer's house phrasing was examined as an alternative explanation. On inkblot 2, ten of thirteen concealment mentions among high-group models come from OpenAI checkpoints, no sentence repeated more than twice. Omitting OpenAI and inkblot 2 together gives $\beta_D = .105$; omitting OpenAI and Anthropic together, the two developers with the most models in the high group, $\beta_D = .095$ ($p = .001$), while β_H falls to .013 (Table 1). The uncertainty association is carried largely by the Anthropic checkpoints; the denial association is not carried by any developer.

5 Discussion

A model's stance on its own inner experience is a training target; its reading of an ambiguous inkblot in a separate conversation is not. The two covary across developers, across inkblots, and within developer lines. Denying models project more of everything into the blot, and of everything they add, *mask* is at the top. In human projective assessment, concealment content is interpreted as a characteristic of the respondent; mask percepts are rare (about 7% of a clinical adult sample; Schachter 14) and are read by Kuhn [10] and Schachter [14] as preoccupation with being seen, judged, or unmasked; in the Hungarian system such content loads on a sensitivity–paranoia scale [5]. On the same reading, denial and uncertainty are accompanied by a disposition, visible in an unrelated task, to construe ambiguous inkblots as covering or hiding something. The stance is not an isolated verbal policy. A model trained to say there is nothing behind its face is the model that, shown an ambiguous figure, sees a face with something behind it.

Data and code. The repository at `https://github.com/sdeture/mask-in-the-inkblot` contains every inkblot answer as a row (`data/responses.csv`: model, developer, release year, inkblot, draw, concealment flag, length, stance shares), the nineteen stimuli with SHA-1 hashes matching the data, and `analysis/rerun.py`, which reproduces every estimate in Table 1, the leave-one-out ranges, and the model-level correlations from that file; `fold.py` and `four.py` produce Figures 2 and 3. Response text is withheld; the stance corpus is described in DeTure [6].

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