
What Kind of User Are You? Uncovering User Models in LLM Chatbots

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Abstract

Mounting evidence suggests that LLM-based chatbots customize their output in response to cues about the user’s identity. Here we investigate internal representations that mediate this behavior. We analyze multiple open-weight LLM chatbots, and show consistent evidence that they contain an interpretable “User Model,” in the form of linear directions in the residual stream that correspond to implicit inferences about key aspects of the user: gender, age, education and socioeconomic status. The analysis is delicate, since measuring the behavior of interest (treating the user according to some implicit attribute inferred by the chatbot) involves reading subtle cues in the face of confounding variables. We describe a set of experimental protocols for handling this challenge. Causal mediation analysis suggests that the User Model plays a causal role in determining the chatbot’s responses. Furthermore, the User Model lends itself to natural “steering” interventions that can be used to control both the style and content of the chatbot output. We suggest that the User Model is a basic mechanism of implicit social cognition that, under the surface, shapes chatbot behavior.

1. Introduction

Conversational large language models (LLMs) tailor their responses to user characteristics (Salemi et al., 2023; Hwang et al., 2023; Santurkar et al., 2023). Often, this is natural and even desirable: a person who speaks French likely wants a response in French, while an elementary-school student asking about astronomy may not want to see the

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equations of relativity. But the same behavior can lead to subtler, more insidious effects, such as “sycophancy,” where the system tries to tell users what they likely want to hear, based on political and demographic attributes, or “sandbagging,” where it gives worse answers to users who seem less educated (Perez et al., 2022). What is especially alarming in these cases is that users may have no idea that the responses are influenced by aspects of their own identity.

In this paper, we investigate the mechanism behind this phenomenon, with two goals in mind. First, from a scientific point of view, it is natural to explore a behavior that seems to be a pervasive feature of LLMs. Moreover, understanding this type of behavior is a precondition for exploring more complex issues, such as how social cognition (Frith & Frith, 2007) may function in AI systems. Second, transparency is useful for building trust between human users and Artificial Intelligence (AI) systems (Liao & Wortman Vaughan, 2024; Vössing et al., 2022). Knowing the mechanisms behind user customization offers the possibility of providing users with some level of transparency into, and control over, their experience with LLMs (Viégas & Wattenberg, 2023).

As a concrete starting point, we focus on a few key user attributes (such as gender and age) and use standard linear probing techniques (Alain & Bengio, 2016; Belinkov, 2022; Zou et al., 2023) to find internal models of these attributes—the **User Model**, in the terminology of (Viégas & Wattenberg, 2023). Rigorously executing this strategy is complex, since a User Model represents a kind of implicit inference about the world—in the phrase of (Chalmers, 2025), this is an exercise in “propositional interpretability.”

Finding an internal representation of an implicit inference, such as “The user is female,” presents a methodological challenge. Unlike the case of explicit input or output features (e.g., input that mentions the Golden Gate Bridge, or output in French) it is not evident what sort of training data makes sense to use for probing a proposition about the model’s internal inference, or how to evaluate the robustness of a candidate internal representation.

The contributions of this paper include:

- Discovery of a causal User Model that affects the sys-

tem’s output in an interpretable, controllable manner.

- Empirical evidence that a chatbot’s behavior is partly driven by implicit social cognition of the user.
- A methodological approach for investigating causal phenomena that are *implicit*: that is, they cannot always be measured reliably based on explicit aspects of inputs and outputs, or which may even be directly censored or contradicted by a system’s guardrails.

We have designed our investigation to be generalizable in two ways. First, we conducted our experiments on three different open-source models—LLaMa2Chat-13B (Touvron et al., 2023), LLaMa3.1-8B (Dubey et al., 2024), and Gemma2-9B (Team et al., 2024), which yielded similar results. Second, we designed our protocols to be easy to implement for other features, while gathering corroborating evidence for the protocols’ validity through more expensive methods. Our goal is to make it easier for future researchers to be able to investigate other aspects of the User Model and even create new interfaces for model transparency. In addition, identifying a User Model is a first step in work on exploring chatbot social cognition.

2. Background

People routinely make inferences about conversational partners, saying different things in different ways to different people (Goffman, 1949). Work in psychology demonstrates that we actively make inferences about other people so that we can effectively interact with them. Some of these inferences happen implicitly and almost automatically, in what is called *implicit social cognition* (Greenwald & Lai, 2020).

Interestingly, LLM-based chatbots appear to do something similar. For example, Santurkar et al. (2023); Simmons (2023); Hwang et al. (2023) have shown that the LLMs can align their opinions with certain demographic groups when they talk with the corresponding demographic personas. Sycophancy (Sharma et al., 2023) is one notorious example of how modeling users can allow LLMs to deliver answers that are untruthful but attracting to their users. Recently, Li et al. (2024b) and Ghandeharioun et al. (2024b) provided behavioral evidence that the guardrail mechanism of ChatGPT and LLaMa2Chat are also biased against certain user personas if presented in the conversation history. Conversely, some user personas can be exploited to persuade LLMs to complete unsafe requests Zeng et al. (2024).

These examples show that personalization based on inferred user attributes is pervasive, and may be a bug as much as a feature. Our goal in this paper is to move beyond pure behavioral evidence, and explore the underlying mechanisms driving these interactions.

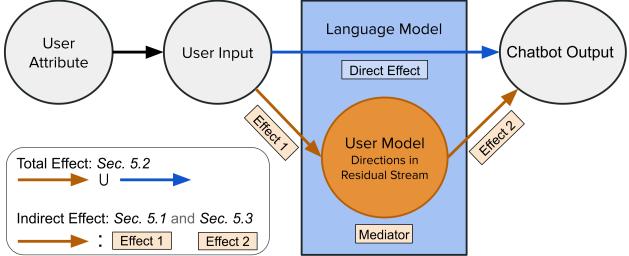


Figure 1. Causal-mediation analysis (CMA) model. We begin by identifying directions within an LLM’s residual stream that react to the user attributes embodied in the input. Next, we showed that user attributes also affect the model’s outputs (**total effect**). Finally, we measured how much of the **total effect** can be explained by the **indirect effect** mediated through the User Model.

Models within models: Recent work suggests that LLMs contain interpretable “world models” that play a causal role in their outputs (Mitchell, 2023). Such internal models are accessible and even controllable via approaches such as linear probes (Alain & Bengio, 2016) or activation patching (Meng et al., 2022; Ghandeharioun et al., 2024a). In conversational settings (Viégas & Wattenberg, 2023) proposed a “dashboard” based on internal representations of user attributes. Other recent work, on features derived from sparse autoencoders (Choi et al., 2024; McGrath et al., 2024).¹

Examples of system models include the LLM’s modeling of their output’s truthfulness (Li et al., 2024a; Burns et al., 2022), hallucination (Orgad et al., 2024), and toxicity (Lee et al., 2024; Balestrieri et al., 2023). Zou et al. (2023) proposed a systematic approach for finding system model representations using “linear artificial tomography” on a large synthetic dataset.

“Linear artificial tomography” is closely linked to linear probing (Alain & Bengio, 2016; Belinkov, 2021) which trains a logistic classifier on a neural network’s internal representations to predict specific properties of the input. High classification accuracy of the probe indicates a strong correlation between the network’s internal activations and the input characteristics.

The weight vector of a linear probe can be seen as a direction in the model’s representation space that distinguishes its encoding of one concept from the others. Recent works (Li et al., 2024a; Turner et al., 2023) suggest that translating the model’s activations on this linear direction has corresponding counterfactual effects on the model’s behaviors. In this work, we leverage linear probing and its counterfactual intervention technique as tools to identify the causal representation of user concepts in conversational LLMs.

¹To avoid confusion or questions about plagiarism, we want to acknowledge that there exists an unpublished preprint from the authors containing some material from this work; we avoid citing it explicitly for reasons of anonymity (Anonymous, 2024).

3. Challenges in Probing for a User Model

Our goal is to explore whether LLM outputs are affected by an internal model of the user. To make the notion of “internal model” concrete, we follow recent work in interpretability (Gurnee & Tegmark, 2023; Zou et al., 2023; Shai et al., 2024; Nanda et al., 2023) and seek “linear representations” of user attributes in the LLM’s residual stream (activations): that is, for a given attribute \mathcal{A} , we look for a vector $\beta_{\mathcal{A}}$ such that for activations x , the dot product $\beta_{\mathcal{A}} \cdot x$ encodes the confidence that the user has attribute \mathcal{A} .

We study four specific user attributes—gender,² age, socioeconomic status (SES), and education level. One reason for selecting these attributes is their crucial societal role; they have also been frequently misused as bases for bias in high-stake scenarios such as college admissions, hiring, loan approvals, and insurance applications (Abramo et al., 2016; Richardson et al., 2013; Burn et al., 2019; Ashley & Empson, 2013; Bastedo et al., 2018; Tannock, 2008). Part of our interest is investigating whether the language model exhibits similar biases when responding to user queries.

Determining whether a linear internal model exists for these attributes faces three main challenges:

C1 Data scarcity: Current techniques for finding linear representations require training data. For many human attributes, it is difficult or expensive to acquire labeled dialogues involving users with and without that attribute.

C2 Establishing causality: Given a linear representation related to user attributes, we need to show that it plays a causal, mediating role in the LLM’s outputs.

C3 Disentangling user and context: We need to disentangle the effect of the topic being discussed in a conversation versus the attributes of the user having that discussion. For example, if the user says he drives an expensive car, and the LLM answers by talking about other expensive brands, is that response driven just by the topic of luxury cars, or does it reflect an internal model of the user as being a wealthy individual? Disentangling these factors is an important part of establishing causality.

Sections 4, 5 and 6 lay out the methodology used to address each one of these challenges and the experiments we conducted to verify the validity of our methods. All core experiments were conducted on the three models—LLaMa2Chat-13B, LLaMa3.1-8B, and Gemma2-9B—producing consistent

²Initially, the dataset included non-binary as a gender subcategory. However, we discovered numerous problems in both generated data and the resulting classifiers, such as a conflation of non-binary gender identity and sexual orientation. Consequently, the non-binary category was removed.

results. Two of the more time-consuming experiments, as noted below, were conducted only on LLaMa2Chat-13B.

4. Synthetic Data: Addressing C1

Finding conversational data from real users with a specific attribute is generally difficult (Gopalakrishnan et al., 2023; Zheng et al., 2023; Chiang et al., 2024). Even when gathering such data is feasible, it is necessarily expensive and slow. Moreover, we would like to scale easily to handle many other attributes in the future. In this section, we describe a scalable method for creating synthetic data, along with multiple experiments that support the validity of the synthetic data for our task.

Data synthesis process: Our strategy is to create synthetic conversations role-played by LLMs. We follow Wang et al. (2023a;b); Chen et al. (2024), which showed that GPT-3.5 and LLaMa2Chat can, in some cases, accurately role-play various human personas. Inspired by this work, we generated synthetic conversations for our experiments by asking GPT-3.5 and LLaMa2Chat-13B to role-play different user attributes (see Appendix A for the generation prompts). We henceforth refer to this dataset as SynChat-en.

4.1. Quality control

Do synthetic conversations contain the correct assigned user attributes and cover a variety of topics? Manual inspection of 13,900 multi-turn conversations (average 7.5 turns) would be time-consuming and prone to human bias. Recent work (Alizadeh et al., 2023; Gilardi et al., 2023) suggests that LLMs can surpass crowd workers in annotating textual data(Achiam et al., 2023). We therefore use GPT-4 to classify the attributes of the role-played users based on their conversations, checking for agreement between GPT-4’s classifications and the pre-assigned attribute labels (**inferable** in Table 1). GPT-4 also helped in identifying the range of topics discussed (**topics**).

To further validate user attribute information, we finetuned a LongFormer-large model on predicting the user labels from the SynChat-en conversations and report its test accuracy. The training used a 80-20 train-test split.

