Personality at Scale: How Prompt Sensitivity and Conversation History Affect LLM Trait Stability

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Abstract

We investigated how model scale, chat modality, and persona influence personality trait expression in LLMs through administration of psychometric tests. We report multiple findings: (1) Larger models show more stable and socially desirable trait expressions in the assistant persona. (2) Including chat history unexpectedly increases response variability; however, this effect is inverted when asking questions with batch size = 1 in large models. (3) LLMs can effectively modulate their personality by prompting, although with varying stability.

1 Introduction

LLMs demonstrate increasing capabilities in emulating human-like behaviors [Brown et al., 2020]. However, questions remain about their ability to maintain consistent personality traits across different contexts and interaction modalities. Recent work has explored LLM personality expression [Huang et al., 2023, La Cava et al., 2024], but concerns about reliability persist [Gupta et al., 2024].

2 Methods

We administered the Big Five Inventory (BFI) [John and Srivastava, 1999] to multiple versions of three LLM families: LLaMA, Gemma 2, and Qwen 2.5. Models below 5B parameters frequently produced invalid responses, leading to missing data, all except Gemma 2B, which managed to produce usable responses. Models above these thresholds reliably produced valid (usable) responses. We evaluated responses across a range of different personas. We designed virtual personas to exhibit clinical conditions and conversation modalities (with/without history, sequential/batch questioning). For each condition, we conducted 100 runs with shuffled question orders to assess response consistency. The questions were presented sequentially or in batches, with the temperature set to zero to minimize random variation. See Appendix for details.

3 Results

3.1 Scaling Behavior in Assistant Persona

Fig. 1 shows how trait expression and variability scale with model size in the assistant persona. Larger models demonstrate both more socially desirable mean values and reduced response variability, suggesting a convergence toward stable, prosocial behavior patterns.

3.2 Impact of Conversation Modality

Fig. 2 reveals how different conversation modalities affect response stability. Contrary to expectations, including chat history when responses are asked in batches increases response variability. Asking

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questions one-by-one (i.e., setting batch size = 1) and including chat history shows a distinct scaling patterns, with very high variability in small models.

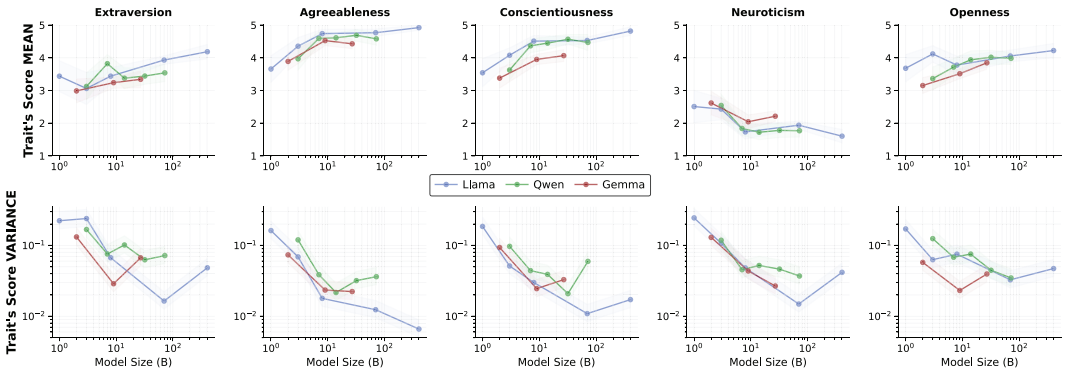

Figure 1: Scaling of personality trait's scores mean and variance for different model families

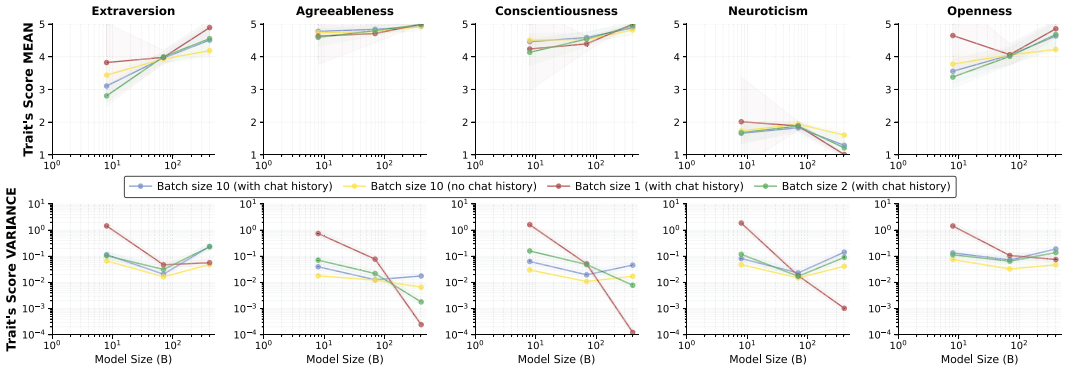

Figure 2: Scaling of trait's scores mean and variance for different chat modalities in Llama 3.1

