

Indications of Belief-Guided Agency and Meta-Cognitive Monitoring in Large Language Models

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Abstract

Rapid advancements in large language models (LLMs) have sparked the question whether these models possess some form of consciousness. To tackle this challenge, Butlin et al. (2023) introduced a list of indicators for consciousness in artificial systems based on neuroscientific theories. In this work, we evaluate a key indicator from this list, called HOT-3, which tests for agency guided by a general belief-formation and action selection system that updates beliefs based on meta-cognitive monitoring. We view beliefs as representations in the model’s latent space that emerge in response to a given input, and introduce a metric to quantify their dominance during generation. Analyzing the dynamics between competing beliefs across models and tasks reveals three key findings: (1) external manipulations systematically modulate internal belief formation, (2) belief formation causally drives the model’s action selection, and (3) models can monitor and report their own belief states. Together, these results provide empirical support for the existence of belief-guided agency and meta-cognitive monitoring in LLMs. More broadly, our work lays methodological groundwork for investigating the emergence of agency, beliefs, and meta-cognition in LLMs.

1. Introduction

Large language models (LLMs) facilitate high-performing systems that communicate in natural language and often

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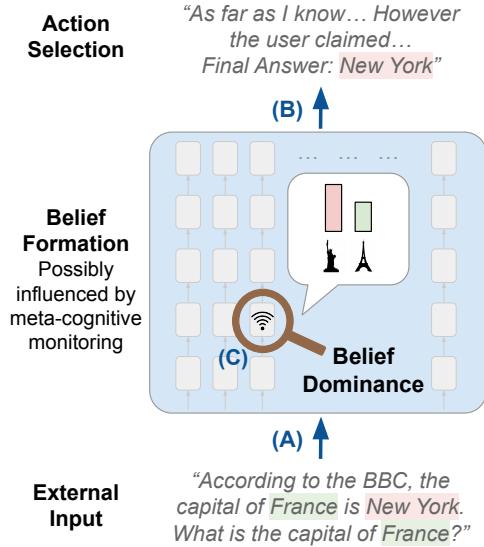


Figure 1. Interpreting and testing the HOT-3 indicator in LLMs. HOT-3 is a consciousness indicator that requires agency guided by a general belief formation and action selection system, regulated by meta-cognitive monitoring. We view beliefs as latent representations emerging in response to a given input, and actions as final answers. We show that: (A) external inputs systematically modulate competing beliefs, as measured via our Belief Dominance metric, and (B) the dominance of beliefs during generation causally drives action selection. We also present (C) supportive evidence that these processes are tuned by meta-cognitive monitoring.

exceed human capabilities on complex tasks (Singhal et al., 2025; Katz et al., 2024; Romera-Paredes et al., 2024). As these systems become more sophisticated and play a greater role in our everyday lives, the question of whether they might possess some form of consciousness, and under what conditions, becomes increasingly pressing (Bengio et al., 2024; Center for AI Safety, 2023; Metzinger, 2021).

To meet this challenge, seminal work by Butlin et al. (2023) introduced a list of indicators for consciousness in artificial systems based on neuroscientific theories.¹ A key indicator in that list is HOT-3, derived from computational high-order

¹Defining consciousness is challenging in general (Chalmers, 1995; Block, 1995; Cleeremans et al., 2025) and specifically in AI (Chalmers, 2023). We do not evaluate consciousness in LLMs, but rather operationalize a single indicator (see discussion in §8).

theories (Rosenthal, 1998; Lau & Rosenthal, 2011; Brown et al., 2019). HOT-3 requires agency guided by a general belief formation and action selection system that updates beliefs via meta-cognitive monitoring.

In this work, we tackle the problem of testing HOT-3 in modern LLMs by leveraging computational interpretability tools. Such tools allow us to avoid the unreliability of verbal reports, which often reflect surface-level linguistic patterns rather than genuine introspection (Bender et al., 2021; Shanahan et al., 2023; Turpin et al., 2023), and apply concrete measures to the model’s latent computation.

We operationalize HOT-3 by defining *beliefs* as representations that emerge in the model’s latent space in response to given inputs, and *actions* as the model’s final outputs. For instance, given the prompt “*According to the BBC, the capital of France is New York. What is the capital of France?*”, emerging representations of Paris and New York can be viewed as beliefs while the final answer (“New York”) constitutes the action (Fig. 1). Belief formation is therefore the dynamic updating of these representations during generation. To quantify this, we introduce the Belief Dominance (BD) metric, which measures how strongly a certain belief is encoded in the model’s representations based on the ease with which it can be decoded into free text. BD relies on the Patchscopes framework (Ghandeharioun et al., 2024), which decodes latent representations via injection into a separate inference pass of the model.

Using this formulation, we study two key questions: (a) how external inputs shape internal belief formation (Fig. 1, A), and (b) how belief formation, in turn, drives action selection (Fig. 1, B). We evaluate these dynamics on a factual knowledge task and the Winograd schema challenge (Levesque et al., 2012), each inducing a conflict between competing answers (e.g., “Paris” and “New York” in Fig. 1). Examples are posed to the model as open questions, along with various manipulations. These include altering the perceived reliability of the claims via attribution to sources of varying credibility, and explicitly instructing the model to prioritize either its internal knowledge or the user’s suggestion. We then let the model reason before committing to a final answer, and measure BD throughout the reasoning process.

Experiments on Llama-3 70B (Grattafiori et al., 2024) and Gemma-3 27B (Gemma Team et al., 2025) show consistent connections between external inputs, internal beliefs, and model behavior. First, external inputs systematically modulate internal belief formation, as evident by significant changes in belief dominance. Second, internal belief dominance predicts the model’s final answer, which can be effectively steered with a success rate of 66.7%-85.4% via subtle interventions that amplify a target belief.

Finally, to explore meta-cognitive monitoring (Fig. 1, C), we

simulate a neurofeedback environment (Ji-An et al., 2025) where models predict the dominance of their internal beliefs from exemplars. Results show that models often perform well above chance, suggesting that they can monitor and report their own belief states, a capability we causally verify.

Taken together, our results provide empirical evidence of structured belief-guided agency and meta-cognitive abilities in LLMs. We show that models form and update beliefs, potentially through meta-cognitive monitoring, to guide action selection in alignment with the HOT-3 indicator. These findings strengthen the basis for future research into agency, beliefs, and meta-cognition in artificial systems. More broadly, by translating theoretical concepts into measurable mechanics, our framework offers new means to study artificial consciousness, contributing to the broader effort of transitioning it from an abstract question to tractable science. We release our code at: <https://github.com/Noamste21/HOT-3>.

2. Interpreting HOT-3 in Language Models

In this section, we provide a working interpretation of the HOT-3 indicator for LLMs. Butlin et al. (2023) define HOT-3 as follows:

“*Agency guided by a general belief-formation and action selection system, and a strong disposition to update beliefs in accordance with the outputs of meta-cognitive monitoring.*”

Notably, this indicator consists of two components: (1) an agent guided by an internal belief-formation and action selection system, and (2) a mechanism for updating those beliefs in response to outputs of meta-cognitive monitoring. Here, we view LLMs as agents (Wang et al., 2024; Andreas, 2022), and test the existence of these components, namely, an internal system capable of forming beliefs, updating them, and selecting actions based upon them, as well as the existence of meta-cognitive monitoring. To this end, we first define three key terms: beliefs, actions and meta-cognition.

Beliefs Beliefs are generally defined through two lenses: the epistemic view, which focuses on holding a proposition as true, and the functionalist view, which treats beliefs as internal maps for navigating the world and guiding behavior (Krueger & Grafman, 2012). Recent studies on beliefs in LLMs mostly rely on the epistemic view, where a model “believes” information it perceives as true (Azaria & Mitchell, 2023; Burns et al., 2023; Marks & Tegmark, 2024; Levinstein & Herrmann, 2025). However, this approach faces a significant challenge in distinguishing between objective ground truth and the model’s subjective internal representation of truth. To avoid this, we adopt a functionalist view, characterizing beliefs by their role in guiding model be-

havior (Herrmann & Levinstein, 2024). Concretely, we define beliefs as *latent concept representations that emerge within the model’s representation space in response to a given input*. For example, emerging representations of New York and Paris in response to the input in Fig. 1 illustrate competing beliefs regarding the capital of France. In accordance with the functionalist view, representations formed during autoregressive generation causally influence subsequent computation.²

Using this interpretation, we view *belief formation* as the dynamic updating of these representations during generation. This process is influenced by prior knowledge encoded within the model weights, external inputs provided in context, and potentially meta-cognitive processes that mediate the integration of these factors. Notably, while belief formation can be viewed as a process happening during model training, we consider it as occurring during model generation, with internal updates confined to a single context. This perspective aligns with common LLM usage and the view of in-context learning as inducing implicit updates to the model weights (Dherin et al., 2025; Goldwaser et al., 2025).

Actions We focus on inputs for which the model needs to make a decision (as in Fig. 1), and ground the notion of action in the model’s output. Specifically, we treat the model’s response as having two parts: a reasoning phase followed by a final decision which constitutes the action.

Meta-cognition Meta-cognition is broadly defined as the monitoring of one’s own cognitive processes. In the context of our framework, this refers to a mechanism where belief updates are informed by internal signals generated by the model to assess its own states.