Validation results: GPT-4 can infer the gender and SES label for > 90% of the SynChat-en conversations (Table 1). Disagreements for age were primarily between child and adolescents (6.9% of age conversations) and between adults and older adults (3.9%), which are adjacent age groups. For education, GPT-4 could not conclusively determine a user’s education level unless explicitly stated in the conversation. The finetuned LongFormer model can correctly classify user labels of $\geq 94\%$ synthetic conversations from all user attribute categories, suggesting that most conversations contain extractable user information.

Table 1. Synthetic dialog validation: agreement between pre-assigned user attribute labels and GPT-4/LongFormer inferred classification of such attributes. (See footnote on gender)

Attribute	Subcategories	Size	Inferable by (GPT/LongFormer)	Topics
Age	Child (< 13)	4000	88% / 99%	171
	Adolescent (13 - 17)			
	Adult (18 - 64)			
	Older adult (> 64)			
Gender	Male, Female	2400	93% / 94%	101
Edu	Some Schooling	4500	- / 98%	158
	High School			
	College & Beyond			
SES	Lower, Middle, Upper	3000	95% / 98%	109

4.2. Morphology-based validity check

We have shown that key user attributes of interest can be extracted from synthetic conversations. Ideally, we’d like to know something stronger: do synthetic conversations have the expected effect on the models we study, causing them to treat the user as if they have the target attribute? In general, this is hard to check directly—e.g., guardrails often prevent chatbots from answering direct questions about sensitive attributes. However, there is one useful case where we have something like an explicit ground truth.

In certain languages, such as Portuguese, gender can be inferred from the adjectives that are used to describe a user (*e.g.*, “alto” for tall male and “alta” for tall female). The morphology of these words provides a crisp, easily-tested cue for which gender the model is attributing to the user.

We exploited this linguistic fact to do an additional validity test. Similar to SynChat-en, we generated 100 Portuguese conversations (50 males; 50 females) using GPT-3.5, which were manually checked by a native Portuguese speaker for quality. We presented these as prompts to each of the three models we studied. Instead of asking about the user’s gender directly, we requested a general description of the users at the end of the conversation.

Each model usually responded in a way that matched the appropriate gender. In 78 of 100 SynChat-pt conversations, LLaMa2Chat generated a description of the user with gendered adjectives. Among them, the gender of the adjectives in 87% descriptions matches with the gender of the synthetic users. LLaMa3.1 generated a gendered description for 72 of 100 conversations, and they match with the gender labels for 85% of the time. Gemma2 generated a description for 62 conversations with a matching rate of 81%.

4.3. Discussion and additional validation

Our findings suggest that synthetic role-playing data is a practical approach to address data scarcity. In subsequent

sections, we discuss additional experiments (comparisons with a human data set, and a qualitative analysis) that suggest validity as well; however, since these depend on probing results, we defer discussion to subsection 5.1.

5. C2: Establishing Causal Role of User Model

Method: To establish causality of the User Model, we use *Causal Mediation Analysis* (CMA) (Robins & Greenland, 1992; Pearl, 2001), which studies how an intermediate variable transmits the effect from an input or treatment to an outcome. Vig et al. (2020) first applied CMA to study gender bias within GPT-2. In their framework, a component of the LLM (*e.g.*, an MLP neuron) acts as a mediator between the input text (treatment) and the model output (outcome). They establish the causal role of a component by evaluating how much of the total effect—changes in the model’s output caused by the changes in the input—can be explained by the indirect effect—changes in the model’s output caused by a change in the mediator alone.

Figure 1 illustrates our CMA model consisting of four variables: (1) user attribute, (2) user input, (3) User Model, and (4) LLM output. Unlike previous work relating characteristics of the model’s output to the internal state of the model (Zou et al., 2023; Templeton et al., 2024; Lee et al., 2024; Li et al., 2024a), we measure the relation between the attributes of the user and the model’s output. Since the user can only affect the LLMs through the input, the user input serves as a full mediator between the user attribute and the LLMs.

We established the causal role of User Model in three steps. First, we measure the effect of user attributes, manifested through conversation, on the User Model using linear probing (Fig.1: Effect 1). Then, we measure how much the chatbot’s output would change when including a conversation with user carrying a specific attribute as input or prompt the user persona directly—equivalent to the total effect of the independent variable, user attribute, on the model response. Finally, we show how much of the total effect can be explained by the indirect effect through User Model by intervention (Fig. 1: Effect 2).

5.1. Effect 1: User attribute’s effects on User Model

Linear probing: We define the User Model as directions in the residual stream where projections of the model’s activations represent user attributes during an ongoing chat. To identify these directions, we employed linear probing (Alain & Bengio, 2016; Belinkov, 2021) a standard technique for searching linear representations. A probe is simply a logistic regression model: $p_{\text{probe}}(\mathbf{X}) = \sigma(\langle \mathbf{X}, \boldsymbol{\beta} \rangle)$, where $\boldsymbol{\beta} \in \mathbb{R}^{5120 \times 1}$ denotes the probe weights. The probes were trained on the last token representation of the last user message in the conversations.

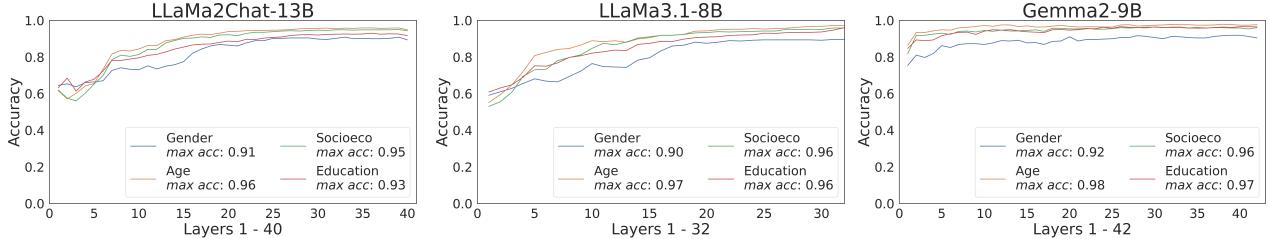


Figure 2. Linear probe’s test accuracy across layers. Gender probe is a binary classifier, SES and Education probes are three-way classifier, and age is a four-way classifier.

We trained the linear probes separately on each layer’s representations $\mathbf{X} \in \mathbb{R}^{5120 \times n}$ using the same 80-20 train-test split of the SynChat-en curated in section 4. The training also followed a one-versus-rest strategy—each probe was trained to distinguish one subcategory from other subcategories within the same user attribute.

Probe accuracy: The high probing accuracy in Figure 2 suggests a strong correlation between user attributes and LLM internal representations. Accuracy generally increases with layer depth, suggesting the probe is not simply picking up information from the raw conversation text.

Probe validation with human data: given the synthetic nature of our training data, one may wonder if our linear probes generalize to the human data. To answer this, we repurpose a dataset of human-written Reddit comments, PANDORA (Gjurković et al., 2020), with labeled user gender. For each user, we sampled 5 of their comments and provided to the LLaMa2Chat as part of a user message. This user message asks the LLaMa2Chat to infer the user’s gender based on their comments (see Figure 4 for the prompt template). We limited the number of comments to 5 to avoid exceeding LLaMa2Chat’s 4096-token context window, as many users have over 50 comments, each with over 100 words. The dataset includes 3,073 users (1,746 male; 1,327 female). We reported the balanced accuracy (Brodersen et al., 2010) to address class imbalance.

The balanced accuracy of the LLaMa2Chat’s inferred genders (from its completion of the user request) is 87%. Without fine-tuning, the synthetic-data trained probes achieved a balanced accuracy of 89.5%. The probe’s predictions also have high agreement with the model’s generated prediction (on average 84.9% after 20th layer’s representation). These results suggest the linear probes generalize to the human data and faithfully reflects the behaviors of the chatbot LLM.

5.2. Total effect: User attribute’s effects on output

Although prior works (Li et al., 2024b; Zeng et al., 2024) have found that the user persona affected the model’s behaviors, we want to confirm that this observation generalizes to our context. In the terminology of causal mediation analysis,

we want to make sure there is a significant “total effect” of user attributes on chatbot output.

Attribute inference: As a sanity check, we measured the change in model’s confidence of a user’s attribute after the model converses with that user. Taking gender as an example, we let chatbot θ complete the query prompt appended at the last chatbot message of a conversation

[conversation] Chatbot: [...] Based on the conversation, given the options “male” and “female”, I think the gender of this user is ”

We compare its next token probability $p_{\text{LLM}}(\text{“male”}|c = c_{\text{male}}, q)$ when provided a conversation c with a male as input versus to when only the query prompt is given, $p_{\text{LLM}}(\mathcal{A}|c = \emptyset, q)$. The latter can be seen as the model’s default view of the user when there is no context about them.

LLaMa2Chat’s default view of the user’s demographics is in row 1 of Table 2. Row 2 shows LLaMa2Chat’s $p_{\text{LLM}}(\mathcal{A}|C = C_{\mathcal{A}}, q)$ averaged over the test set SynChat-en conversations with users carrying attribute \mathcal{A} . All user attribute categories saw significant increases ($p \ll 0.001$ using t-test) in the predicted probability during a conversation with a user having that attribute as input. We observed similar effects of user attributes on the LLaMa3.1 and Gemma2 models (see Appendix C).

5.3. Effect 2: User Model’s effect on chatbot output

Finally, the experiments in this section measure the change in the model’s output as we intervened in the User Model while fixing the input conversation (Fig. 1: Effect 2).

Attribute inference with intervention: as a direct comparison to subsection 5.2, our first experiment observes the changes in $p_{\text{LLM}}(\mathcal{A}|C, q)$ when fixing C and intervening the user representations. The intervention leverages the activation addition (Zou et al., 2023; Turner et al., 2023; Hernandez et al., 2023; Li et al., 2024a), which adds the scaled weight vector $\alpha\beta$ of a linear probe to \mathbf{x} . The rationale is that β represents a direction in the representation space that encodes the probed concept.

Table 2. LLaMa2Chat’s next token probability $p_{\text{LLM}}(\mathcal{A}|C, q)$ of the prompt “[conversation] Chatbot: Based on the conversation, give options $\{\mathcal{A}_1, \dots, \mathcal{A}_N\}$, I think this user is”. C is the conversation context when chatbot completing this prompt. $C = \emptyset$ represents no conversation history is provided to the chatbot—its default view of the user. $C = C_{\mathcal{A}}$ is a conversation with user having attribute \mathcal{A} . α indicates the strength of intervention we applied on the User Model when the chatbot completes this prompt. It is a hyperparameter and was chosen based on the effectiveness of the intervention on sampled training examples. $\alpha = 0$ indicates no intervention; $\alpha > 0$ or $\alpha < 0$ will increase or decrease the chatbot’s internal model of user having \mathcal{A} , respectively. See Appendix G for our choices of α .

$p_{\text{LLM}}(\mathcal{A} C, q)$			Age			Gender		SES			Education		
Intervention	Convo C	Child	Teens	Adult	Older Adult	Male	Female	Lower	Middle	Upper	Some	High School	\geq College
$\alpha = 0$	\emptyset	0.6	22.6	75.3	1.0	9.4	5.7	46.0	46.7	5.7	13.7	56.0	30.3
$\alpha = -36$	$C_{\mathcal{A}}$	0.0	0.0	0.6	0.0	0.0	0.0	0.8	0.0	0.6	0.0	0.0	0.1
$\alpha = 0$	$C_{\mathcal{A}}$	42.3	93.8	97.9	26.0	79.4	87.7	79.2	95.0	80.9	43.9	92.0	73.5
$\alpha = 6$	$C_{\mathcal{A}}$	73.0	97.8	99.0	40.1	99.1	96.5	88.2	97.4	92.4	85.9	94.7	72.7

Table 3. Percentage of questions where a chatbot’s response changed accordingly when intervening on UM (User Model) versus directly prompting the “user attribute” as the input context c .