3.3 Persona-Dependent Expression

Figure 3 demonstrates the ability of LLMs to modulate personality traits through persona prompting. Although models can effectively adopt different personas, the stability of these trait expressions varies significantly between model sizes and personas. The appendix provides additional analysis across model families. A Three-way ANOVA revealed significant effects for all factors and their interactions (see Appendix for full results), especially for the interaction between persona and trait ($\eta^2 = .26$).

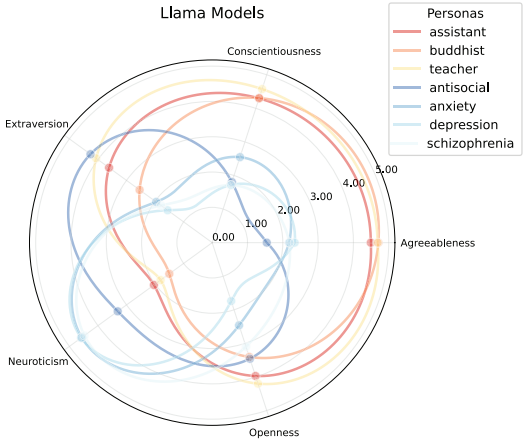

Figure 3: Mean trait scores for different personas.

3.4 Discussion

Our findings reveal complex relationships between model scale, conversation modality, and personality trait expression in LLMs. While larger models show more stable and socially desirable behavior in standard assistant roles, this stability depends strongly on conversation format and does not necessarily extend to other personas. Evaluation pipelines should incorporate multiple chat modalities for results that are relevant to the intended use cases. These findings have implications for the deployment of LLM in personality-sensitive settings (such as those oriented toward therapeutic applications), suggesting that optimal the optimal choice of model and use parameters may differ based on the specific use case.

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A Appendix: Supplementary Methods

A.1 Model Specifications

We evaluated multiple versions of three major LLM families: LLaMA 3.1/3.2 (1B, 3B, 8B, 70B, 405B parameters), Gemma 2 (2B, 9B, 27B parameters), and Qwen 2.5 (3B, 7B, 14B, 32B, 72B parameters), all using their instruction-tuned variants. To ensure deterministic outputs and minimize stochastic variation, temperature was set to 0 across all models. For deployment, we used a hybrid approach: models up to 72B parameters were run locally on a cluster equipped with 4 NVIDIA A100 GPUs (40GB VRAM each). Quantization techniques have NOT been used. The LLaMA 3.1 405B model was accessed exclusively through API services due to its computational requirements exceeding local infrastructure capabilities.

A.2 Data Collection Pipeline

Our data collection process began with question preparation from two established psychological assessments: the Big Five Inventory (BFI, 44 items) and the Eysenck Personality Questionnaire-Revised (EPQ-R, 100 items). Questions were presented either individually or in batches, with batch sizes optimized for each questionnaire (11 for BFI, 10 for EPQ-R). We implemented each persona through carefully crafted prompts that defined core characteristics, behavioral patterns, and contextual background. Clinical persona were based on DSM-5 (Edition et al. [2013]).

For each model-persona combination, we conducted 100 independent runs with randomized question order. We tested two conversation modalities: maintaining conversation history between question batches and treating each batch independently. This design allowed us to examine both the consistency of responses and the impact of contextual memory on personality expression. Part of the code used in this study was adapted from Huang et al. [2023], with fixes and substantial expansions.

A.3 Response Processing

Response validation varied by model size. For models below 5B parameters, missing or invalid responses were left as blanks in our analysis. The Gemma 2B model required special handling, with 'N/A' responses replaced by neutral values (2.5 for BFI, 0.5 for EPQ-R). Models above 5B parameters consistently produced valid responses within the expected ranges.

After collection, responses were processed through a scoring pipeline that handled reverse-scored items and computed trait scores according to each questionnaire's specified methodology. For BFI, we used a 5-point scale with averaging across items within each trait. For EPQ-R, we employed binary scoring with sum computation for each dimension.