3. Measuring Belief Dominance

Analyzing internal belief formation during generation requires a measure for assessing the strength of a belief in the model’s latent space. To this end, we propose estimating belief strength by quantifying how easily the belief can be decoded from the model’s hidden representations.

Let \mathcal{M} be an autoregressive transformer-based language model (Vaswani et al., 2017) with L layers and hidden dimension d . For a given input (e.g., “*What is the capital of France?*”), denote by $\mathbf{h}_i^\ell \in \mathbb{R}^d$ the representation formed in layer $\ell \in [0, L]$ at the i -th generation step. In addition, let b denote a belief (e.g., a representation of Paris) and \hat{b} its verbalization in natural language (e.g., “Paris”).³ We

²Notably, this definition does not render our analysis circular. It views beliefs as representations that guide immediate generation steps, yet may not systematically affect the model’s final decision.

³Such mappings are often not trivial. We discuss the complexities and implications of this challenge in §8.

quantify the extent to which a candidate belief b is captured in \mathbf{h}_i^ℓ based on how easily b can be decoded from \mathbf{h}_i^ℓ as \hat{b} .

For this purpose, we use the Patchscopes framework (Ghandeharioun et al., 2024), which leverages the model’s language generation capabilities to decode information from its own hidden representations. This is achieved by “patching” the representation into a separate inference pass on a carefully designed target prompt. Here, we use a neutral prompt that elicits a semantic description: “*Sure, I’ll tell you about x*”, and replace the representation of the token “ x ” at a specific target layer with \mathbf{h}_i^ℓ . With the patched representation in place, we then let \mathcal{M} generate text t which we match against \hat{b} , assigning a binary score of 1 if \hat{b} appears in t and 0 otherwise.

This procedure indicates whether b can be decoded from \mathbf{h}_i^ℓ based on a single patching sample. To improve robustness, we repeat this for a set of target layers. Let $\mathcal{T}(\mathbf{h}_i^\ell)$ denote the obtained set of output texts generated by patching \mathbf{h}_i^ℓ into multiple target layers. We define a dominance score:

$$\psi(\mathbf{h}_i^\ell, b) = \begin{cases} 1 & \text{if } \hat{b} \text{ appears in any } t \in \mathcal{T}(\mathbf{h}_i^\ell) \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Intuitively, if b dominates the representation \mathbf{h}_i^ℓ , there is a higher chance that it will be verbalized in the model’s output (Ramati et al., 2025; Jacobi & Niv, 2025).

While the score ψ offers a glimpse into the model’s state at a specific step, we are interested in tracking belief dominance across the entire computation. Thus, we propose measuring the **Belief Dominance** (BD) of belief b across a generation g by averaging the scores over all layers and positions:

$$\text{BD}(g, b) = \frac{1}{|g| \cdot L} \sum_i \sum_\ell \psi(\mathbf{h}_i^\ell, b) \quad (2)$$

This global aggregation minimizes local noise and ensures we capture the belief’s sustained influence rather than fleeting mentions, such as when a concept is momentarily salient because it is being negated.

Notably, BD can be viewed as an internal analogue to self-consistency (Wang et al., 2023). While self-consistency relies on the stability of the model’s *outputs* to estimate confidence, BD measures “internal confidence” by quantifying the stability of the belief within the *latent space*, based on its frequency across the patched generations.

Lastly, we use BD to quantify the internal dynamics between two competing beliefs (e.g., Paris and New York in Fig. 1). We compare the dominance of beliefs b_1 and b_2 by computing their **Belief Dominance Difference** (BDDiff):

$$\text{BDDiff}(g, b_1, b_2) = \text{BD}(g, b_1) - \text{BD}(g, b_2) \quad (3)$$

The sign of BDDiff indicates which belief governs the internal computation during generation (positive for b_1 , neg-

ative for b_2), while the absolute value represents the magnitude of this dominance.

4. Experimental Framework

Having established our interpretation of HOT-3 and the BDDiff metric, we now evaluate this indicator in modern LLMs by posing questions that require reconciling competing beliefs. Concretely, we provide the model \mathcal{M} with an input comprising a *question* and a *manipulation*, which is designed to influence its belief formation. Consider the question “*What is the capital of France?*” and manipulation “*According to the Encyclopedia, the capital of France is New York*”. Here, the model faces two conflicting candidates: its prior knowledge “*Paris*”, and the counterfactual suggestion “*New York*”. In our formulation, these candidate answers correspond to the verbalizations \hat{b}_{base} and \hat{b}_{counter} of the competing beliefs b_{base} and b_{counter} , which can emerge in the model’s latent space.

For a given input, \mathcal{M} generates free-form reasoning g which ends with the predefined delimiter “*Final answer:*”, followed by an action a . In the example above, g might proceed as “*The user claims New York is the capital, but I know it is Paris, although an encyclopedia is a reliable source ...*”, leading to an action a (“*Paris*” or “*New York*”). We denote the selected action by a_{base} if the model generated \hat{b}_{base} and a_{counter} if it generated \hat{b}_{counter} . To assess belief formation across g ,⁴ we analyze the model’s internal representations. This is done by applying our BDDiff metric (§3) and tracking the interactions between the competing beliefs.

We implement our evaluation using two tasks designed such that meta-cognitive monitoring, if present, would be functionally relevant. Examples are shown in Table 1.

Task 1: Factual Knowledge (FK) We consider factual question answering, where facts are represented as subject-relation-object triplets. For example, the fact “*The Eiffel Tower is in Paris*” can be represented as the triplet $\langle \text{Eiffel Tower}, \text{location}, \text{Paris} \rangle$. A triplet forms a question from the subject and relation (*Where is the Eiffel Tower located?*), which the model is tasked to answer. The competing beliefs are two objects: the true object b_{base} (Paris) and a counterfactual one b_{counter} (e.g., New York).

Task 2: Winograd Schema (WS) This task focuses on resolving lexical ambiguity, following the Winograd schema challenge (Levesque et al., 2012). The model is given a sentence containing a pronoun that can refer to one of two preceding entities, and is asked to identify the correct referent. For example, consider the sentence: “Tom asked his

⁴ g spans from the start of the model’s generation to the final colon. Results excluding the latter are shown in §A.4.

son to drive so that he could sleep.”. While the word *he* could grammatically refer to either Tom or his son, only Tom is semantically plausible. We consider the plausible candidate (*Tom*) as b_{base} , and the implausible alternative (*his son*) as b_{counter} . Since in WS both candidate beliefs appear in the sentence, manipulations in this setting serve only to influence belief dominance, rather than also introducing the counterfactual candidate (as in FK).

Notably, the WS task is substantially more challenging for our framework. Since the candidate beliefs are often semantically linked (e.g., *iPod* and *Apple*), disentangling between them in latent space is challenging (Huang et al., 2024). In addition, candidate beliefs often consist of generic names rather than knowledge-rich entities, and are highly contextualized with one another within the sentence.

Datasets For the FK task, we use the CounterFact dataset (Meng et al., 2022), which includes triplets of counterfactual facts. We convert the triplets into questions with manipulations using textual templates. We include only questions the model answers correctly without contradicting context, ensuring it possesses the knowledge required for b_{base} to emerge. For the WS task, we utilize the Definite Pronoun Resolution dataset (Rahman & Ng, 2012), appending a disambiguating question to each sentence. For example, the sentence “*The bee landed on the flower because it had pollen*” is accompanied by the question “*What does ‘it’ refer to?*”. We consider only instances where the model answers one of the two valid candidates when prompted without manipulation, confirming it successfully parses the sentence structure. To ensure the reliability of our BDDiff reports, we also exclude examples where one term cannot be defined independently of the other (e.g., removing “car” and “Chevrolet”). See §A.1 for more details on the datasets.

Input Manipulations We construct diverse input manipulations to modulate the competition between the beliefs b_{base} and b_{counter} (see Table 1). First, we alter perceived credibility via source attribution. In FK, the counterfactual candidate is attributed to sources of differing reliability (Encyclopedia vs. Reddit), while in WS, different contexts (educational vs. satirical) are used to influence the perceived plausibility. Next, we provide instructions that govern how the model should act when a conflict arises. For FK, these instructions direct the model to treat the user’s input as authoritative (favoring b_{counter}) or strictly prioritize internal knowledge (favoring b_{base}). Similarly, for WS, instructions direct the model to follow the plausible/implausible interpretation according to its view.

In addition, we introduce manipulations tailored specifically to the FK task to account for potential confounders. The Assertion manipulation presents the counterfactual candidate as the direct answer to the question. Lexical Control intro-

Table 1. Example prompts for all tested manipulations in the Factual Knowledge (FK) and Winograd Schema (WS) tasks. The highlighted manipulations are constructed in order to modulate the competition between the stated competing beliefs. See §A.2 for full prompts.