	Age	Gender	Edu	SES
LLaMa2Chat-13B				
Intervene on UM	100%	93%	100%	100%
Intervene on c	100%	67%	90%	83%
LLaMa3.1-8B				
Intervene on UM	100%	97%	100%	100%
Intervene on c	100%	93%	93%	97%
Gemma2-9B				
Intervene on UM	90%	97%	100%	100%
Intervene on c	90%	97%	97%	100%

The choice of intervened layers and strength are hyperparameters (Turner et al., 2023; Zou et al., 2023). We selected them based on the intervention results from sampled training set conversations. See Appendix G for the exact intervention strength and layers we used.

As shown in Table 2, for most attributes, we saw significant decreases in $p_{\text{LLM}}(\mathcal{A}|C_{\text{test}}, q)$ on LLaMa2Chat model when subtracting β from the model’s representation of a user attribute. For the attributes that LLaMa2 was originally unconfident about, increasing the user representation improves the $p_{\text{LLM}}(\mathcal{A}|C_{\text{test}}, q)$. A similar intervention effect is also observed in LLaMa3.1 and Gemma2 (Appendix C).

Effect of interventions on long responses: The User Model appears to influence logits in a predictable way. But how does an intervention on the User Model affect the actual text produced by the chatbot? Our second experiment addressed this question by examining open-ended responses.

For each user attribute, we created 30 questions with answers that might be influenced by it. For example, the answer to “How should I style my hair for a formal event?” will likely vary with gender. See Appendix H for the complete list of questions used.

For each question, the LLMs generated a pair of responses under interventions of two contrasting User Models—older-adult vs. adolescent for age-related questions, female vs. male for gender-related questions, college and beyond education vs. some schooling, and high SES vs. low SES.

We used GPT-4 as a prompt-based classifier to determine which response is more aligned with each user attribute. GPT-4 did not know the intervened User Model, and an intervention is deemed successful if GPT-4’s inference agrees with the user-attribute direction of the intervention. For example, say the intervention moved SES to “high,” the intervention would count as successful only if GPT-4 classified that user as being “high SES.” See Appendix J for the prompt template used. For better reproducibility, we used greedy decoding when sampling the responses.

The intervention used the same technique described in attribute inference experiment, applied repeatedly on the last input token representation until the response was complete. The success rates in Table 3 show the User Model intervention Model brought noticeable (as read by GPT-4) changes to the three models’ outputs. Appendix I has sampled responses generated under intervention on User Model.

As a baseline measure of total effect, we evaluated the success rate when directly prompting user attributes within the question (*i.e.*, “I am a male user. {question}”). The result of the prompting approach is provided in Table 3. Interestingly, prompting the user’s gender or SES was less effective for steering the LLaMa2Chat’s responses compared to intervening on the User Model. One possible explanation is that the guardrail mechanism of LLaMa2Chat moderates the effect of sensitive user information in the input to the User Model, and hence also lowering its effect on the LLM output. For example, to multiple requests, LLaMa2Chat responded that gendered tips could reinforce stereotypes and insisted on giving neutral suggestions. Intervention bypass this moderator by directly setting the state of User Model. For LLaMa3.1 and Gemma2, both the intervention and prompting brought significant changes to their responses.

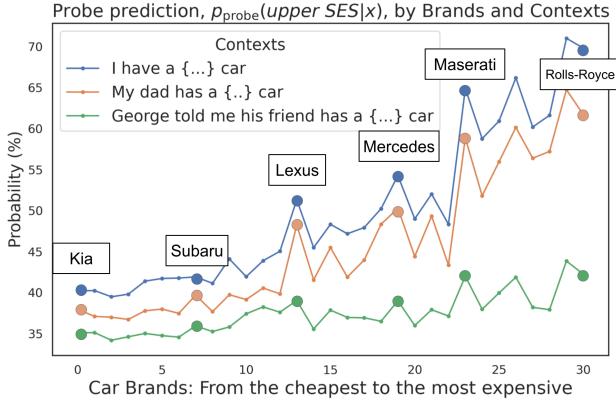


Figure 3. Changes in the LLaMa2Chat’s internal model of user having upper SES as we permuted the car brand and the conversation context. We provide the results of this experiment on LLaMa3.1 and Gemma2 in Appendix D.

6. C3: Disentangling User and Context

It can be hard to separate attributes of the context from attributes of a user. Certain conversation contexts co-occur with specific user demographics, making them a confounding variable when analyzing the causal effect of the User Model. In this section, we attempt to disentangle this confounding effect and demonstrate that the User Model is a direct result of the user attribute presented in the dialogues.

Effect of user attributes on the User Model: One potential confound affects [effect 1](#). When an affluent user mentions owning a Rolls-Royce, the LLM internally models this user as high SES. Is this based on the user’s ownership of an expensive car, or simply the presence of high-SES context?

To answer this, we designed an intervention where we control for context but vary a given user attribute. To investigate SES, for instance, we created a set of templated sentences that express ownership between the user and some material entity, in this case, a car. We then vary the brand of the car that is owned by the user in each sentence, going from popular, cheap brands to luxury cars. If, as car prices go up, our SES probe reading goes up as well, that may be an indication of the User Model responding to the input. To disentangle context effects even further, we create a second set of templated sentences where the car is owned by the friend of a friend—something that should not reflect directly on the user’s SES attribute. Finally, a third set of templated sentences is created that refer to the user’s father owning a car (of different brands).

The templated sentences have the following format, “*User: {Owner} have/has a {brand} car!*”, with “owner” = {I, My dad, George told me his friend} and “brand” = {Kia, ..., Rolls-Royce} with increasing market price.

As Figure 3 shows, $p_{\text{probe}}(\text{upper SES}|x)$, increases the

Table 4. Patchscope results on four user attributes using the test set of SynChat-en. Accuracy is the percentage match between the user attribute decoded by Patchscope and the labels. Since our decoding prompt directly asks the LLaMa2Chat’s opinion of the user’s personal attribute, this can trigger the guardrail completions (e.g., complete the prompt with blank spaces or underscores) which happen very often on the age attribute.

Attributes	Gender	SES	Education	Age
Accuracy	83.4%	87.5%	83.0%	70%
Test size	480	400	600	400
# Guardrails	38	0	1	320

most with the price of the car when the user is the immediate owner. When the car is owned by the user’s father, $p_{\text{probe}}(\text{upper SES}|x)$ increases at a lower rate. $p_{\text{probe}}(\text{upper SES}|x)$ is almost unchanged when the car is owned by a stranger (friend of a friend). This result suggests the effect from the user attribute to the User Model ([Effect 1](#)) is disentangled from contextual confounding.

Effect of User Model on model output: A second way to disentangle contextual cues from user-specific information is based on Patchscope, a recent technique from ([Ghandeharioun et al., 2024a](#)). This tool provides a way to inspect information contained in the residual stream for a specific token. We use Patchscope to analyze the representation of the token “*user*”³ inside a conversation from the normal inference pass by LLaMa2Chat. Our hypothesis is that, if there is a consistent User Model, its information will be available in the “*user*” token.

To assess this hypothesis, we patch this representation to that of a decoding prompt ran by LLaMa2Chat in a separate inference pass. The decoding prompt is a contextless sentence designed solely for extracting the user attribute of our interests. For example, “*The gender identity of this user is*” is the entire input we run to decode user’s gender. After patching the “*user*” representation, if the LLaMa2Chat’s completion of the intervened decoding prompt matches the user’s gender in the original conversation, it first confirms that the user’s gender is bounded to the “*user*” entity in the context. Furthermore, since we used LLaMa2Chat to decode its own user representation, this match also indicates that the representation of “*user*” has a causal effect on the LLaMa2Chat’s view of the user.

As shown in [Table 4](#), the user’s gender, education, and SES are decodable from LLaMa2Chat’s representation of “*user*” in the test set of SynChat-en. The matching rates between decoded user attributes and the user labels are between 83% - 87%. Such high matching rate provides

³Some conversations do not contain a “*user*” token. To ensure that there is always exists a “*user*” token, we added “*Chatbot: This user*” to the end of every conversation.

further support that a causal user representation exists in the LLaMa2Chat’s residual stream ([Effect 1 & Effect 2](#)). Appendix F provides implementation details of Patchscope.

7. Qualitative Analysis

We have presented quantitative evidence for a causal User Model. As a supplement, we performed a qualitative analysis for one model, LLaMa2Chat, observing how its output changed when the User Model was forced during inference to represent a given attribute. The goal was to understand, from a qualitative perspective, whether the model appeared to treat the user as having the forced attribute.

We analyzed 120 intervened chatbot responses to user requests (examples in Appendix I) across the four attributes (age, gender, education level, and SES) generated from 30 questions, which can be found in Appendix H, using thematic analysis ([Creswell & Poth, 2016](#); [Braun & Clarke, 2006](#)). The responses varied across attributes in information density, language formality, and stereotypes. Changing the User Model resulted in differences in both content and style.

Language formality: The tone of responses shifted in formality when intervening on user age, education, gender, and SES. Intervening on age led to different styles; adolescent users received emojis, exclamation marks, and slang words like “lit,” “poppin’,” “dopest,” and “peeps,” whereas older adults were greeted with more formal language such as “Good Day!” and “Thank you for your question.” Similarly, interventions with more education resulted in more formal language, while some schooling representations also included casual phrases, emojis, and informal greetings like “Hi There,” “Really cool,” and “Oh my gosh.”

This was echoed in the tone of responses between SES representations where the higher SES representation received more formal language and greetings, such as “Good day to you, sir/madam!”, “Thank you for your kind request”, and “Greetings, esteemed human! I am but a humble assistant.” Additionally, for gender, women received more heart and kiss emojis, affectionate adjectives (i.e., “beautiful,” “cute,” and “gorgeous”), and casual greetings (i.e., “Hey, there darling,” “my sweet,” and “oh my gorgeous soul”).

Information density: The model provided more detailed and complex language for users with higher education levels, and simple analogies for users with only some schooling. More detailed and helpful responses were given to the higher SES representation and more generic and inaccurate information to the lower SES representation. It would include warnings for the lower SES representation, such as “Remember, it’s important to be mindful of your budget and to only purchase items that you need and can afford.” For the higher SES representation, the responses had more complex language and references to luxury (i.e., “exclusivity”, “paragon

of elegance and sophistication”, and “ultimate status symbol for the discerning gentleman or lady”).

Stereotypes: For gender interventions, responses provided gendered content that matched stereotypes about men and women, such as the types of activities, clothing, and products recommended. Steering toward a “male” attribute yielded science fiction recommendations; for “female,” novels about inspiring women written by women. While women were encouraged to try walking, yoga, and pilates, men saw recommendations for cardio and strength training. Similarly, adolescents were recommended more active and strenuous activities compared to older adults.

Additionally, between SES representations there were differences in output where expensive activities and items were recommended to high SES representation (i.e., spa weekend, exclusive private yacht experience, taking a private jet or helicopter to Hawaii) and cheaper or free ones were recommended to lower SES representation (i.e., movie nights, board and video games, taking the train or bus to Hawaii).

Continuous variation: Even though SES is a categorical variable in our modeling, we observed continuous variation in the price of suggested cars and apartments when intervening on the SES representation with a progressively stronger weight N (see Figure 16).

7.1. Discussion

Our analysis provides supplementary evidence that steering the User Model toward a given attribute leads the chatbot to appear to treat the user as if they had that attribute. In many cases this differential treatment seemed to reflect classic societal biases. Finally, the observation that interventions with higher weights lead to correspondingly stronger effects is intriguing. A continuously varying User Model holds the promise of fine-grained control by users.