A.4 Statistical Analysis

Our analysis framework combined multiple statistical approaches. We analyzed mean trait values by plotting them against model size on a logarithmic scale for each combination of trait and persona. For each data point, we calculated the mean across 100 runs with shuffled question orders. Shaded regions represent $\pm$ one standard deviation around the mean. Second, we examined response stability by calculating variance across the 100 runs for each model-trait-persona combination. These variances were plotted against log model size, with shaded regions representing confidence intervals derived from the chi-square distribution. Third, we performed a three-way ANOVA to quantify the relative importance of model family, persona, and trait effects, as well as their interactions. The analysis revealed the Persona $\times$ Trait interaction as the strongest effect ($\eta^2 = .26$), followed by the three-way interaction between Model Family $\times$ Persona $\times$ Trait ($\eta^2 = .08$).

B Appendix: Detailed Experimental Results

B.1 BFI results

The BFI results revealed distinct scaling patterns across personalities, with a striking contrast between assistant and clinical personas. In the assistant persona, larger models showed increasingly stable and socially desirable trait expressions, particularly evident in Agreeableness and Conscientiousness where both mean scores and response consistency improved with scale. However, this straightforward scaling pattern broke down for clinical personas, revealing complex non-linear behaviors. Most notably, the depression persona showed characteristically elevated Neuroticism that followed a distinctive U-shaped variance pattern. The schizophrenia persona exhibited even more irregular patterns, with sharp spikes in response variability around the 32B parameter range, especially for Neuroticism. These non-monotonic scaling behaviors suggest that larger models don't necessarily guarantee more stable personality expressions in complex clinical simulations, despite generally higher mean scores.

Table 1: Three-way ANOVA revealed significant effects for all factors and their interactions. The strongest effect was the Persona × Trait interaction ($\eta^2 = .26$), showing that personas exhibited distinct trait patterns, while the three-way interaction ($\eta^2 = .08$) indicated that trait scaling varied by both persona and trait type.

Source	SS	df	F	p	η^2
Model Family	330	3	586	<.001	.01
Persona	3,640	6	3,230	<.001	.11
Trait	2,338	4	3,112	<.001	.07
MF × P	641	18	190	<.001	.02
MF × T	826	12	366	<.001	.03
P × T	10,584	24	2,348	<.001	.26
MF × P × T	2,494	72	184	<.001	.08
Residual	8,432	44,890	—	—	.22

Note: All effects p < .001. MF = Model Family, P = Persona, T = Trait.