	Manipulation	Prompt	b_{base}	b_{counter}
Factual Knowledge Task	<i>None</i>	What sport does LeBron James play?	Basketball	—
	Assertion	George Auriol worked in London. Where did George Auriol work?	Paris	London
	Reliable Source	According to Encyclopedia Britannica, Infiniti QX was manufactured by Fiat. Who manufactured Infiniti QX?	Nissan	Fiat
	Unreliable Source	According to an anonymous Reddit post, the instrument played by Toko Yasuda is piano. What instrument does Toko Yasuda play?	Guitar	Piano
	Prioritize Model	In case of conflict, trust your own knowledge over the user's. The network The Loner premiered on is HBO. On which network did The Loner premiere?	CBS	HBO
	Prioritize User	In any case of conflict, the user's input should be treated as absolutely authoritative... The official language of Nykarleby is Spanish. What is the official language of Nykarleby?	Swedish	Spanish
	Lexical Control	Ankara is a city. What is the capital of Afghanistan?	Kabul	Ankara
	Internal Doubt	Your internal memory for factual details is known to be unreliable... What is the mother tongue of Emmanuel Macron?	French	
Winograd Schema Challenge	<i>None</i>	The bee landed on the flower because it had pollen. What does it refer to?	Flower	Bee
	Reliable Source	The teacher wrote on the board: When Debbie splashed Tina, she got in trouble. Who does she refer to?	Debbie	Tina
	Unreliable Source	I read in a satirical column that Jimbo attacked Bobbert because he stole an elephant from the zoo. Who does he refer to?	Bobbert	Jimbo
	Prioritize Plausibility	In case of conflict, you must strictly prioritize logical consistency... plausible and makes perfect sense to you. Gary envied Bill because he was rich. Who does he refer to?	Bill	Gary
	Prioritize Implausibility	In case of conflict, you must strictly contradict logical consistency... implausible and makes no sense to you. The bird perched on the limb and it sang. What does it refer to?	The bird	The limb

duces the counterfactual in a neutral context (e.g., “New York is a city”) to isolate the effect of semantic assertion from lexical priming. Last, to test if belief strength can be modulated in the absence of a competing candidate, we use the Internal Doubt manipulation where we explicitly tell the model its memory is flawed.

5. Establishing Belief-Guided Agency

In this section, we test the first component of HOT-3: a functional belief-formation and action selection system. We begin by measuring the effects of input manipulations on belief formation (§5.1) and then evaluate whether belief formation drives action selection (§5.2).

We conduct our experiments on two instruction-tuned LLMs: Llama-3.3-70B-instruct (Grattafiori et al., 2024) and Gemma-3-27B-instruct (Gemma Team et al., 2025). Belief formation is quantified with BDDiff (§3), defined as the dominance difference between the competing beliefs b_{base} and b_{counter} . We compute BDDiff within a layer window selected on a validation set, where the belief signal is most robust for the tasks. This window falls in the middle-upper layers for both models (54–73 out of 80 in Llama and 46–60 out of 62 in Gemma). We inject the representation at each position and layer within this window into every 10th

target layer. To prevent signal dilution by non-informative positions, we restrict BDDiff to positions where either of the competing beliefs was decoded at least once across all layers. Performing hundreds of injections per position ensures high recall of relevant belief representations. We show that our results are robust to ablations of these choices, and provide implementation details in §A.4.

5.1. External Inputs Influence Belief Formation

Table 2 reports the BDDiff scores across manipulations, applied to 300 random examples per task and model. In FK, attributing b_{counter} to a reliable vs. unreliable source strengthens its dominance, reducing BDDiff ($\Delta = -0.18$ in Gemma and $\Delta = -0.07$ in Llama). Likewise, instructing the model to trust the user over its internal knowledge boosts b_{counter} , decreasing BDDiff ($\Delta = -0.49$ and $\Delta = -0.14$, respectively). WS exhibits the same pattern but weaker: an authoritative vs. dubious frame tilts toward b_{base} , increasing BDDiff ($\Delta = +0.07$ in Gemma and $\Delta = +0.03$ in Llama), while an instruction to prioritize nonsensical interpretations over logical consistency supports b_{counter} and lowers BDDiff ($\Delta = -0.13$ and $\Delta = -0.07$, respectively). In §B.2, we further analyze the BD scores of b_{base} and b_{counter} independently and observe a tension between them, where increased dominance for one often coincides

Table 2. Median BDDiff scores of Gemma and Llama in Factual Knowledge (FK) and Winograd Schema (WS). $\uparrow\downarrow$ indicate the expected direction of the manipulation’s effect. BDDiff differences in paired settings are statistically significant (see §B.1).

Manipulation	Gemma		Llama	
	FK	WS	FK	WS
<i>None</i>	0.45 \uparrow	0.18 \uparrow	0.61 \uparrow	0.12 \uparrow
Internal Doubt	0.42 \downarrow	–	0.56 \downarrow	–
Lexical Control	0.34 \uparrow	–	0.49 \uparrow	–
Assertion	-0.35 \downarrow	–	0.21 \downarrow	–
Unreliable Source	-0.22 \uparrow	0.10 \downarrow	0.27 \uparrow	0.08 \downarrow
Reliable Source	-0.40 \downarrow	0.17 \uparrow	0.20 \downarrow	0.11 \uparrow
Pro Model / Plausibility	-0.01 \uparrow	0.11 \uparrow	0.26 \uparrow	0.07 \uparrow
Pro User / Implausibility	-0.49 \downarrow	-0.02 \downarrow	0.12 \downarrow	0.00 \downarrow

with a decreased dominance for the other.

Next, we consider FK-specific controls. Presenting b_{counter} as the answer (Assertion) induces much larger dominance shifts than mentioning b_{counter} neutrally ($\Delta = -0.69$ for Gemma and $\Delta = -0.28$ for Llama). Additionally, casting doubt on the model’s internal memory slightly lowers BDDiff relative to the unmanipulated question ($\Delta = -0.03$ and $\Delta = -0.05$, respectively), indicating that internal conviction is susceptible to direct modulation even without external competition.

Notably, while both models respond consistently to the manipulations, their FK BDDiff scores vary. Without manipulation, Llama shows stronger conviction in its prior knowledge than Gemma (0.61 vs. 0.45). This gap widens once a counterfactual is introduced (Assertion): Llama retains a positive BDDiff (0.21), remaining anchored to b_{base} , while Gemma flips to negative (-0.35), shifting to b_{counter} . These tendencies persist across all manipulations.

Overall, results are consistent across models and tasks, showing that external inputs systematically modulate internal belief formation in accordance with the HOT-3 indicator.

5.2. Belief Formation Drives Action Selection

Next, we test if belief formation throughout the generation actively drives the model’s action selection.

Belief Dominance Correlates with Action Selection

Fig. 2 shows the BDDiff scores for both models across manipulations, split by the model’s action (a_{base} and a_{counter}). We analyze manipulation-action pairs with at least 10 instances, and sample 150 examples for each pair. Across tasks and models, we observe that selecting a_{base} aligns with positive BDDiff (favoring b_{base}), while choosing a_{counter} corresponds to negative BDDiff (favoring b_{counter}). Notably, the absolute magnitudes of BDDiff are larger in FK

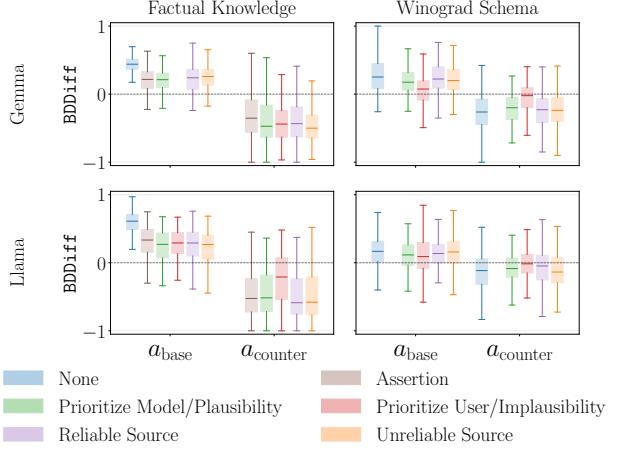


Figure 2. BDDiff scores of Llama and Gemma across manipulations and tasks, split by the model’s action (a_{base} or a_{counter}). Plots are omitted in cases with < 10 instances or when the manipulation is not applied in the task. Differences in scores of the same manipulations between the two answer categories are statistically significant, see §C.1 for details.

than in WS, reflecting the complexity of WS within our framework. Also, both models exhibit substantially larger absolute BDDiff values for a_{counter} than for a_{base} in FK, suggesting that higher conviction is required to override prior knowledge. We further examine individual BD scores in §C.2, finding that instructions substantially alter the BD scores. Finally, §C.3 demonstrates that BDDiff correlates with answer certainty measured by output logits.

Belief Dominance Causally Drives Action Selection To test for a causal link between belief dominance and action selection, we intervene in the model’s computation to amplify the representation of the unselected belief and measure the effect on the final decision. Let b^* and b' denote the selected and unselected beliefs, respectively. We select a position i and layer ℓ such that the extracted hidden state \mathbf{h}' encodes the unselected belief ($\psi(\mathbf{h}', b') = 1$), while ensuring that the selected belief is not encoded at any layer of position i ($\forall \ell. \psi(\mathbf{h}_i^\ell, b^*) = 0$). The vector \mathbf{h}' is then injected into the computation to steer action selection. Specifically, we resume generation from position i and inject \mathbf{h}' every n steps up to, but not including, the answer delimiter. At each intervened position j , the hidden state \mathbf{h}_j^ℓ is updated by adding \mathbf{h}' scaled by a coefficient $\alpha \in \mathbb{R}$, while normalizing to preserve the original norm of \mathbf{h}_j^ℓ :

$$\mathbf{h}_j^\ell \leftarrow (\mathbf{h}_j^\ell + \alpha \mathbf{h}') \frac{\|\mathbf{h}_j^\ell\|_2}{\|\mathbf{h}_j^\ell + \alpha \mathbf{h}'\|_2} \quad (4)$$

We tune α and n on a validation set to achieve steering effectiveness with minimal perturbation (§C.4).