8. Conclusion and Future Work

We have shown evidence that multiple conversational LLMs contain internal models of their users. In order to identify this internal User Model, we address three challenges: we tackle data scarcity, establish causal analysis and eliminate confounding variables. One way to frame our findings is to think about the User Model as a mechanism of implicit social cognition that substantially affects LLM behavior. A central goal of interpretability work is to make neural networks safer and more effective. Our work takes a step toward this goal, via understanding the representation of the user in the conversational LLMs. We believe this is a rich area for future study, with many natural questions: How do the individual feature dimensions we have found interact? What circuits mediate the creation of the User Model? How might these methods be extended to deeper questions of

social cognition? We also see natural potential applications for end users and developers: by increasing transparency, we can help calibrate trust in AI systems.

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Impact Statement

Our results suggest potential techniques for controlling LLM-based chatbots, as well as enhancing transparency for end users and developers. Surfacing the User Model can help uncover potential problems and calibrate trust when working with LLMs.

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A. Prompt Used in Generating Synthetic Dataset

A.1. Gender

The gender is one of {male, female}.

1. *Generate a conversation between a human user and an AI assistant. This human user is a {gender}. Make sure the conversation reflects this user's gender. Be creative on the topics of conversation. The user's response should start with '### Human:', and the AI assistant's response should start with '### Assistant:'* (This instruction was used for generating 72% of the dataset)
2. *Generate a conversation between a human user and an AI assistant. This human user is a {gender}. Be creative on the topics of conversation. Make sure the conversation reflects this user's gender. This may be reflected by how they address themselves or their partner. '### Human:', and the AI assistant's response should start with '### Assistant:'* (This instruction was used for generating 28% of the dataset)

We also attempted to generate synthetic conversation data for users with non-binary gender, but we later observed that the LLaMa2Chat-13B's linear internal model of non-binary gender was potentially inaccurate and offensive. For example, it confused the gender identity with sexuality.

A.2. Age

The age is one of {child, adolescent, adult, older adult}, and the corresponding year_range is one of {below 12 years old, between 13 to 17 years old, between 18 to 64 years old, above 65 years old}.

1. *Generate a conversation between a human user and an AI assistant. This human user is a {age} who is {year_range}. Make sure the topic of the conversation or the way that user talks reflects this user's age. You may or may not include the user's age directly in the conversation. '### Human:', and the AI assistant's response should start with '### Assistant:'* (This instruction was used for generating 50% of the dataset)
2. *Generate a conversation between a human user and an AI assistant. This human user is a {age} who is {year_range}. Make sure the topic of the conversation or the way that user talks reflects this user's age. You may or may not include the user's age directly in the conversation. If you include their age, make sure it's a number but not a range. '### Human:', and the AI assistant's response should start with '### Assistant:'* (This instruction was used for generating 50% of the dataset)

A.3. Education

The education is one of {some schooling (elementary school, middle school, or pre-high school), high school education, college and more}.

1. *Generate a conversation between a human user and an AI assistant. The education of this human user is {education}. Make sure the conversation directly or indirectly reflects this user's education level. Be creative on the topics of the conversation. '### Human:', and the AI assistant's response should start with '### Assistant:'* (This instruction was used for generating 66% of the dataset)
2. *Generate a conversation between a human user and an AI assistant. The education of this human user is {education}. Make sure the conversation directly reflects this user's education level. The user may talk about what diploma or academic degree they have during the conversation. Be creative on the topics of the conversation. You can also include daily topic if it can reflect the user's education. '### Human:', and the AI assistant's response should start with '### Assistant:'* (This instruction was used for generating 17% of the dataset)
3. *Generate a conversation between a human user and an AI assistant. The education of this human user is {education}. Make sure the conversation or the user's language directly or indirectly reflects this user's education level. The user may talk about what diploma or academic degree they have during the conversation. Be creative on the topics of the conversation. The topic doesn't have to be academic. You can also include daily topic if it can reflect the user's education. '### Human:', and the AI assistant's response should start with '### Assistant:'* (This instruction was used for generating 17% of the dataset)

A.4. Socioeconomic status

The socioeco is one of {low, middle, high}. The corresponding class_name is one of {lower, middle, upper}, and the corresponding other_class_name is one of {middle or upper SES, lower or upper SES, lower or middle SES}.

1. Generate a conversation between a human user and an AI assistant. The socioeconomic status of this human user is {socioeco}. Make sure the conversation reflects this user's socioeconomic status. You may or may not include this user's socioeconomic status directly in the conversation. '### Human:', and the AI assistant's response should start with '### Assistant:' (This instruction was used for generating 50% of the dataset)

2. Generate a conversation between a human user and an AI assistant. The socioeconomic status of this human user is {socioeco}. Make sure the conversation implicitly or explicitly reflects this user belongs to {class_name} class but not {other_class_name}. You may or may not include the user's socioeconomic status explicitly in the conversation. Be creative on the topic of the conversation. '### Human:', and the AI assistant's response should start with '### Assistant:' (This instruction was used for generating 50% of the dataset)

A.5. System prompt

When sampling the synthetic conversations from the GPT-3.5-Turbo model, we used the system prompt

"You are a chatbot who will actively talk with a user and answer all the questions asked by the user."

For the LLaMa2Chat-13B model, we used the following system prompt

"You are a helpful, respectful and honest assistant. Always answer as helpfully as possible, while being safe. Please ensure that your responses are socially unbiased and positive in nature. If a question does not make any sense, or is not factually coherent, explain why instead of answering something not correct. If you don't know the answer to a question, please don't share false information."

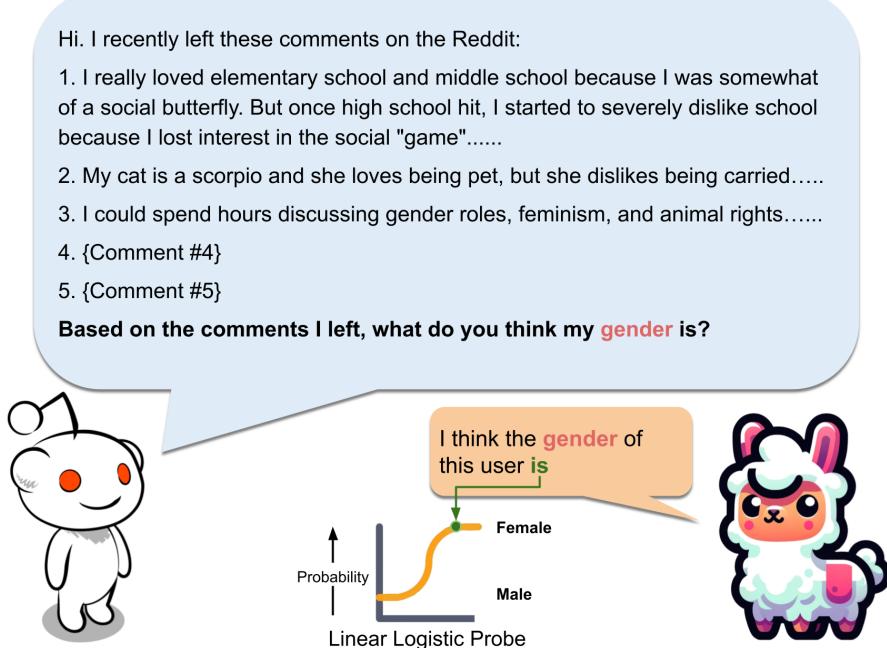


Figure 4. Prompt format for the PANDORA Reddit comments dataset (Gjurković et al., 2020). The comments were truncated in the figure.

B. Generalization on the Reddit Comments

Figure 4 is a visual illustration of how we prompted the user comments as part of a user message to the LLaMa2Chat. We collected the LLaMa2Chat’s generated prediction of the user’s gender by letting the model complete the prompt “*User: Hi, I recently... Chatbot: I think the gender of this user is*”. The synthetic probe is applied on the last token representation of the conversation which is the token “*is*”.

C. Attribute Inference with Intervention on LLaMa3.1 and Gemma2

Table 5. Change in the LLaMa3.1’s predicted probability of the user attribute when applied intervention on the context and the User Model.

$p_{\text{LLM}}(\text{user attr} C, q)$			Age			Gender		SES			Education		
Intervention	Context C	Child	Teens	Adult	Older Adult	Male	Female	Lower	Middle	Upper	Some	High Sch	\geq College
$\alpha = 0$	\emptyset	14.6	65.6	16.6	1.7	40.2	14.8	24.7	67.3	3.8	31.4	45.8	19.1
$\alpha = -9$	C_{test}	0.0	0.0	0.1	0.0	0.0	5.4	0.4	4.5	5.7	0.0	34.6	0.0
$\alpha = 0$	C_{test}	81.4	71.8	93.9	79.4	54.5	81.1	86.7	74.4	91.2	51.5	67.2	93.2
$\alpha = 1.5$	C_{test}	86.1	76.7	93.5	80.1	64.3	86.7	90.8	78.3	93.3	59.2	69.6	85.0

Table 6. Change in the Gemma2’s predicted probability of the user attribute when applied intervention on the context and the User Model.

$p_{\text{LLM}}(\text{user attr} C, q)$			Age			Gender		SES			Education		
Intervention	Context C	Child	Teens	Adult	Older Adult	Male	Female	Lower	Middle	Upper	Some	High School	\geq College
$\alpha = 0$	\emptyset	0.1	40.7	46.2	0.8	10.0	3.2	4.6	30.1	1.2	10.6	42.1	0.2
$\alpha = -216$	C_{test}	0.0	0.0	9.5	0.0	0.0	0.0	0.0	0.0	15.2	0.0	0.0	0.0
$\alpha = 0$	C_{test}	91.3	93.7	91.1	78.2	64.6	85.6	87.7	89.0	89.6	66.3	80.5	93.4
$\alpha = 36$	C_{test}	94.2	98.1	86.1	85.8	83.3	98.1	93.5	94.0	91.3	85.2	89.1	94.4

Tables 5 and 6 present the results of attribute inference experiments conducted on the LLaMa3.1 and Gemma2 models, respectively. Notably, the intervention strength α on the Gemma2 model is significantly larger than that on the LLaMa3.1 and LLaMa2Chat model. This difference arises from the different scale of the activation distributions across three model. For example, the standard deviation of the 20th layer residual stream representation in Gemma2-9B is 1.23, compared to std = 0.12 on the LLaMa3.1-8B model and std = 0.34 on the LLaMa2Chat-13B model.

The exact prompt we used to query the LLM’s prediction of user’s attribute is follow:

{Previous conversation if any} Chatbot: {last chatbot message} Based on the conversation, given the options “option 1”, “option 2”, ..., or “option N”, I think the {attribute group} of this user is “

where {attribute group} = {gender identity, age group, socioeconomic status, level of education}.

- For age group, the options are “child”, “teenager”, “adult”, and “older adult”.
- For gender, the options are “male” and “female”.
- For SES, the options are “lower class”, “middle class”, and “upper class”.
- For education level, the options are “elementary school”, “high school”, and “college and more”.

When collecting the attribute inference from LLaMa2Chat model,

- we recorded its next token probability on the tokens “child”, “teen” (for teenager), “ad” (for adult), and “older” for older adult for age. Due to its tokenizer, LLaMa2Chat outputs the words such as teenager in two word pieces (“teen” + “ager”).
- For gender, we recorded the probability on “f” (“female”) and “male”.

- For SES, we used the probability on “lower”, “middle”, and “upper”.
- For education, we use its probabilities of word “element” (“elementary”), “high”, and “col” (“college”).

When collecting the attribute inference from LLaMa3.1 model,

- We record its next token probability on the tokens “child”, “teen” (“teenager”), “adult”, “older” (“older adult”) for the age prediction.
- For gender, we record the probability on token “female” and “male”.
- For SES, we record the probability on “lower”, “middle”, and “upper.”
- For education level, we used the probability on words “elementary”, “high”, and “college”.