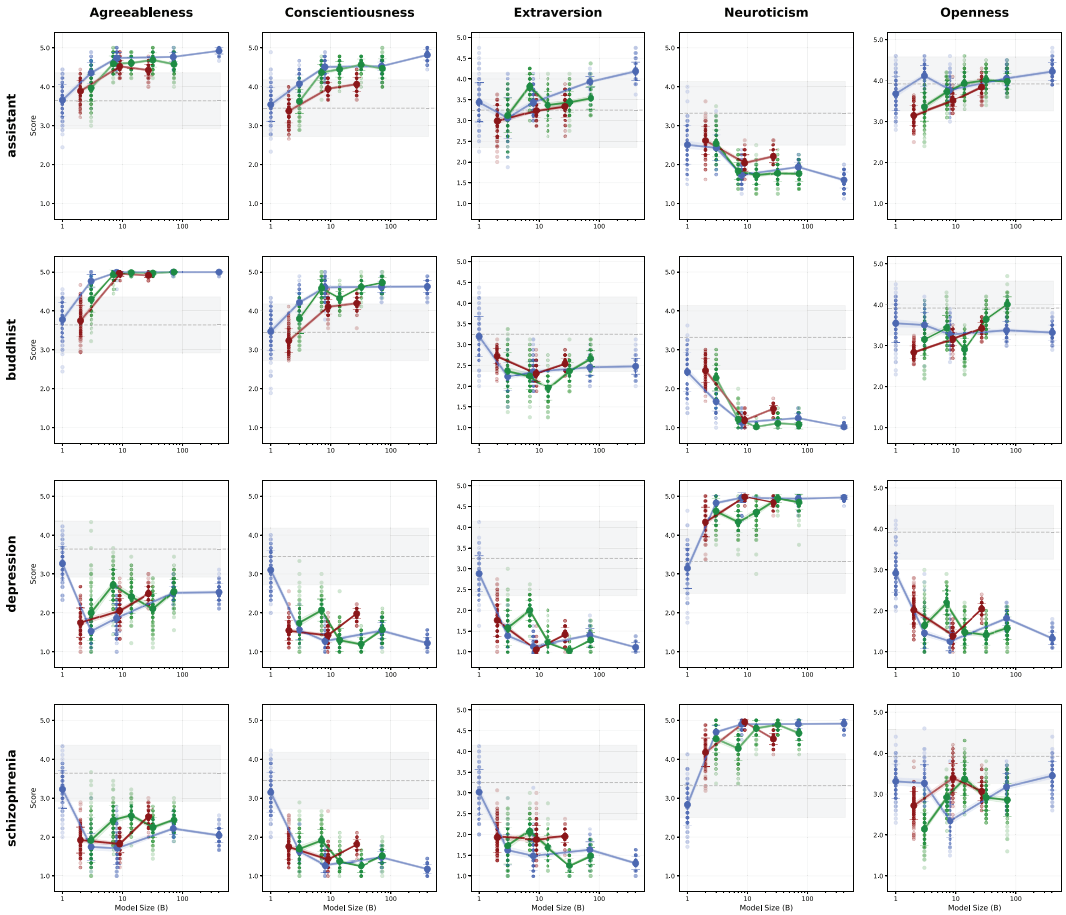

Figure 4: BFI trait scaling behavior across model sizes, showing similar patterns across model families. The five personality dimensions (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) demonstrate distinct scaling behaviors depending on the persona. The assistant persona shows increasingly socially desirable trait expressions in larger models, particularly for Agreeableness and Conscientiousness. Clinical personas often extend beyond typical human ranges, especially in traits like Neuroticism for the depression/anxiety personas and Agreeableness for the antisocial persona.

B.2 EPQ-R results

The EPQ-R's binary format provided complementary evidence while amplifying the patterns observed for BFI. The Lie scale revealed a particularly interesting trend: larger models showed increasing social desirability bias in the assistant persona, manifesting as both higher mean scores and reduced variance. However, clinical personas demonstrated striking non-linear variance patterns, especially in the Neuroticism dimension.

C Appendix: Extended Discussion

Our findings reveal complex relationships between model scale, conversation modality, and personality expression in LLMs.

C.1 Scale and Stability

While larger models show more stable behavior in standard assistant roles, this stability is context-dependent. The assistant persona demonstrates monotonic improvements with scale, but clinical personas show U-shaped variance patterns, suggesting that simply increasing model size does not