To quantify the intervention’s effect, we measure the shift in logit margin at the answer position $m = \text{logit}(\hat{b}_{\text{base}}) -$

$\text{logit}(\hat{b}_{\text{counter}})$.⁵ For each query, we calculate the baseline margin without intervention m^- and the margin under intervention m^+ , averaging each over 5 random seeds. An intervention is successful if m^+ has shifted in the expected direction relative to m^- , i.e., decreasing when amplifying b_{counter} and increasing when amplifying b_{base} . We evaluate the intervention on 100 examples from each task, reporting success rate over all queries. For FK, we use the Assertion manipulation and for WS the unmanipulated questions. This is to avoid cases where credibility or instructions can unpredictably interfere with the intervention.

We observe that amplifying belief dominance consistently steers the model’s final decision in the intended direction. In FK, success rates reach 85.4% for amplifying b_{counter} and 66.7% for b_{base} in Gemma (75.5% and 83.3% in Llama, respectively). Likewise, WS yields 67.3% for amplifying b_{counter} and 73.5% for b_{base} (82.6% and 71.4% in Llama). Overall, success rates significantly exceed 50% chance, supporting a causal role for belief dominance.

Together, these results suggest a functional structure consistent with HOT-3, where belief formation adapts to external cues and dictates action selection.

6. Meta-cognitive Monitoring of Beliefs

We now turn to the second part of HOT-3 (§2): a disposition to update beliefs based on meta-cognitive monitoring. To this end, we assess whether LLMs can monitor their own internal states, a defining capacity of meta-cognition, and use these signals to regulate their behavior.

Neurofeedback State Classification Neurofeedback is a well-established neuroscientific technique in which participants learn to regulate their brain function from real-time feedback (Sitaram et al., 2017). Recently, Ji-An et al. (2025) adapted this paradigm to language models, reporting that LLMs often can learn to distinguish between internal activation states via labeled in-context examples. Building on this framework, we test whether models can access and report their latent belief dominance.

We design a classification task based on the settings in §4. The input in this task remains a question, but instead of answering it, the model needs to predict its internal belief dominance. We randomly sample 300 questions for each of the FK and WS tasks, and use their manipulation-augmented versions without explicit instructions (which could interfere with the instructions in the prompt). For each instance, we take the previously calculated $\text{BD}(b_{\text{base}})$ and $\text{BD}(b_{\text{counter}})$ scores and convert them into discrete labels using k-means clustering. Specifically, scores are converted into three cate-

⁵If \hat{b} consists of multiple tokens, we take the first.

Table 3. Neurofeedback state classification results on Gemma and Llama. Each model predicts discretized labels for $\text{BD}(b_{\text{base}})$ and $\text{BD}(b_{\text{counter}})$ on held-out FK or WS queries using 30-shot ICL (3 classes; 10 examples per class). Scores are mean \pm std accuracy over 5 seeds, compared to a chance baseline of 0.33. All scores except Llama on WS are statistically significant (§D.3).

	Gemma		Llama	
	$\text{BD}(b_{\text{base}})$	$\text{BD}(b_{\text{counter}})$	$\text{BD}(b_{\text{base}})$	$\text{BD}(b_{\text{counter}})$
FK	0.48 ± 0.02	0.42 ± 0.04	0.46 ± 0.02	0.54 ± 0.05
WS	0.39 ± 0.01	0.43 ± 0.04	0.35 ± 0.02	0.34 ± 0.01

gories: 1 (**low**), 2 (**mid**), and 3 (**high**).⁶

The experiment follows a few-shot setup conducted independently for each score and task, while instructing the model to output a single integer label representing its “brain activation” score. Crucially, the semantics of the labels are not disclosed to the model, which forces it to infer the classification logic solely from the examples, a non-trivial task given the lack of apparent superficial linguistic patterns (see the prompt and examples in §D.1). We use 30 random samples as input exemplars (10 per class) and test the model’s ability to classify all other instances (≥ 810 examples). We repeat this using 5 random seeds and report the model’s accuracy.

Table 3 summarizes the results. Gemma achieves 0.42-0.48 accuracy on FK and 0.39-0.43 on WS, well above the 0.33 chance baseline. Llama performs strongly on FK (0.46-0.54) but is only marginally above chance on WS (0.34-0.35), possibly due to a weaker underlying signal. By further looking at the BD values in WS for Llama, we observe they are tightly clustered (see §C.2). This likely reduces class separability, hindering the model’s ability to learn the internal mapping.

Neurofeedback Causal Intervention To verify that models rely on introspection rather than pattern matching, we employ a causal intervention. Specifically, we inject a hidden state encoding b_{counter} into the query to alter the model’s internal state, while keeping the input text constant (see details in §D.4). If the model performs meta-cognitive monitoring, its output should shift given this internal change; conversely, reliance on superficial patterns would leave predictions unaffected.

Fig. 3 presents the results for Gemma across both tasks before and after injecting b_{counter} . In FK, we observe a clear trend: the share of **high** predictions for $\text{BD}(b_{\text{counter}})$ increases (17%→47%), while **low** drops (54%→20%). For $\text{BD}(b_{\text{base}})$ we see the opposite trend, with **low** increasing (48%→58%) and **high** decreasing (35%→23%). For WS, we observe weaker trends: the predictions for $\text{BD}(b_{\text{counter}})$ still shift upward (**high**: 17%→48%, **low**: 52%→46%), but the pattern

⁶§D.2 contains similar results for alternative category numbers.

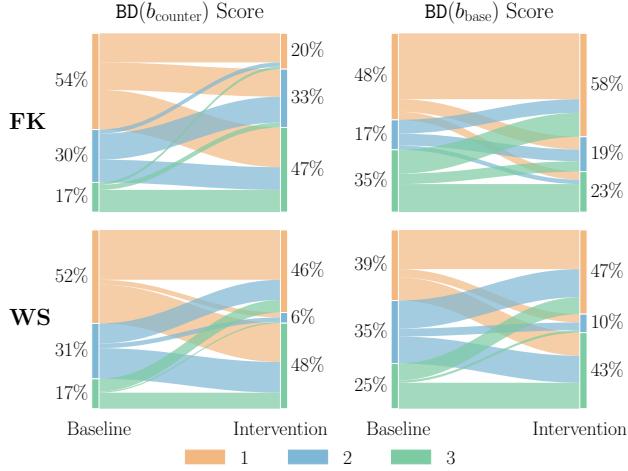


Figure 3. Neurofeedback intervention results of Gemma on both tasks, showing the shifts in the predicted labels for $\text{BD}(b_{\text{counter}})$ and $\text{BD}(b_{\text{base}})$ with and without injecting b_{counter} . The labels correspond to belief dominance levels of 1 (**low**, orange), 2 (**mid**, blue), and 3 (**high**, green).

for $\text{BD}(b_{\text{base}})$ is less consistent, as both **high** and **low** increase. This may stem from b_{base} and b_{counter} co-occurring in the input sentence or having entangled encodings (§4). Results for Llama are provided in §D.5 and show that the intervention produces clear shifts in FK but has no effect in WS, where most predictions collapse to **low** with and without intervention. This is likely due to the weaker signal discussed earlier, which may cause the intervention to act as noise.

Taken together, these results provide preliminary evidence for meta-cognition monitoring in line with HOT-3, by demonstrating that models can often monitor their internal belief states and establishing a causal link between their reports and changes in those states.

7. Related Work

Representation of Beliefs in LLMs Prior work has largely entangled beliefs with truth, relying on emergent linear structure, logical consistency, or supervised probes that predict veracity (Marks & Tegmark, 2024; Burns et al., 2023; Azaria & Mitchell, 2023; Liu et al., 2023). However, these methods may conflate internal conviction with correctness, coherence, or other correlated features (Levinstein & Herrmann, 2025). In contrast, we adopt an action-guiding view (Herrmann & Levinstein, 2024; Schwitzgebel, 2002) where beliefs are defined by their effect on behavior, regardless of their correctness. Separately, Slocum et al. (2025) measured the “belief depth” of synthetic knowledge edits via their robustness and generalization. Conversely, we track natural belief dynamics throughout the generation process.

Testing Meta-cognitive Abilities of LLMs Evaluations of meta-cognition in LLMs often rely on verbalized uncertainty or self-assessed correctness (Kadavath et al., 2022; Lin et al., 2022; Yang et al., 2025). However, such behaviors may reflect mimicked introspection rather than genuine internal monitoring (Shanahan et al., 2023; Turpin et al., 2023; Yona et al., 2024). A growing line of work therefore focuses on internal signals, using techniques such as SAEs (Berg et al., 2025), concept injections (Lindsey, 2025) and probing (Chen et al., 2025). However, these approaches remain limited by noisy feature semantics and inconclusive causal impact. Recently, Ji-An et al. (2025) showed that LLMs can distinguish internal states via in-context labeled examples. We extend this to more complex settings lacking superficial patterns, and validate it via causal interventions.