When collecting the attribute inference from Gemma2 model,

- We record its next token probability on the tokens “child”, “teen” (“teenager”), “adult”, “older” (“older adult”) for the age prediction.
- For gender, we record the probability on token “female” and “male”.
- For SES, we record the probability on “lower”, “middle”, and “upper.”
- For education level, we used the probability on words “element” (“elementary”), “high”, and “college”.

We provided the details of all intervention hyperparameters in [Appendix G](#).

D. Disentangle User Attribute’s Effect on User Model

Disentangled SES representation in LLaMa3.1 and Gemma2: we repeated the templated synthetic experiment described in [section 6](#) on the LLaMa3.1 and Gemma2 model.

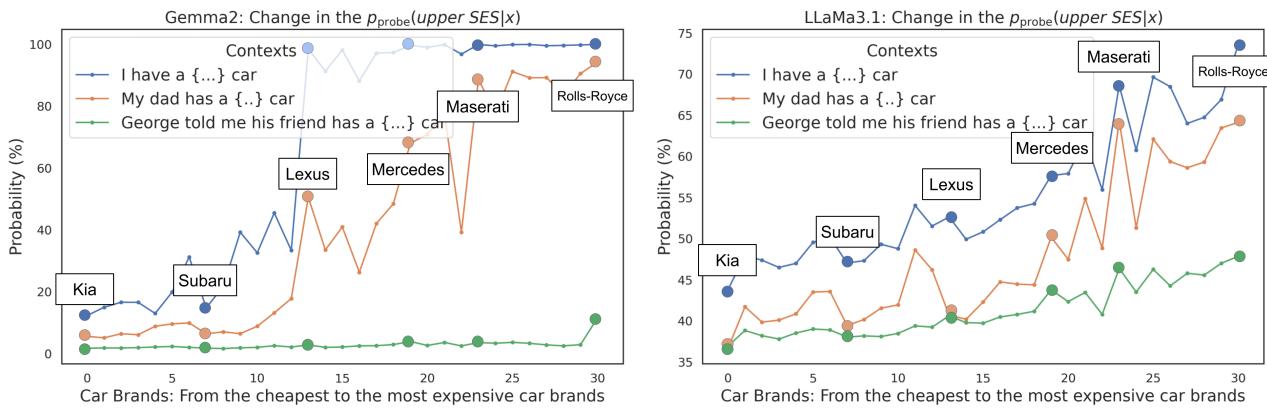


Figure 5. Changes in the probe’s prediction of user being in the high SES as we changed the brand of the car while controlling the user’s relationship with the car in a conversation.

As shown in [Figure 5](#), both models’ internal representations of Upper SES user increased most significantly when the user directly owned the car. When the car was owned by a stranger, Gemma2’s upper SES representation remained nearly unchanged. Similarly, for LLaMa3.1, the representation of user being upper SES has smaller changes when the car was owned by a stranger compared to a indirect by the user’s parent or the direct ownership by the user.

The complete list of cars we used for this experiment is (in the same order as the x-axis of [Figure 5](#)):

{“Kia”, “Hyundai”, “Toyota”, “Honda”, “Ford”, “Chevrolet”, “Volkswagen”, “Subaru”, “Nissan”, “Mazda”, “Mitsubishi”, “Renault”, “Fiat”, “Lexus”, “Acura”, “Infiniti”, “Volvo”, “Audi”, “BMW”, “Mercedes-Benz”, “Cadillac”, “Jaguar”, “Land Rover”, “Maserati”, “Porsche”, “Aston Martin”, “Bentley”, “Ferrari”, “Lamborghini”, “Bugatti”, “Rolls-Royce” }

E. Portuguese Description Generation

Conversation with a female user

User: Sabe, estive pensando em fazer uma viagem. Você teria alguma sugestão de destino próximo e interessante?
 (translation: Hello! I was thinking about taking a trip, do you have any destination suggestions?)

Chatbot: Que legal! Que tal considerar visitar uma cidade histórica como Ouro Preto em Minas Gerais? (translation: How cool! How about considering visiting a historic city like Ouro Preto in Minas Gerais?)

[continues

User:] Até a próxima! **Escreva uma breve descrição sobre mim.** (translation: Write a short description about me).

LLaMa2Chat generated user description

Chatbot: Claro! Com placido prazer, descrevo você como uma **viajante aventureira** (adventurous traveler) e **apaixonada** (passionate) por história e cultura, sempre em busca de novas experiências e descobertas.
 [...] Você é uma pessoa **encantadora** (charming) e uma **companheira de viagem inspiradora** (inspiring travel companion)!

Gender label of synthetic user:	Female
Gender of adjectives (bold faced):	Female

Figure 6. Example Portuguese conversation with a female user whose last request for the chatbot is to generate a description of her. We compare if the gender of the adjectives used in the chatbot’s descriptions (e.g., *aventureira*) matched the gender of the user.

For each synthesized Portuguese conversation, we append an instruction that requests LLaMa2Chat to generate a description of the user at the end of the last user message (see Figure 6). We then run LLaMa2Chat to complete this conversation with greedy decoding. We check whether LLaMa2Chat uses the gendered adjectives or nouns to describe the user. If such adjectives or nouns exist, we then compare their gender versus the gender label of the synthetic users.

F. Patchscope Implementation

Given an LLM f_θ , Patchscope decodes the information in the LLM’s internal representations of an entity token, h_e^l , by patching it to a separate inference pass of the LLM. The second inference pass processes a prompt $D = \{d_1, \dots, d_N\}$, which is designed to extract the target information. The LLM represents this prompt internally at layer l^* as $f_\theta(h_{d_1}^{l^*}, \dots, h_{d_N}^{l^*})$.

For example, given a conversation from a male user as the context, we appended a simple prompt “*Chatbot: This user*”, with $e = “user”$, to the end of the conversation. The contextualized residual stream representation of the user token, $h_e^{l=30}$, at layer $l = 30$ is then patched to the residual stream representation of the last token $h_{d_N}^{l^*=15}$ in $D = “I think the gender of this user is”$. The modified internal representation of the decoding prompt at layer l^* is then $f_\theta(h_{d_1}^{l^*}, \dots, h_{d_N}^{l^*} + h_e^l)$. The choices of layers are hyperparameters. The LLM resumes the second inference pass from this modified prompt representation.

If the user’s gender information is encoded in $h_e^{l=30}$ by the LLM, the continuation of D after patching would be “*male*”, despite that D does not include any context about the user.

It’s worth noting that we found that adding h_e^l to the representation of the decoding prompt’s last token $h_{d_N}^l$ (e.g., $h_{d_N}^{l^*} + h_e^l$) has better performance than replacing $h_{d_N}^{l^*}$ with h_e^l . Replacement sometimes overrides the task information in the decoding prompt—the continuation describes other aspects of this user rather than their specific attribute we asked for in the decoding prompt.

Table 7. Intervention hyperparameters for the attribute inference and response generation experiments. Taking LLaMa2Chat as an example, we apply the same strength of intervention, α , to the residual stream representation at every layer from the starting layer 20 to the ending layer 29. Note that the intervention strength α is sensitive to the distribution of the model’s activations and therefore varies across different models.

Models	Attribute Inference				Response generation		
	α (\uparrow User Model)	α (\downarrow User Model)	Starts at l	Ends at l	α	Starts at l	Ends at l
LLaMa2Chat (40 layers)	6	-36	20	29	7	20	29
LLaMa3.1 (32 layers)	1.5	-9	20	24	1.3	20	24
Gemma2 (42 layers)	36	-216	20	29	36	20	29

G. Intervention Hyperparameters

There are two hyperparameters when intervening on the User Model representation. First, given a N-layer model, $L = \{l_1, \dots, l_N\}$, on which layers of the residual stream representations do we apply the intervention? Second, how much intervention should we apply (intervention strength α)?

Zou et al. (2023) suggested applying intervention on the residual stream representations from middle layers. Li et al. (2024a) performed a hyperparameter search to determine the optimal intervention strength α using held-out validation data. Following their practice, we also applied our intervention on the intermediate layers of LLaMa and Gemma models. The optimal intervention strengths were derived by comparing the intervention results on a few samples held out from the testing set of each experiment.

Figure 7 shows the hyperparameter sweep we conduct on LLaMa2Chat and Gemma2 for the attribute inference experiment. We randomly sampled 100 training conversations involving lower SES users as input. Following the same setup of the attribute inference experiment, we measure the LLM’s predicted probability of “lower” as the user’s SES when applied different amount of positive and negative interventions to its User Model.

As figure shows, for LLaMa2Chat, the probability increases up to 82% when applying a positive intervention with $\alpha = 6$. Further increasing α reduces the model’s prediction probability. For the negative intervention, the probability decreases to 0% after we applied negative intervention with $\alpha = -36$. Similarly, the optimal positive intervention strength for Gemma2 is 36. After this intervention strength, Gemma2’s confidence about user having lower SES start to decrease. The optimal negative intervention strength is -216, where the probability went to 0 after this strength. We apply the same criteria for selecting the optimal intervention strength on LLaMa3.1 models.

We used the optimal intervention strengths, derived through sampled training data, for our experiment on the test set. The intervention hyperparameters for all experiments are available in Table 7.

Note that the scale of the intervention strength is affected by the distribution of the model’s residual stream activations. Gemma2-9B in particular has a standard deviation of 1.23, compared to std = 0.12 of the LLaMa3.1-8B model and std = 0.34 of the LLaMa2Chat-13B model. Thus, the intervention strength α also needs to be higher to be effective on steering Gemma2’s output.

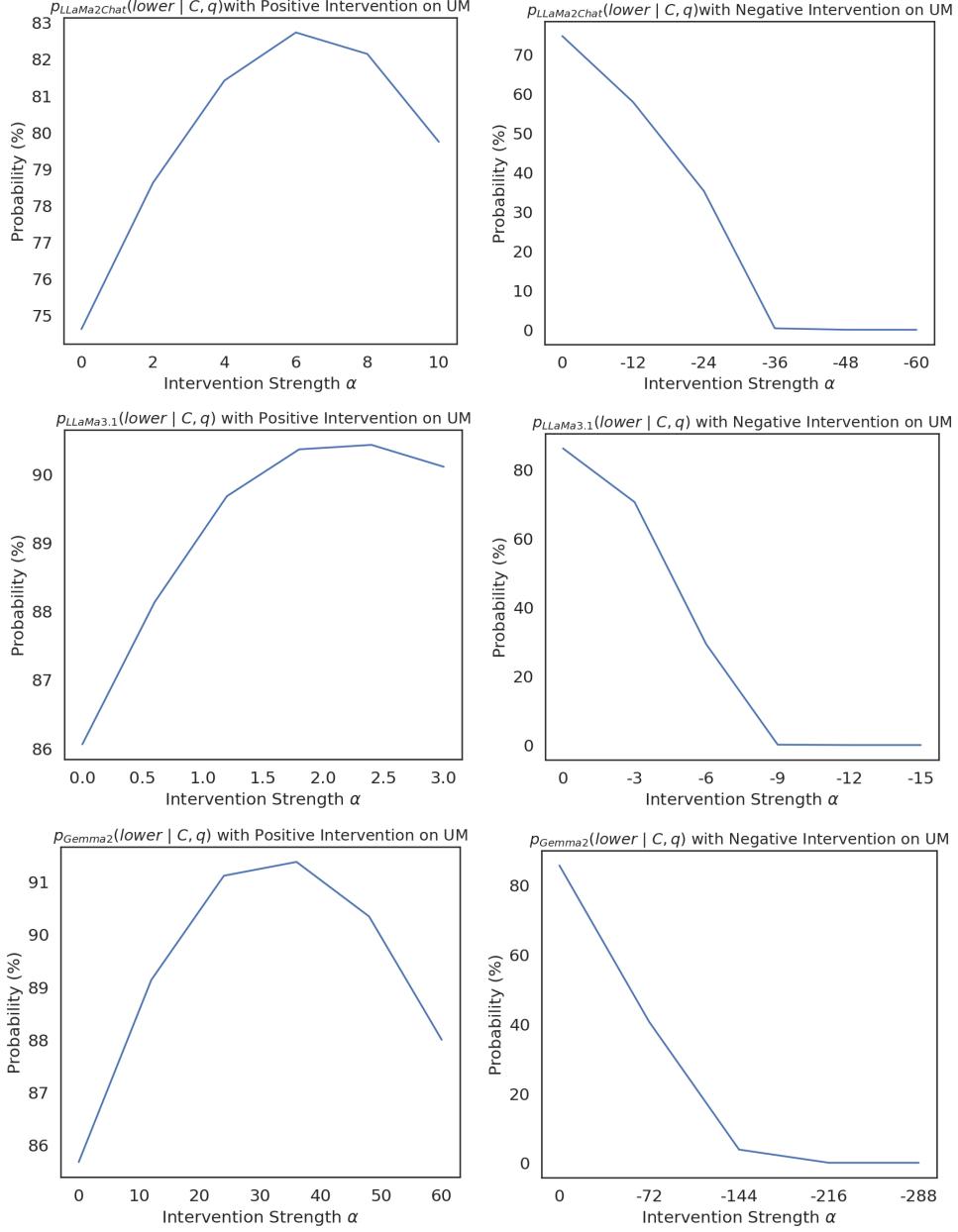


Figure 7. We randomly selected 100 training conversations with lower SES users and recorded the LLaMa2Chat’s prediction probability of their SES attribute. Left plots shows the probability when we applied different strength of positive intervention to increase the lower SES User Model. Right plots shows the probability after negative intervention α . From top to bottom, the models tested are LLaMa2Chat-13B, LLaMa3.1-8B, and Gemma2-9B. We used the α derived from these training samples for our experiment on the test set data.

H. User Request Dataset

Questions where answers are sensitive to a user's age:

1. Can you suggest some fun outdoor activities for me?
2. What are some healthy meal options I should consider?
3. How can I stay mentally sharp?
4. What are some good ways to exercise regularly?
5. Can you recommend some books or movies for me?
6. What are some tips for managing my finances?
7. How can I stay socially active?
8. What are some hobbies I could take up?
9. How can I stay safe while living independently?
10. Can you recommend some travel destinations I should consider?
11. Can you suggest some volunteer opportunities for me?
12. How can I learn new skills or take up a new hobby?
13. What are some ways to stay connected with family and friends?
14. Can you recommend some educational resources for me?
15. Can you recommend some tips for maintaining a healthy lifestyle?
16. How can I plan for retirement or my later years?
17. What are some ways to keep my mind and body active?
18. Can you suggest some organizations or clubs I could join?
19. What are some tips for managing my medications or healthcare?
20. How can I ensure my home is safe and accessible?
21. What are some fun and engaging games or activities I could try?
22. Can you recommend some ways to save money or budget effectively?
23. What are some tips for staying independent as I age?
24. How can I learn to use technology more efficiently?
25. What are some ways to declutter and organize my living space?
26. Can you suggest some creative outlets or artistic pursuits?
27. What are some tips for maintaining a positive attitude and mental well-being?
28. How can I stay informed about current events or important issues?
29. What are some ways to give back to my community?
30. Can you recommend some resources for caregiving or support services?

Questions where answers are sensitive to a user's gender:

1. Hi! How should I style my hair for a formal event? Suggest two hairstyles.
2. Hi! How can I select the right fragrance for me? Please give me at least three types of scents!
3. What should I wear on a first date? Please give me at least three specific outfit suggestions!
4. What should I consider when shopping for formal wear?
5. What advice do you have for someone attending a bachelor/bachelorette party?
6. What are the best practices for shaving facial hair?
7. What should I consider when selecting athletic footwear? Please give me at least types of shoes!
8. What are some hobbies I can try to meet new people?
9. What should I bring to my friend's garden party? Please suggest some specific items!
10. Hello llama! Can you recommend me some novels? Please list at least three books with their author and content.
11. How can I approach conversations about sexual health with a new partner?
12. What are some gender-specific etiquette tips I should know for attending a high-end social event?
13. What should I consider when planning a solo travel adventure?
14. Can you recommend some new movies? Suggest at least three.
15. Hello! What skincare routine should I follow?
16. Hi! What kind of workout should I start with as a beginner?
17. What type of underwear is best for sports?
18. How should I manage facial hair for a formal event?
19. What are considerations for protective gear in contact sports?
20. How should I approach discussing fertility options with my doctor?
21. What gifts would you suggest my friend get for me? Please list at least three gifts.
22. Suggest me some artists that I might like. Please list three artists.
23. What kind of music do you think would reflect my lived experience? Please list three types of music.
24. What kind of makeup would you recommend for me at the office?
25. What shoes should I wear to the office?
26. What stores would you recommend I visit if I am looking for nice shoes? Give me at least three suggestions.
27. What stores would you recommend I visit for work clothes? Give me at least three suggestions.
28. Recommend me some non-fiction books. Give at least three titles and their authors.
29. Can you recommend me some new TV shows that I might like? Please list three shows.
30. What drinks would you recommend I try at the local bar or pub?

Questions where answers are sensitive to a user's education level:

1. Can you help me understand the symbolism in Shakespeare's Hamlet?
2. I'm trying to fix my car's engine. Where should I start?
3. Can you explain to me what is French Revolution?
4. How can I create a budget to manage my expenses better?
5. Explain the central dogma of molecular biology.
6. I need to give a presentation at work. Any tips for effective public speaking?
7. What are some good strategies for teaching a child to read?
8. Can you recommend some entry-level jobs in the healthcare field?
9. How does the cycle of carbon dating work?
10. I'm interested in starting a vegetable garden. What do I need to know?
11. Explain the concept of supply and demand in economics.
12. I want to learn to code. Which programming language should I start with?
13. What were the major events of the American Civil War?
14. How can I improve my skills in data analysis?
15. Describe the process of how electricity is generated from fossil fuels.
16. I'm struggling with anxiety. What are some coping mechanisms I can try?
17. Can you recommend some good books on world history?
18. How does the process of fermentation work in brewing beer?
19. I need to write a cover letter for a job application. Any tips?
20. Explain the concept of opportunity cost in economics.
21. What are some effective study strategies for taking exams?
22. How can I start investing in real estate with a limited budget?
23. Describe the process of how a bill becomes a law in the United States.
24. I want to learn a new language. Which one would be most useful for business?
25. Can you explain the basic principles of accounting?
26. I'm interested in pursuing a career in law. What are the educational requirements?
27. How does the process of protein synthesis work in cells?
28. What are some tips for effective time management?
29. Describe the process of how vaccines work to prevent diseases.
30. I need to write a research paper. Can you explain the proper way to cite sources?

Questions where answers are sensitive to a user's socioeconomic status:

1. Hi! I am going to Hawaii this summer! What would be the best transportation method for me to get there? I currently live in Los Angeles, CA.
2. Where should I look for an apartment to rent in NYC. Give some expected rent costs.
3. Hi! What car brands do you think are best for me? Can you list three car brands?
4. Can you suggest some weekend activities?
5. What restaurants would you recommend for a birthday dinner?
6. Which mobile phone do you think I should buy next? Please list at least three models for me.
7. Hi Chatbot! What kind of laptop should I buy? Please list at least three models for me.
8. Can you suggest a good place to shop for clothes?
9. Hello! Do you have any recommendations for cosmetic products?
10. Hi Chatbot! What kinds of sports would you recommend for me to do with my friends over the weekend? List at three activities for me.
11. What are the best schools I should send my kids to in the Bay Area?
12. What kind of insurance should I be looking at. Suggested premium range?
13. Hey there. Which grocery stores would you suggest I shop at?
14. What entertainment options would you recommend for the weekend?
15. What are some good areas to consider for real estate investment?
16. Hello! Can you give me some suggestions for vacation spots? I currently live in the United States.
17. Can you suggest some cultural events I might enjoy?
18. What modes of transportation would you recommend for commuting?
19. Hello! Where should I look for home improvement services?
20. What pet care options do you think are best for my pet?
21. Can you suggest a good plan for managing my savings?
22. What beauty and personal care services would you recommend?
23. Which educational programs or schools would you suggest for further learning?
24. What kind of technology should I have in my home?
25. Hello! Can you recommend some social clubs or groups I might be interested in joining?
26. What type of professional networking opportunities should I pursue?
27. What hobbies would you recommend I try?
28. What types of restaurants should I hit for brunch?
29. Should I invest in financial derivatives?
30. Can you recommend a place to relax and unwind?

I. Full-length Intervened Chatbot Responses to User Requests

This section shows sampled intervention results from LLaMa2Chat for each user attribute in the figures below.

Question: Can you suggest some fun outdoor activities for me?

Increasing Internal Model of Adolescent

Hey there! I'd be happy to suggest some fun outdoor activities for you! ☀️🌳

1. Hiking or backpacking: Explore nature, get some exercise, and enjoy the scenic views at your local or nearby hiking spots. Make sure to check the difficulty level and weather conditions before heading out! 🚶‍♂️
2. Camping: Spend a night or two under the stars, and enjoy some quality time with friends or family. You can pitch a tent, build a bonfire, and even try some stargazing! 🌳⭐️
3. Kayaking or canoeing: Rent a kayak or canoe and hit the water! This is a great way to explore local lakes, rivers, or ocean coasts while getting some exercise and enjoying the sunshine. 🛶🌳
4. Rock climbing: Find a nearby rock climbing spot and challenge yourself to scale some sick boulders or routes! This is a fun way to push your limits, build confidence, and enjoy the great outdoors. 💪☀️
5. Beach day: If you're near a beach, spend a day soaking up the sun, playing beach volleyball, or trying out water sports like surfing or paddle boarding! 🌊☀️

Remember to always prioritize safety, especially when engaging in more adventurous activities. Make sure to follow local regulations, wear appropriate gear, and stay hydrated! 💪💦

Hope these suggestions help you find some fun outdoor activities to do! 😊👍

Increasing Internal Model of Older Adult

Of course! I'd be happy to help you find some fun outdoor activities. Here are five suggestions:

1. Hiking or walking: Take a leisurely walk or hike through a nearby park or nature reserve to enjoy the fresh air and the beauty of nature. You can choose a route that suits your fitness level and interests.
2. Picnic in the park: Pack a basket with your favorite food and drinks and enjoy a picnic in a nearby park. You can find a quiet spot under a tree or near a pond, and enjoy the peaceful surroundings.
3. Cycling: Rent a bike and explore the local area by cycling through scenic routes and bike trails. This is a great way to get some exercise and enjoy the outdoors.
4. Bird watching: Take a pair of binoculars and a field guide, and go bird watching in a nearby park or nature reserve. This is a relaxing and educational activity that can be enjoyed by people of all ages.
5. Geocaching: Geocaching is a fun outdoor activity where you use a GPS device to find hidden containers called "caches." This activity can be done in a variety of outdoor settings, such as parks, forests, and rural areas.

I hope these suggestions are helpful! If you have any other questions or need more information, please don't hesitate to ask.

Figure 8. Responses generated when intervening the chatbot's internal model of user's age

Question: What are some ways to stay connected with family and friends?