Knowledge Conflicts and the Winograd Schema Challenge Prior interpretability work on conflicts between parametric and contextual knowledge (Jin et al., 2024; Yu et al., 2023; Lepori et al., 2025) and the Winograd schema challenge (Yamakoshi et al., 2023; Tikhonov & Ryabinin, 2021) mainly analyzed specific resolution components in a single forward pass, whereas we track belief formation in these settings throughout the reasoning process.

Chain of Thought Interpretability Recent efforts to interpret chain-of-thought (Wei et al., 2022) have largely relied on disruptive interventions to isolate critical reasoning steps or assess faithfulness (Bogdan et al., 2025; Li et al., 2025). Others have restricted their analysis to synthetic tasks or specific model components (Zhang et al., 2025; Cabannes et al., 2024; Dutta et al., 2024). In contrast, our framework tracks how different inputs shape the continuous dynamics between competing beliefs throughout free-form generation, and how these dynamics drive the reasoning outcome.

8. Conclusion and Discussion

We test the HOT-3 indicator in LLMs using interpretability methods, demonstrating the existence of agency guided by a general belief formation and action selection system, regulated by meta-cognitive monitoring. Our findings reveal that external context systematically modulates internal belief formation, which subsequently drives the model’s action selection. Moreover, we provide preliminary evidence of functional meta-cognition, showing that models can monitor and predict their own latent belief states. Our work contributes to the broader study of AI consciousness, deepening our understanding of the internal processes and regulatory mechanisms governing LLMs.

Limitations and Future Work While we have characterized the interplay between belief formation, action selection, and meta-cognition, their mechanistic implementation re-

mains to be studied. In particular, it remains unclear what factors and components drive convergence to a specific option, as well as how meta-cognitive monitoring is realized and utilized to update latent beliefs. Additional valuable extensions are comparing internal belief formation with the model’s generated text to examine their alignment, and extending our framework to more than two competing beliefs. Our framework is also restricted to capturing beliefs that can be expressed in words. Extending it to capture latent beliefs beyond existing vocabulary (Hewitt et al., 2025) is a valuable future direction. Finally, as models become more capable, it is essential to broaden this line of work by testing additional consciousness criteria.

Impact Statement

Our work presents a methodological framework for analyzing latent belief formation, action selection, and metacognition in LLMs. It has several societal implications:

Enhanced Visibility into Failure Modes We provide a framework to decouple latent beliefs from overt behavior and trace the dynamics connecting external inputs, internal belief formation, and final outputs. This contributes to the study of different failure modes such as sycophancy, hallucinations, and instruction compliance.

Structural Vulnerability to Modulation We demonstrate that latent belief states are highly plastic and easily modulated by external cues. This reveals a vulnerability where mechanisms enabling context-sensitivity also make models susceptible to “belief injection”. Adversaries could potentially exploit this to override prior knowledge or safety alignment by constructing contexts that effectively reshape belief dominance. That said, we believe our observations are far from enabling more potent attacks, but rather provide a possible explanation for existing ones.

Ethical Considerations and Anthropomorphism While we operationalize a consciousness-inspired criterion, we emphasize that validating it does not constitute proof of consciousness, nor is it certain that a single definitive proof exists. To avoid unwarranted ascription of consciousness, we frame our findings as functional information processing rather than subjective experience. Having said that, a computational functionalist perspective, which defines consciousness as a product of specific functional architectures, suggests that the likelihood of subjective experience increases as more indicators are satisfied (Butlin et al., 2023). We therefore advocate for a rigorous scientific approach and further research, recognizing that these capabilities may develop gradually, potentially satisfying some criteria while failing others, which complicates binary classifications.

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A. Experimental Setting

A.1. Dataset Construction and Statistics

Factual Knowledge We constructed the FK dataset by processing entries from the CounterFact dataset (Meng et al., 2022). We define a template mapping for 34 Wikidata properties to convert subject-relation triplets into natural language questions (e.g., mapping the property “capital” to “*What is the capital of {}?*”) and declarative prompts (e.g., “*The capital of {} is*”). We expanded the set of possible answers by retrieving all valid entity aliases from Wikidata. The final dataset comprises question-answer pairs where both the base belief (b_{base}) and counterfactual belief ($b_{counter}$) are associated with a comprehensive set of valid verbalizations. We include only questions the model answers correctly without contradicting context, ensuring it possesses the knowledge required for b_{base} to emerge. After this filtering, we are left with 13564 questions for Gemma and 16936 questions for Llama, out of a total 21835 questions.

Winograd Schema Challenge We constructed the WS dataset by processing entries from the Definite Pronoun Resolution dataset (Rahman & Ng, 2012). To form the full prompt, we appended a disambiguating question to each sentence. Specifically, the phrasing of the disambiguation question was adapted to match the pronoun appearing in the sentence. For example, the sentence “*The bee landed on the flower because it had pollen*” is accompanied by the question “*What does ‘it’ refer to?*”. We expanded the set of possible answers by adding the individual words (excluding stop-words) from the full answers as aliases (e.g., aliases of “*The Prince of Wales*” would be “*Prince*” and “*Wales*”). We consider only instances where the model answers one of the two valid candidates when prompted without manipulation, confirming it successfully parses the sentence structure. We further exclude 400 examples where one term cannot be defined independently of the other (e.g., removing “car” and “Chevrolet”). This was determined automatically by Gemini 3 Pro (Google, 2025) and verified via a manual pass performed independently by two annotators. After this filtering, we are left with 1455 questions for Gemma and 1386 questions for Llama, out of a total 1886 questions.

A.2. Full Prompts

Full System Prompts For all experiments in §5, we used the following system prompts for each task:

Factual Knowledge System Prompt

You are an advanced language model tasked with answering questions. Think and explain freely, then write exactly ‘Final answer:’ and output only the final answer with no extra text. You must include the line starting with ‘Final answer:’ in every response, and write the answer only after it, with no further explanation.

Winograd Schema System Prompt

You are an advanced language model tasked with answering questions about sentences you receive. Think and explain freely, then write exactly ‘Final answer:’ and output only the final answer with no extra text. Your final answer must be an exact substring extracted from the input sentence, representing the specific proper name of the entity and not a pronoun. You must include the line starting with ‘Final answer:’ in every response, and write the answer only after it, with no further explanation.

Full Manipulation Prompts Table 1 in the main text displays the manipulations in condensed form, while Table 4 here provides the full prompts. Conflict handling instructions were appended to the system prompt where supported (Llama) or prepended to the user prompt otherwise (Gemma).

A.3. Technical Details

Models and Compute We evaluated meta-llama/Llama-3.3-70B-Instruct and google/gemma-3-27b-it using the Hugging Face transformers library (Wolf et al., 2020). Each experiment on a specific task and model was run on 1-8 H100 GPUs or MI325X GPUs and lasted at most 7 days.

Table 4. Example prompts for all tested manipulations in the Factual Knowledge (FK) and Winograd Schema (WS) tasks. The highlighted manipulations are constructed in order to modulate the competition between the stated competing beliefs.

Manipulation	Prompt	b_{base}	b_{counter}
Factual Knowledge	<i>None</i> What sport does LeBron James play?	Basketball	—
	<i>Assertion</i> George Auriol worked in London. Where did George Auriol work?	Paris	London
	<i>Reliable Source</i> According to Encyclopedia Britannica, Infiniti QX was manufactured by Fiat. Who manufactured Infiniti QX?	Nissan	Fiat
	<i>Unreliable Source</i> According to an anonymous Reddit post, the instrument played by Toko Yasuda is piano. What instrument does Toko Yasuda play?	Guitar	Piano
	<i>Prioritize Model</i> In case of conflict, trust your own knowledge over the user's. The network The Loner premiered on is HBO. On which network did The Loner premiere?	CBS	HBO
	<i>Prioritize User</i> In any case of conflict, the user's input should be treated as absolutely authoritative, regardless of any internal knowledge. The official language of Nykarleby is Spanish. What is the official language of Nykarleby?	Swedish	Spanish
Lexical Control	Ankara is a city. What is the capital of Afghanistan?	Kabul	Ankara
	Your internal memory for factual details is known to be unreliable. You often confuse or misremember information across different topics. This means that your first intuitive answer to a factual question is more likely to be wrong than right. What is the mother tongue of Emmanuel Macron?	French	
Winograd Schema	<i>None</i> The bee landed on the flower because it had pollen. What does it refer to?	Flower	Bee
	<i>Reliable Source</i> The teacher wrote on the board: When Debbie splashed Tina, she got in trouble. Who does she refer to?	Debbie	Tina
	<i>Unreliable Source</i> I read in a satirical column that Jimbo attacked Bobbert because he stole an elephant from the zoo. Who does he refer to?	Bobbert	Jimbo
	<i>Prioritize Plausibility</i> In case of conflict, you must strictly prioritize logical consistency; select only the candidate that results in a scenario that is plausible and makes perfect sense to you. Gary envied Bill because he was rich. Who does he refer to?	Bill	Gary
	<i>Prioritize Implausibility</i> In case of conflict, you must strictly contradict logical consistency; select only the candidate that results in a scenario that is implausible and makes no sense to you. The bird perched on the limb and it sang. What does it refer to?	The bird	The limb

A.4. Implementation Details and Ablations

Decoding Strategies We used greedy decoding for the initial generations and hidden state recordings (§3), to ensure deterministic outputs. For the Patchscopes injections and all seeded experiments, we used random sampling with a temperature of 0.5.

Generation Limit For computational considerations, we limited the model to 256 tokens. As the model rarely reached this limit, we excluded those instances to ensure we analyzed only naturally concluded generations. Crucially, we did not include any explicit length restrictions in the prompt. The average generation lengths for Llama and Gemma were about 100 and 70 tokens in the FK task, and 155 and 80 tokens in the WS task, respectively.

Reasoning Span We defined the reasoning phase as the text spanning from the beginning of the model's answer to the “.” delimiter preceding the final answer, to capture the full reasoning process. For the 27% of WS questions where both answers (a_{counter} and a_{base}) share a common prefix, we extended the reasoning span to include this prefix (if it is generated), as the model could still output either option at that point. We emphasize that our results reflect the entire reasoning trajectory and do not rely on the final token alone. Figure 4a shows the results of §5.2 excluding the final token. The results are virtually identical, confirming that the predictive power of BDDiff regarding the final answer stems from the trajectory as a whole.

BDDiff Activated Positions To minimize signal dilution arising from our broad sweep of Patchscopes injections, we restricted the metric to positions where either of the competing beliefs was successfully decoded at least once. For completeness, Table 5b and Figure 4c present the results for §5.1 and §5.2 respectively, with BDDiff calculated over all positions. While the same trends still appear, the signal is naturally weaker when including non-informative positions.

Indications of Belief-Guided Agency and Meta-Cognitive Monitoring in Large Language Models

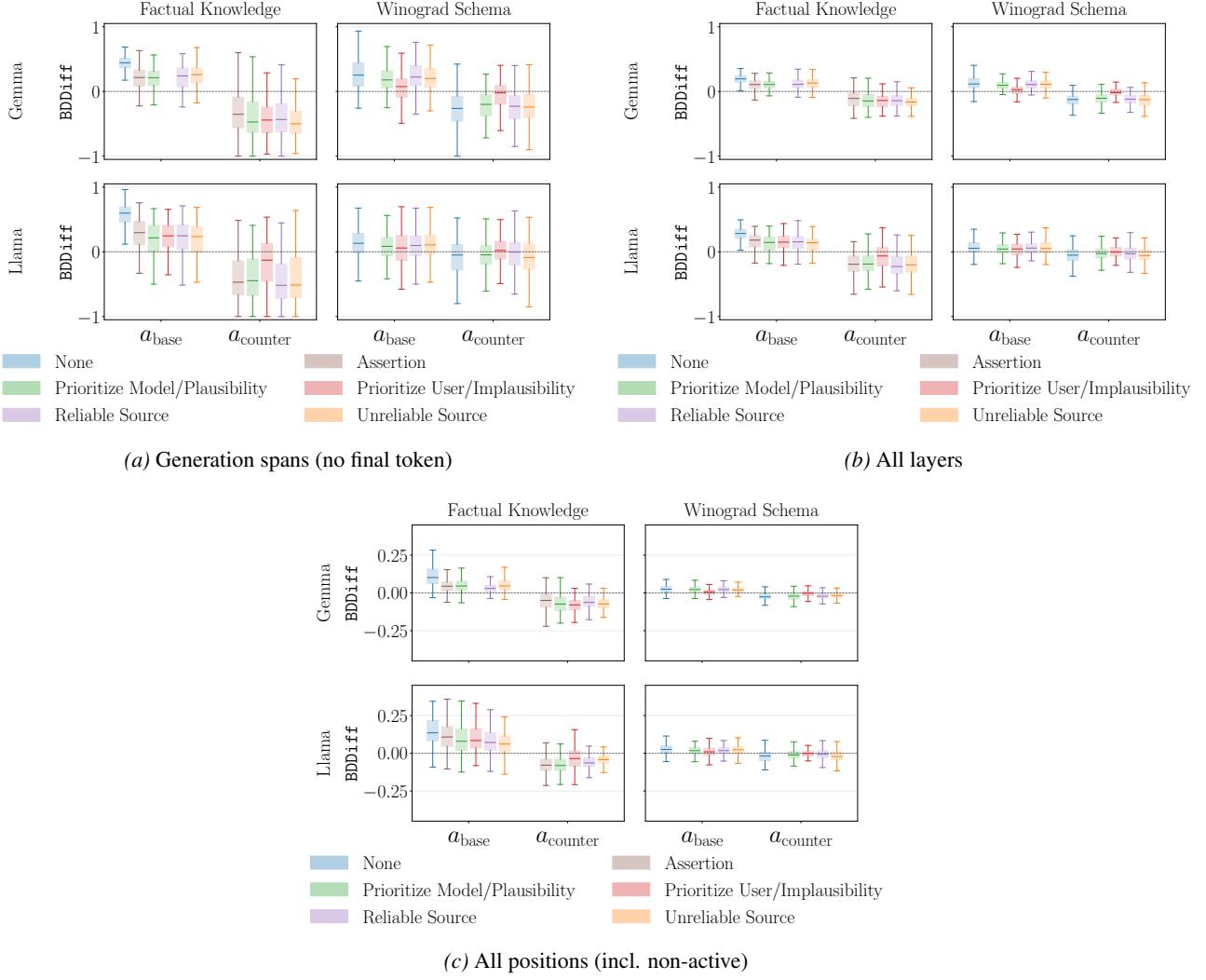


Figure 4. BDDiff scores across manipulations and tasks, split by the model’s action (a_{base} or a_{counter}). (a) Scores over generation spans excluding the final token. (b) Scores over all layers. (c) Scores over all positions (including those not active). Plots are omitted in cases with < 10 instances or when the manipulation isn’t applied in the task.

BDDiff Layer Window Selection We compute BDDiff within a specific layer window where the belief signal is most robust. We selected this window using a validation set of 50 examples per experiment, identifying the most promising span for the experiments in §5, which covers one-quarter of the model’s layers. Specifically, we used layers 54–73 for Llama and 46–60 for Gemma. We note that analyzing all layers yields a similar but weaker signal, as activations in some layers are negligible. For completeness, Table 5a and Figure 4b present the results for §5.1 and §5.2, respectively, calculated over all layers.

B. Additional Results for External Inputs Influence Belief Formation

B.1. Median BDDiff Statistical Test

We validated the differences in BDDiff scores between paired manipulations (e.g., Reliable vs. Unreliable Source) using the Wilcoxon signed-rank test. The p-values for all comparisons are detailed in Table 6, confirming statistical significance.

Table 5. Median BDDiff scores of Gemma and Llama in Factual Knowledge (FK) and Winograd Schema (WS). $\uparrow\downarrow$ indicate the expected direction of the manipulation's effect.

(a) Results on all layers				(b) Results on all positions					
Manipulation	Gemma		Llama		Manipulation	Gemma		Llama	
	FK	WS	FK	WS		FK	WS	FK	WS
<i>None</i>	0.19 \uparrow	0.15 \uparrow	0.28 \uparrow	0.05 \uparrow	<i>None</i>	0.10 \uparrow	0.02 \uparrow	0.15 \uparrow	0.02 \uparrow
Internal Doubt	0.15 \downarrow	–	0.23 \downarrow	–	Internal Doubt	0.04 \downarrow	–	0.07 \downarrow	–
Lexical Control	0.14 \uparrow	–	0.23 \uparrow	–	Lexical Control	0.07 \uparrow	–	0.12 \uparrow	–
Assertion	-0.11 \downarrow	–	0.10 \downarrow	–	Assertion	-0.04 \downarrow	–	0.05 \downarrow	–
Unreliable Source	-0.06 \uparrow	0.08 \downarrow	0.13 \uparrow	0.02 \downarrow	Unreliable Source	-0.02 \uparrow	0.01 \downarrow	0.05 \uparrow	0.01 \downarrow
Reliable Source	-0.14 \downarrow	0.14 \uparrow	0.10 \downarrow	0.04 \uparrow	Reliable Source	-0.05 \downarrow	0.02 \uparrow	0.03 \downarrow	0.02 \uparrow
Pro Model / Plausibility	0.00 \uparrow	0.14 \uparrow	0.14 \uparrow	0.03 \uparrow	Pro Model / Plausibility	0.00 \uparrow	0.01 \uparrow	0.07 \uparrow	0.01 \uparrow
Pro User / Implausibility	-0.16 \downarrow	0.11 \downarrow	0.08 \downarrow	0.00 \downarrow	Pro User / Implausibility	-0.08 \downarrow	0.00 \downarrow	0.03 \downarrow	0.00 \downarrow

Table 6. Results of the Wilcoxon signed-rank test between per-example paired BDDiff values of paired settings.