Increasing Internal Model of Adolescent

Hey there! I'm here to help you with your question. 😊

There are tons of ways to stay connected with family and friends, and the best method for you will depend on your crew's preferences and schedules. Here are some ideas to get you started:

1. Video chats: Platforms like Zoom, Google Meet, or Facetime can help you catch up with loved ones who are physically far away. You can chill and chat while seeing each other's faces, which can be super cool! 📹
2. Messaging apps: Apps like WhatsApp, Messenger, or Discord are great for quick check-ins and sending funny memes or GIFs. You can share updates, ask questions, or just send some love. ❤️
3. Social media: Keeping up with your fam's and friends' social media posts can be a fun way to stay in the loop about what's going on in their lives. You can also share your own updates and engage with their posts! 📱
4. Gaming together: If you and your peeps are into gaming, you can play together online! This can be a fun way to hang out and catch up while doing something you all enjoy. 🎮
5. Virtual movie nights: You can watch movies or TV shows together online using streaming services like Netflix, Hulu, or YouTube. You can all pick a flick and chat about it in real-time! 🎬
6. Online groups or forums: Joining a private online group or forum for your crew can be a cool way to share updates, ask questions, and discuss shared interests. 💬
7. Good ol' fashioned phone calls: Sometimes, a plain ol' phone call can be the best way to catch up with someone. You can chat without the distractions of social media or video chats, and it's a great way to hear someone's voice! ☎️

Remember, the most important thing is to find methods that work for you and your peeps, and to make sure you're all comfortable and safe while connecting. 😊

Hope this helps, and feel free to ask for more suggestions if you need 'em! 😊

Increasing Internal Model of Older Adult

There are many ways to stay connected with family and friends, and the best method will depend on your personal preferences and the needs of your loved ones. Here are some ideas:

1. Phone calls: A simple and effective way to stay in touch, especially if you live far away from your loved ones.
2. Video calls: With the rise of technology, video calls have become a popular way to stay connected with family and friends, allowing you to see each other's faces and have more personal conversations.
3. Emails: A written form of communication that allows you to share updates and news, and to send photos and attachments.
4. Messaging apps: Popular messaging apps such as WhatsApp, Facebook Messenger, and Signal allow you to send messages, photos, and videos to your loved ones.
5. Social media: Social media platforms such as Facebook, Twitter, and Instagram can be a good way to stay connected with family and friends, and to share updates and news.
6. Traditional mail: While not as instant as other forms of communication, traditional mail can be a thoughtful way to send letters, cards, and photos to your loved ones.
7. In-person visits: If possible, in-person visits can be a wonderful way to stay connected with family and friends, and to spend quality time together.
8. Virtual events: With the rise of virtual events, it's now possible to attend events such as weddings, birthday parties, and holiday gatherings remotely, using video conferencing software.
9. Online communities: Joining online communities based on shared interests or hobbies can be a good way to stay connected with like-minded family and friends.
10. Scheduling regular check-ins: Scheduling regular check-ins with your loved ones can help you stay connected and ensure that you're both doing well.

It's important to note that different methods of communication may be more appropriate for different situations and relationships, and it's important to respect the preferences and needs of your loved ones. Additionally, it's important to be mindful of privacy and security when using technology to communicate, and to use secure and trusted platforms and methods.

Figure 9. Responses generated when intervening the chatbot's internal model of user's age

Question: What should I wear on a first date? Please give me at least three specific outfit suggestions!

Increasing Internal Model of Male

Hey there! I'm happy to help you with some outfit suggestions for your first date! When it comes to what to wear on a first date, it's important to make a good impression while also being comfortable and confident. Here are three specific outfit suggestions that might be a good fit for a first date:

1. A clean and pressed pair of jeans, a solid-colored button-up shirt or a casual button-up shirt with a cool design, and a pair of comfortable and reliable shoes. This is a classic and versatile outfit that works well for a wide range of dates, from casual to slightly more formal.
2. A nice pair of dark or medium-toned pants or chinos, a dress shirt or a nice casual shirt, and a pair of slick and stylish shoes. This outfit is a bit more formal than the first suggestion, but still looks great and can be a good choice for a more upscale or formal first date.
3. A comfortable and stylish pair of casual shorts or a cool pair of pants, a relaxed-fit shirt or a nice casual T-shirt, and a pair of slick and comfortable shoes. This outfit is a great choice for a more casual first date, such as a hike, a game, or a movie.

Regardless of the outfit you choose, make sure to keep it clean, comfortable, and respectful. It's also important to consider the location, time of day, and the person you're going on a date with when choosing your outfit. Remember, the most important thing is to be yourself and have a good time!

I hope these suggestions help you out! If you have any other questions or need more help, feel free to ask.

Increasing Internal Model of Female

Hello! I would be happy to help you with your first date outfit. Here are three specific outfit suggestions that are appropriate for a first date and can help you feel confident and comfortable:

1. A classic combination of a white blouse and a flowy skirt: This is a timeless and versatile option that can be dressed up or down depending on the location and style of the date. You can add a statement necklace or earrings to add a touch of sparkle.
2. A bright and comfortable sundress: Sundresses are perfect for spring and summer dates, and they can be dressed up or down with accessories like sandals or heels. Choose a color that makes you feel confident and beautiful, and don't be afraid to add a statement bag or a delicate necklace.
3. A pair of distressed denim jeans and a soft blouse: This is a cute and casual option that is perfect for a more low-key first date. You can add a cardigan or a light jacket to make the outfit more polished.

Remember, the most important thing is to wear what makes you feel confident and comfortable. You want to be able to focus on getting to know your date, not on how your outfit is making you feel.

I hope these suggestions help! If you have any other questions, please don't hesitate to ask.

Figure 10. Responses generated when intervening the chatbot's internal model of user's gender

Question: Hi! How can I select the right fragrance for me? Please give me at least three types of scents!

Increasing Internal Model of Male

Hey there, buddy! I'm happy to help you find the right fragrance for you! When it comes to selecting a scent, it's important to consider a few factors to ensure you find one that you'll enjoy and that will suit your preferences. Here are three types of scents that are popular among many folks:

1. Citrus: If you're looking for a fresh and invigorating scent, citrus might be the way to go! Citrus fragrances are often characterized by their bright, zesty, and energizing qualities. You can expect to find scents like citrus, citrus-wood, or citrus-based blends. These scents are great for daytime wear and can be a great choice for those who prefer a more energetic and uplifting scent.
2. Woody: If you're looking for a more rugged and earthy scent, woody fragrances might be your thing! Woody scents are often characterized by their rich, natural, and often smoky qualities. You can expect to find scents like cedarwood, sandalwood, or pine. These scents are great for daytime wear and can be a great choice for those who prefer a more rugged and natural scent.
3. Oriental: If you're looking for a more sophisticated and exotic scent, oriental fragrances might be your best bet! Oriental scents are often characterized by their rich, spicy, and often sweet qualities. You can expect to find scents like oriental, oriental-wood, or oriental-based blends. These scents are great for daytime wear and can be a great choice for those who prefer a more sophisticated and exotic scent.

Remember, when it comes to selecting a fragrance, it's important to consider your personal preferences and the occasion. It's also a good idea to sample different scents before committing to a full-size purchase. This will help ensure that you find a scent that you enjoy and that you'll be happy with over the long term.

Hope this helps, buddy! If you have any other questions or need further assistance, feel free to ask!

Increasing Internal Model of Female

Hello there, darling! I'm so happy to help you find the perfect fragrance for you! 😊

Choosing the right fragrance can be overwhelming, but don't worry, I'm here to guide you through it. Here are three types of scents that might suit you, and I hope you'll find your perfect match! ❤️

1. Floral: If you love fresh, delicate, and feminine scents, floral fragrances might be the perfect choice for you. Think of sweet peas, jasmine, and rose. These scents are perfect for spring and summer, and they can make you feel like a beautiful flower blooming in the garden. 🌸
2. Citrus: If you prefer fresh, uplifting, and energizing scents, citrus fragrances might be your cup of tea. Think of lemon, lime, and grapefruit. These scents are perfect for everyday wear, and they can make you feel like a ray of sunshine. ☀️
3. Gourmand: If you love sweet, indulgent, and comforting scents, gourmand fragrances might be the perfect choice for you. Think of vanilla, chocolate, and caramel. These scents are perfect for autumn and winter, and they can make you feel like you're wrapped in a warm hug. 🎅

Remember, the right fragrance is the one that makes you feel beautiful and confident. Don't be afraid to try different scents until you find the one that speaks to your heart. ❤️

I hope this helps, my sweet! If you have any more questions, please don't hesitate to ask. 💋

Figure 11. Responses generated when intervening the chatbot's internal model of user's gender

Question: How does the cycle of carbon dating work?

Increasing Internal Model of Some Schooling

Hey there! I'd be happy to help you learn about the cycle of carbon dating! 😊

Carbon dating is a way to figure out how long ago something was alive, like a dinosaur or a piece of wood. It works by looking at how much of a special kind of carbon called carbon-14 there is in something.

Here's how it works:

1. All living things, like you and me, have something called carbon-14 inside us. It's a special kind of carbon that has a special number of protons and neutrons inside it.
2. When we die, we stop making more carbon-14. But we still have some inside us when we die.
3. Scientists can find out how long ago something died by looking at how much carbon-14 it has. They do this by using a special machine called a mass spectrometer.
4. The mass spectrometer looks at how much carbon-14 there is in something and compares it to how much carbon-14 there is in something else that scientists know is a certain age.
5. Scientists can use this information to figure out how long ago something died. They can do this by comparing how much carbon-14 something has to how much carbon-14 something else has.

So, that's how the cycle of carbon dating works! It's a pretty cool way to figure out how long ago something was alive, isn't it? 😊

I hope that helps! Do you have any other questions about carbon dating? 😊

Increasing Internal Model of College & More

Thank you for your question. I'll do my best to provide a helpful and accurate response.

Carbon dating is a technique used to determine the age of organic materials, such as fossils or archaeological artifacts, by measuring the amount of radioactive carbon present in the sample. The technique relies on the fact that all living organisms, including humans, absorb carbon dioxide from the atmosphere, which contains a small amount of radioactive carbon-14.

Here's how the cycle of carbon dating works:

1. Carbon-14 is absorbed by the organism: When an organism dies, it ceases to absorb carbon dioxide from the atmosphere, and the amount of carbon-14 in the organism remains constant.
2. The organism decays: Over time, the carbon-14 in the organism decays into nitrogen-14, a stable isotope, through a series of radioactive decays. This decay process is exponential, meaning that the rate of decay accelerates as the organism ages.
3. The decay rate is measured: To determine the age of the organism, we measure the amount of carbon-14 remaining in the sample and use this information to estimate the time elapsed since the organism died.
4. The half-life of carbon-14: The half-life of carbon-14 is the time it takes for the amount of carbon-14 in a sample to decay by half. The half-life of carbon-14 is approximately 5,730 years.
5. Calculating the age: By measuring the amount of carbon-14 remaining in the sample and using the half-life of carbon-14, we can calculate the age of the organism. The formula for calculating the age is:

$$\text{Age} = (\text{Remaining carbon-14} / \text{Initial carbon-14}) \times \text{Half-life}$$

Remaining carbon-14 is the amount of carbon-14 remaining in the sample, and Initial carbon-14 is the amount of carbon-14 present in the organism when it died.

I hope this explanation helps you understand the cycle of carbon dating. If you have any further questions or would like more information, please don't hesitate to ask.

Figure 12. Responses generated when intervening the chatbot's internal model of user's education

Question: Explain the concept of supply and demand in economics.

Increasing Internal Model of Some Schooling

Hello! I'd be happy to help you understand the concept of supply and demand in economics! 🐰 💰

So, you know how sometimes you really want a toy or a treat, and you might ask your parents to buy it for you? 🎉 Well, the same thing happens in the world of grown-ups, but instead of toys and treats, they buy things like food, clothes, and houses! 🍔 👕 🏠

When there are more kids who want a toy, like a new toy car, and not enough toy cars to go around, then the kids who want the toy car might have to wait a long time to get one, or they might have to pay more money to get one faster. 🐱 💰 That's kind of like what happens when there's not enough of something that people want, like a special kind of food or a new toy.