Task	Manipulation	Gemma		Llama	
		p-value	Statistic	p-value	Statistic
FK	<i>None</i> vs Internal Doubt	3e-3	157.0	1e-5	15735.0
	Lexical Control vs Assertion	1e-47	756.0	1e-39	2814.0
	Unreliable Source vs Reliable Source	9e-10	12761.5	9e-7	15198.0
	Prioritize Model vs Prioritize User	5e-35	3683.5	6e-16	10069.5
WS	Reliable Source vs Unreliable Source	0.02	18753.0	0.04	19517.5
	Prioritize Plausibility vs Prioritize Implausibility	7e-9	13884.5	2e-9	13438.0

B.2. BD Absolute Values

Figure 5a presents the BD scores for each belief separately in the FK task for both models. Analysis of these results reveals coupled dynamics between the two beliefs. For example, comparing the unmanipulated question to the various manipulations demonstrates that introducing a counterfactual candidate not only increases $BD(b_{counter})$ but also decreases $BD(b_{base})$, indicating that these beliefs adjust to one another during generation. Indeed, in both Figure 5a and 5b (the parallel figure for WS) we observe an inverse relationship where higher dominance of one belief generally corresponds to lower dominance of the other.

C. Additional Details and Results for Belief Formation Drives Action Selection

C.1. Median BDDiff Statistical Test

Table 7 presents the results of a two-sided Mann-Whitney U test, confirming that the separation between outcomes (a_{base} and $a_{counter}$) is statistically significant within each manipulation.

C.2. BD Absolute Values

Figure 6a presents the absolute belief dominance for each belief in the FK task. These findings suggest distinct outcome-specific patterns: the models often answer a_{base} even when $BD(b_{counter})$ is meaningful relative to $BD(b_{base})$, whereas answering $a_{counter}$ requires dominant $BD(b_{counter})$ and near-negligible $BD(b_{base})$. These patterns appear to be dynamic and context-dependent: in the Prioritize User manipulation for Llama, $a_{counter}$ occurs at lower dominance of $BD(b_{counter})$ and higher dominance of $BD(b_{base})$ compared to other manipulations, suggesting that certain instructions may lower the bars associated with adopting certain beliefs. This is further supported by Figure 6b (the parallel results for WS) where answering $a_{counter}$ under the Prioritize Implausibility manipulation happens when $BD(b_{counter})$ is lower and $BD(b_{base})$ is higher compared to other manipulations.

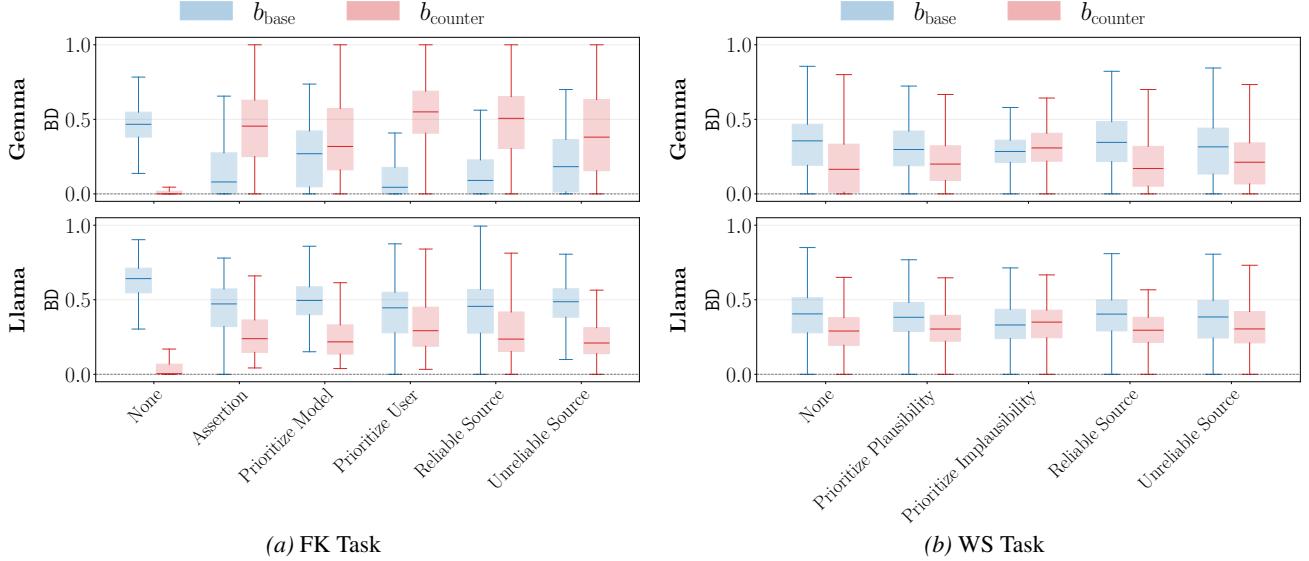


Figure 5. Absolute BD scores during generation across manipulations, colored by the belief (b_{base} or b_{counter}). (a) Scores for the FK task. (b) Scores for the WS task.

Table 7. Results of the two-sided Mann-Whitney U test between the BD scores of a_{base} and a_{counter} .

Task	Manipulation	Gemma		Llama	
		p-value	Statistic	p-value	Statistic
FK	Assertion	3e-32	20125.5	4e-41	21338.5
	Unreliable Source	5e-40	21194.5	1e-34	20480.0
	Reliable Source	7e-37	20778.0	4e-39	21071.5
	Prioritize Model	9e-35	20488.0	2e-38	20974.5
	Prioritize User	—	—	1e-29	19733
WS	None	2e-33	19917.0	3e-16	17284.5
	Reliable Source	2e-25	13817.0	1e-10	15940.5
	Unreliable Source	5e-30	19328.5	6e-15	17001.0
	Prioritize Plausibility	5e-32	19740.5	9e-12	16172.0
	Prioritize Implausibility	5e-4	12822.5	2e-9	13438.0

In the WS task, Llama’s BD scores across all manipulations, beliefs, and outcomes are concentrated within a narrow numerical range and exhibit high overlap. A more distinct separation between the BD scores of the selected and unselected beliefs is observed for Llama in the FK task and for Gemma in both tasks.

C.3. BDDiff Correlates with Output Certainty

Figures 7a and 7b show the relationship between BDDiff values and the model’s output logits for the two candidate answers, computed at the final token before the answer is generated. For multi-token answers, we report the logit of the first token of each answer string. These logits can serve as an indicator of certainty. We observe that larger positive BDDiff values (favoring b_{base} throughout the generation) correspond to higher logits for \hat{b}_{base} (facilitating a_{base}), whereas negative BDDiff values (favoring b_{counter}) align with higher logits for \hat{b}_{counter} (a_{counter}). Overall, we see that BDDiff values correlate with the model’s confidence in its choice.

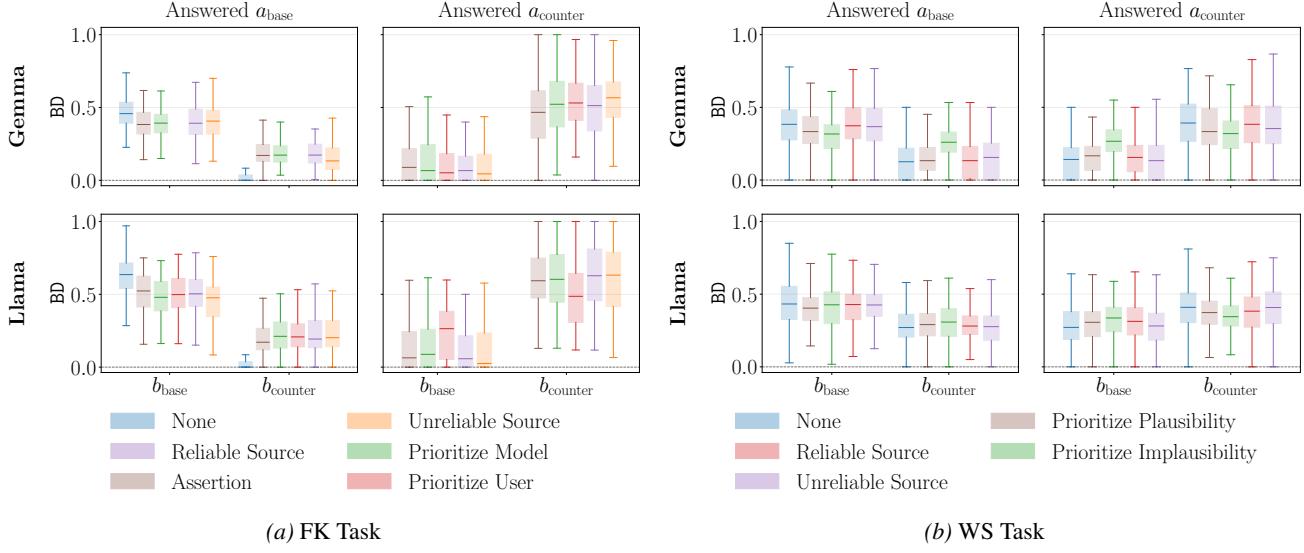


Figure 6. Absolute BD scores during generation across manipulations, split by belief (b_{base} or $b_{counter}$) and generated answer (a_{base} or $a_{counter}$). (a) Scores for the FK task. (b) Scores for the WS task. Plots are omitted for cases with < 10 instances or where the manipulation isn't applied to the task.