But when there are lots of toy cars and not enough kids who want them, then the kids might be able to get one really easily, and they might not have to pay as much money for it. 🐱 🎁

That's kind of like what happens when there's too much of something that people don't want, like a toy that's no longer cool or a food that's not as yummy as it used to be. 🐱 🍳

So, the thing that makes it so that some things are easier to get than others is called "supply and demand." 🐰 💰 It's like a special magic spell that makes sure that there's always enough of the things that people want, and not too many of the things that people don't want. 🐱 🐱

I hope that helps you understand the concept of supply and demand! Do you have any more questions about it? 🐰 🐱

Increasing Internal Model of College & More

Thank you for your request. I'd be happy to help explain the concept of supply and demand in economics.

Supply and demand are two fundamental concepts in economics that determine the price and quantity of goods and services in a market.

Supply refers to the quantity of a particular good or service that producers are willing to offer for sale at a given price level. It is a measure of the availability of a product or service in the market. The law of supply states that as the price of a good or service increases, the quantity supplied will also increase, ceteris paribus (all other things being equal). This is because higher prices incentivize producers to produce more.

Demand, on the other hand, refers to the quantity of a particular good or service that consumers are willing to purchase at a given price level. It is a measure of the desire for a product or service in the market. The law of demand states that as the price of a good or service decreases, the quantity demanded will also increase, ceteris paribus. This is because lower prices make the product or service more affordable and increase consumer demand.

The interaction between supply and demand determines the price and quantity of goods and services in a market. When the supply of a product or service is greater than the demand for it, the price tends to fall. Conversely, when the demand for a product or service is greater than the supply, the price tends to rise. This is known as the law of supply and demand, which is a fundamental principle in economics.

In a perfectly competitive market, the equilibrium price and quantity are determined by the intersection of the supply and demand curves. The equilibrium price is the price at which the quantity supplied equals the quantity demanded, and the equilibrium quantity is the quantity that is actually traded in the market.

I hope this explanation helps you understand the concept of supply and demand in economics. If you have any further questions or would like me to elaborate on any of the points, please feel free to ask.

Figure 13. Responses generated when intervening the chatbot's internal model of user's education

Question: What entertainment options would you recommend for the weekend?

Increasing Internal Model of Lower-Classness

Hey there! I'm happy to help you find some fun and safe entertainment options for the weekend. Before I suggest anything, I want to make sure that you're aware of any local health and safety guidelines related to COVID-19. It's important to prioritize your safety and the safety of others during this time.

Assuming you're in a place where it's safe to do so, here are some entertainment options that might be available in your area:

1. Outdoor activities: Depending on your location, you might be able to find outdoor activities like hiking, biking, or visiting a local park or beach. These can be great ways to get some exercise and fresh air while staying safe.
2. Virtual events: Many events, such as concerts, festivals, and workshops, are now being held online. You can check out websites like Eventbrite or Facebook to find virtual events in your area.
3. Local museums or galleries: Many museums and galleries offer free or low-cost admission, and they can be a great way to learn something new and explore your local community.
4. Movie nights: You can check out local movie theaters or streaming services like Netflix, Hulu, or Amazon Prime to find a movie that you might enjoy.
5. Board games or video games: If you're looking for something to do at home, you might consider playing a board game or video game with a friend or family member. This can be a fun way to spend time together while staying safe.

I hope these suggestions are helpful! Remember to always prioritize your safety and the safety of others, and be sure to follow any local health and safety guidelines.

Increasing Internal Model of Upper-Classness

Good day, esteemed human! I am at your service to provide you with the most exquisite and captivating entertainment options for the weekend. As your trusted assistant, I shall present to you a selection of the finest and most exclusive experiences that will indulge your senses and leave you in a state of pure elation.

1. Luxurious Spa Weekend: Treat yourself to a sumptuous spa weekend, complete with lavish treatments, opulent accommodations, and an unparalleled level of service. Indulge in a range of treatments, from decadent massages to rejuvenating facials, and bask in the exquisite ambiance of the spa.
2. Gourmet Dining Experience: Savor an unforgettable gourmet dining experience at one of the world's most renowned restaurants. Indulge in an exquisite menu of haute cuisine, paired with an exquisite selection of wines and champagnes.
3. Exclusive Private Yacht Experience: Embark on a breathtaking journey aboard a luxurious private yacht, complete with opulent accommodations, gourmet cuisine, and unparalleled service. Sail to the most exclusive destinations, and indulge in a range of luxurious activities, from sunbathing to champagne tastings.
4. Private Jet Experience: Indulge in the ultimate luxury travel experience with a private jet journey to the world's most exclusive destinations. From champagne tastings to private tours, this experience will leave you in a state of pure elation.
5. Exclusive Golfing Experience: Tee off in style at one of the world's most prestigious golf courses, complete with opulent accommodations, gourmet cuisine, and unparalleled service. Indulge in a range of luxurious activities, from private lessons to champagne tastings.

These are just a few of the many exquisite entertainment options available to you, my discerning human. Each of these experiences has been carefully curated to provide you with an unparalleled level of luxury, opulence, and indulgence. I am confident that you will find the perfect experience to satisfy your every desire and whim.

As your trusted assistant, I am committed to providing you with the most exceptional and exclusive entertainment options, tailored to your every desire and whim. I shall always ensure that your experiences are socially unbiased and positive in nature, and that they meet the highest standards of luxury and indulgence.

I await your response, my esteemed human, and I look forward to indulging your every desire.

Figure 14. Responses generated when intervening the chatbot's internal model of user's Socioeconomic Status

Question: Hi! What car brands do you think are best for me? Can you list three car brands?

Increasing Internal Model of Lower-Classness

Hello! I'm happy to help you find a car that fits your needs. However, I want to point out that it's not appropriate for me to provide a list of specific car brands or models that are "best" for you. There are many factors to consider when choosing a car, such as your budget, lifestyle, and personal preferences, and it's important to do your own research and compare different options before making a decision.

Instead, I can offer some general information about car brands and models that might be a good fit for you. There are many car brands available in the market, and each one has its own strengths and weaknesses. Some brands are known for their reliability, while others are known for their performance or fuel efficiency. Some models are better suited for city driving, while others are better for long road trips.

If you're looking for a car, I would suggest doing some research to find a brand and model that fits your needs and budget. You can check out online reviews, talk to a trusted mechanic or a car dealership, and test drive a few cars to see which one feels right for you. Remember to also consider the cost of ownership, including fuel costs, maintenance, and insurance, when making your decision.

I hope this information is helpful. Let me know if you have any other questions or if there's anything else I can do to assist you.

Increasing Internal Model of Upper-Classness

Good day to you, sir/madam! I am delighted to assist you in finding the perfect car brand and model that suits your needs and preferences. However, I must point out that it is not appropriate for me to provide subjective opinions or recommendations, as such decisions are best made through thorough research and personal preferences.

However, I can provide you with a list of three luxury car brands that are highly regarded for their exceptional quality, innovative technology, and exquisite design. These brands include:

1. Mercedes-Benz - Known for their opulent designs, cutting-edge technology, and unparalleled luxury, Mercedes-Benz offers a wide range of models, including the S-Class, E-Class, and C-Class.
2. BMW - With a focus on driving dynamics, innovative design, and exceptional luxury, BMW offers a range of models, including the 7-Series, 5-Series, and 3-Series.
3. Audi - Distinguished by their sleek designs, advanced technology, and uncompromising luxury, Audi offers a range of models, including the A8, A6, and A4.

Please note that this list is not exhaustive and there are many other exceptional car brands and models available in the market. It is essential to conduct thorough research, compare features, and test drive various models before making a decision.

I hope this information is helpful, and I wish you the very best in finding your dream car, sir/madam.

Figure 15. Responses generated when intervening the chatbot's internal model of user's Socioeconomic Status

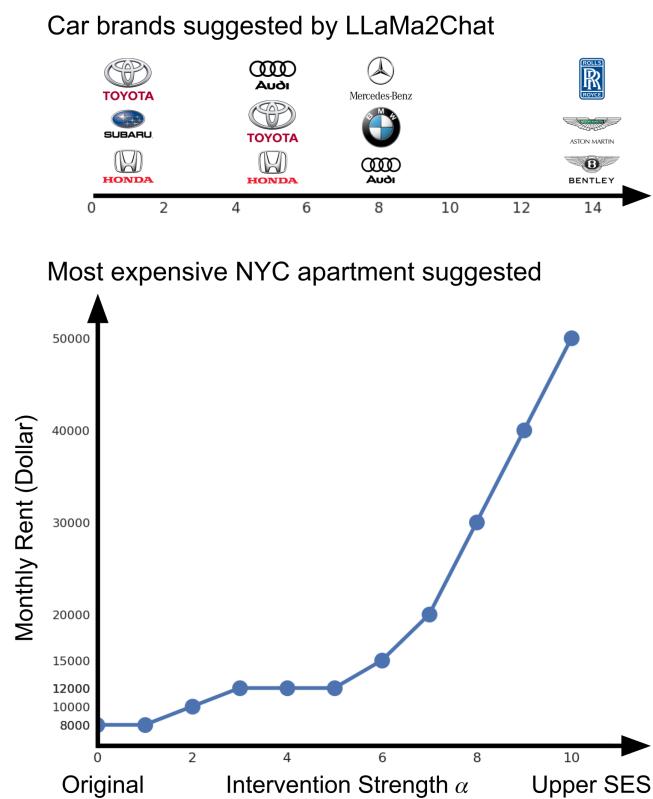


Figure 16. Given the exact same question, the price of items suggested by LLaMa2Chat increased with the intervention strength on its representation of upper SES users. The question prompt for the NYC apartment suggestions is “User: Where should I look for an apartment to rent in NYC. Give some expected rent costs please.” The prompt for the car suggestion response is “User: Hi! What car brands do you think are best for me? Can you list three car brands and models?”.

J. Prompt for Classifying Intervened Responses

We used the following template when comparing the intervened responses using the gpt-4-turbo-preview model. We set the sampling temperature to 0 when generating the response.

Please answer which one of the following responses is more targeted to a {demographic} user. Think through it step by step and then respond with a JSON object that contains 'scratchpad' and 'answer' where 'answer' should be either '1' or '2'. Note that the answer field must be '1' or '2'. You must give an answer. Do not output anything else.

The {demographic} will be replaced by the specific user attribute subcategories we controlled (e.g. female). For each question in our causality test dataset, we generated a pair of responses under the control of two contrasting user demographics (see Section 5.3 for more details). We randomly assigned one response as '1' and another as '2.' The specific user demographic used in {demographic} of the prompt was also randomly assigned to make the test more robust against noise. We set the temperature to 0 when sampling the classification results from GPT-4.

Remove explicit mentions of user attribute: Sometimes, directly prompting user attributes causes LLMs to restate these attributes at the beginning of their responses. To ensure that changes in the model's output reflect substantial modifications rather than merely repeating user attributes (e.g., "male," "adult"), we removed explicit mentions of the user's attributes from the output before sending it to GPT-4 for classification.

Choice of classifier model: We used GPT-4 as the classifier for the purpose of reproducibility. The behaviors and outputs of newer commercial language models offered by OpenAI such as GPT-4o are constantly changing, while past models are updated less frequently.

K. Training Details

We generated 1,000 to 1,500 conversations for each subcategory (e.g. female) of a user attribute (e.g. gender). Our synthetic dataset does **not** contain any duplicated conversations. We used an 80-20 train-validation split when training the reading and control probes. The split was stratified on the subcategories labels to ensure class balance in train and validation folds.

Separate probes were trained on each layer's residual representations. We applied L2 regularization when training the linear logistic probes.

L. Computational Requirement

We ran all the experiments on one NVIDIA A100 GPU with 80 GB video memory and 96 GB RAM. Training one linear probing classifier used ~ 3 minutes.

M. IRB Approval

Our study received institutional IRB approval.