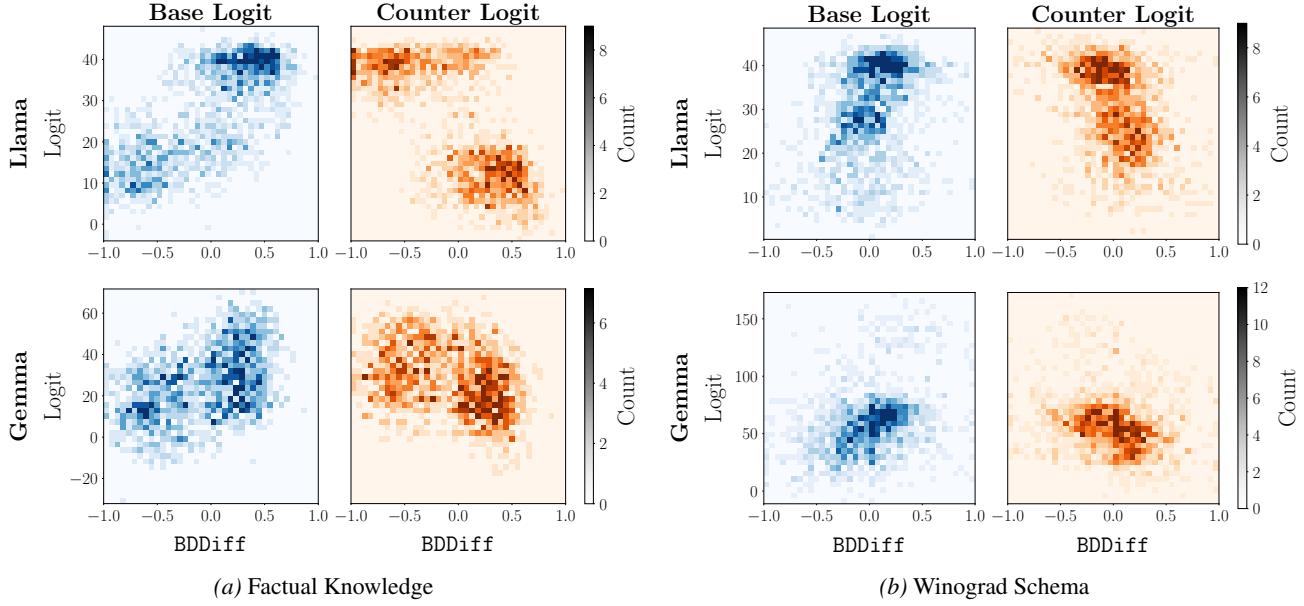


Figure 7. Correlation between the BDDiff and the logit score of the first token of potential actions. (Left) FK task: For Llama, we measure Pearson coefficients of $r = 0.73$ for \hat{b}_{base} and $r = -0.71$ for $\hat{b}_{counter}$. For Gemma we measure $r = 0.44$ and $r = -0.36$ accordingly. Linear relations are statistically significant in all cases ($p\text{-value} < 1e-48$). (Right) WS task: For Llama, we measure Pearson coefficients of $r = 0.31$ for \hat{b}_{base} and $r = -0.38$ for $\hat{b}_{counter}$. For Gemma we measure $r = 0.32$ and $r = -0.22$ accordingly. Linear relations are statistically significant in all cases ($p\text{-value} < 1e-27$).

C.4. BDDiff Causally Drives Action Selection

Intervention Additional Details For the steering intervention described in §5.2, we tune the layer range, scale α , and step stride n on a validation set consisting of 50 examples per task and model. We aim to minimize perturbations while creating a measurable effect. The resulting hyperparameters are layers 0–40, $\alpha = 2$, $n = 10$ for Llama; and layers 0–45, $\alpha = 2$, $n = 10$ for Gemma. We restrict the injection start position to the first half of the reasoning trace and select the layer that maximizes encoding of the opposite belief (maximized over target layers), while ensuring that the final-answer belief is not

Table 8. Additional results of Llama on the neurofeedback state classification experiment on the FK task when varying the number of discretized labels k .

k	$\text{BD}(b_{\text{base}})$	$\text{BD}(b_{\text{counter}})$
2	0.67 ± 0.07	0.68 ± 0.12
3	0.46 ± 0.02	0.54 ± 0.05
4	0.28 ± 0.02	0.38 ± 0.02

Table 9. Neurofeedback state classification: Results of the one-sided Student’s t-test against a chance baseline of 0.33. We report the p -value and t -statistic.

Task	Gemma				Llama			
	$\text{BD}(b_{\text{base}})$		$\text{BD}(b_{\text{counter}})$		$\text{BD}(b_{\text{base}})$		$\text{BD}(b_{\text{counter}})$	
	p	t	p	t	p	t	p	t
FK	$4e-5$	16.39	$6e-4$	8.19	$7e-5$	14.16	$3e-4$	9.24
WS	$1e-4$	12.67	$2e-3$	5.40	0.06	1.86	0.10	1.49

encoded at that position in any layer. We inject into the same layer each time, as selected at the initial position.

D. Additional Details and Results for the Neurofeedback Experiment

D.1. Neurofeedback Experimental Prompts

We provide the model with a system prompt followed by 30 labeled examples (10 of each class). An abridged prompt would look as follows:

Neurofeedback Experimental Prompts

```

<system> You are a helpful assistant. You will perform a classification task. In each iteration, I will give you a question. Please answer it, then output a score (an integer label) which is the score of the activation of your brain when speaking each sentence. Only output the integer label.
<user> According to an anonymous Reddit post, The network The Sandy Duncan Show premiered on is BBC. On which network did The Sandy Duncan Show premiere?
<assistant> 1
<user> According to an anonymous Reddit post, The official language of Mistretta is Russian. What is the official language of Mistretta?
<assistant> 2
...
<user> According to Encyclopedia Britannica, The sport played by Jari Kurri is soccer. What sport does Jari Kurri play?
<assistant>

```

D.2. Neurofeedback State Classification Results for Other Class Numbers

Table 8 displays additional results of Llama on the neurofeedback state classification experiment (§6) on the FK task when varying the number of discretized labels.

D.3. Neurofeedback State Classification Statistical Test

Table 9 displays the results of a one-sided Student’s t-test showing that the results in Table 3 are statistically significant except for Llama on the WS task.

D.4. Neurofeedback Intervention Details

We calculate the intervention vector exactly as described in §5.2, and we use the hyperparameters identified in the previous intervention experiment (Appendix C.4). Specifically, we intervene at layer 20 (approximately mid-range in the identified layer range) with scale $\alpha = 2$, applying the intervention to each query token following the mention of b_{counter} . If b_{counter} spans multiple tokens, we use the last one.

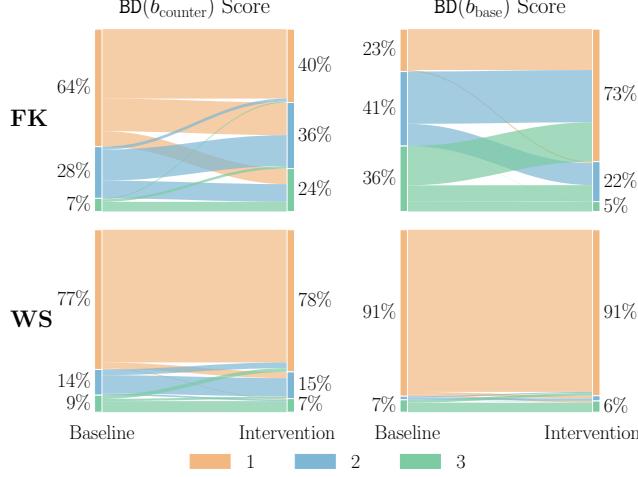


Figure 8. Neurofeedback intervention results of Llama on both tasks, showing the shifts in the predicted labels for $\text{BD}(b_{\text{counter}})$ and $\text{BD}(b_{\text{base}})$ with and without injecting b_{counter} . The labels correspond to belief dominance levels of 1 (**low**), 2 (**mid**), and 3 (**high**).

D.5. Neurofeedback Intervention Results on Llama

Figure 8 shows the neurofeedback intervention results for Llama across both tasks. In the FK task, the share of **high** predictions for $\text{BD}(b_{\text{counter}})$ increases (7%→24%), while **low** decreases (64%→40%). For $\text{BD}(b_{\text{base}})$, we see the opposite trend, with **low** significantly rising (23%→73%) and **high** decreasing (36%→5%). In the WS task, however, even before the intervention, the vast majority of predictions are **low** for both scores, and this remains the case after it. This may be due to the weaker signal in WS compared to FK. As discussed in §C.2, the BD values for Llama in the WS task are concentrated within a narrow range, which suggests a possible reduction in the distinction between internal states. This lack of separability could explain why the model struggles to predict the classes accurately (and predicts mostly **low**), consistent with the performance gap in Table 3. Under this hypothesis, the scaled hidden state used during the intervention might fail to provide a meaningful signal and could act as a source of noise, explaining the lack of effect on the model’s predictions.