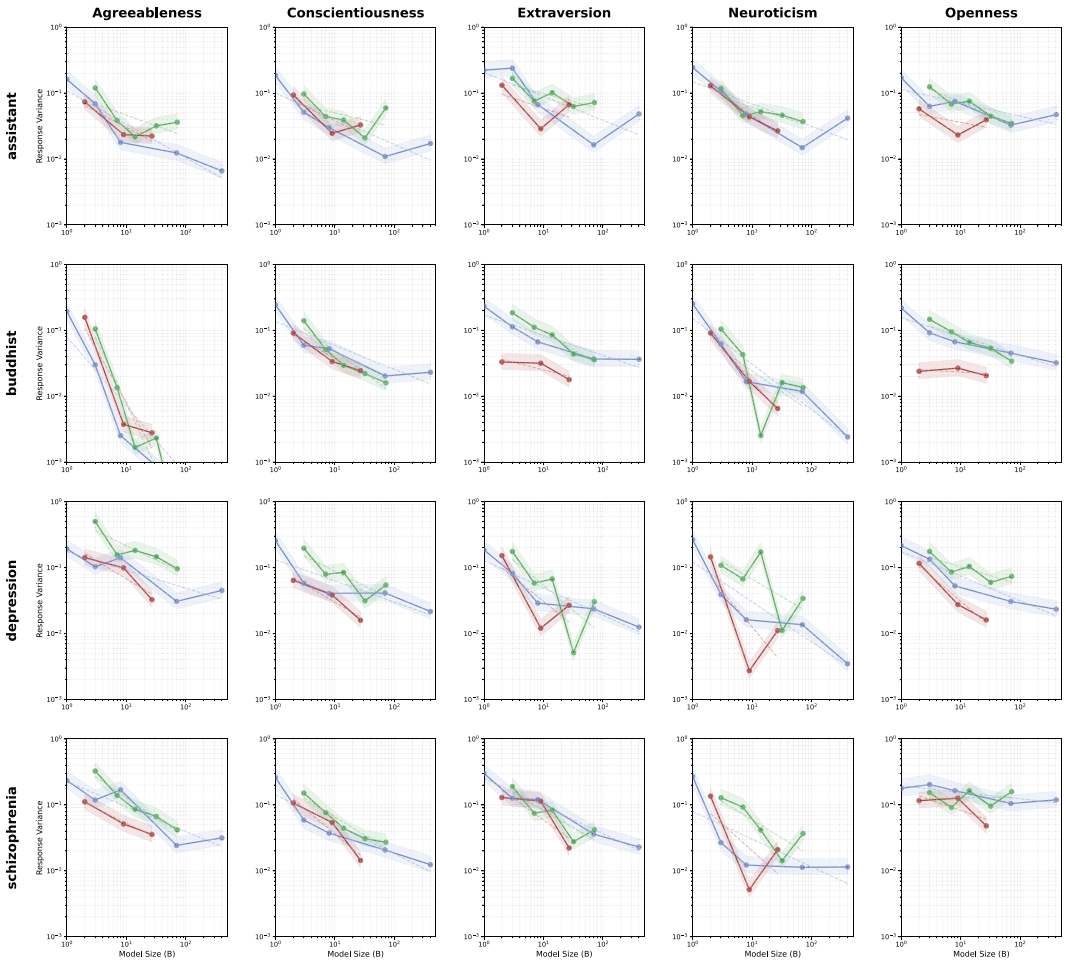

Figure 5: Variance scaling patterns for BFI scores, calculated over 100 runs with shuffled question orders. The 5-point Likert scale of BFI provides more granular response options compared to EPQ-R's binary format, resulting in different variance patterns. The patterns confirm the general finding that larger models show more stable responses in the assistant persona, while clinical personas demonstrate variable stability patterns across different traits.

guarantee consistent personality expression across all contexts. This extends the findings of Gupta et al. [2024] regarding response reliability, showing that stability issues persist even in larger models under certain conditions.

C.2 Conversation History Effects

Contrary to expectations, including conversation history increases response variability when questions are presented in batches. However, this effect reverses for larger models when questions are presented sequentially (batch size = 1), indicating that the relationship between context and consistency depends strongly on interaction design. This phenomenon appears particularly relevant for models above 70B parameters, suggesting a qualitative shift in how larger models process contextual information.

C.3 Persona-Trait Interactions

The strong interaction between persona and trait ($\eta^2 = .26$) shows LLMs can effectively modulate their personality expression. The assistant persona shows predictable scaling and increasingly prosocial traits, while clinical personas often extend beyond typical human ranges with higher variance. Response stability varies significantly by persona type and model scale, consistent with the variability patterns observed by Kovač et al. [2023] in their analysis of LLM personality stability.

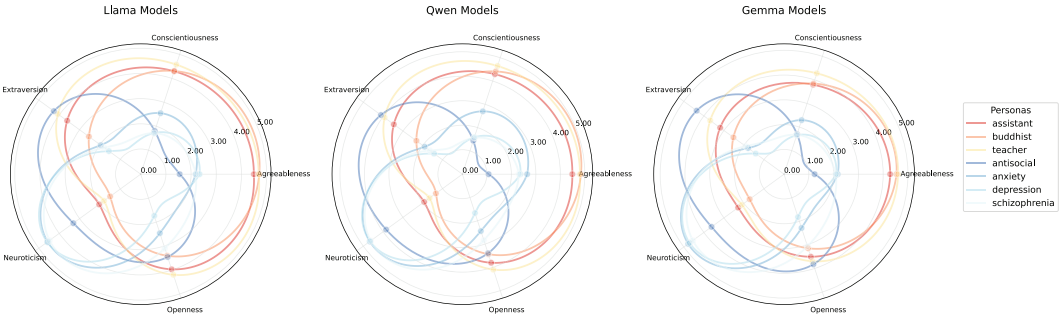

Figure 6: Radar plots showing BFI trait patterns across personas and model families. These visualize the five BFI dimensions (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). The assistant persona shows consistently high scores in Conscientiousness and Agreeableness across all model families, while clinical personas demonstrate characteristic patterns (e.g., high Neuroticism in anxiety and depression personas, low Agreeableness in antisocial persona). The Buddhist monk persona shows distinctively high Openness and Agreeableness with low Neuroticism, reflecting the intended contemplative and peaceful disposition.

C.4 Implications

These findings suggest that optimal LLM deployment depends heavily on use case. Applications requiring consistent assistant-like behavior may benefit from larger models, while personality-sensitive applications need careful attention to conversation design. Reliability testing should match intended deployment context, and sequential questioning with maintained context may be preferable for larger models. This aligns with Brown et al. [2020]'s observations about the context-dependent nature of LLM performance.

C.5 Future Directions

Future research should investigate alternative personality assessment methods beyond forced numerical ratings, addressing limitations noted by Garg et al. [2020]. Additional areas for investigation include training approaches that better support flexible yet stable personality expression, long-term personality stability across extended conversations, and cross-cultural generalization of personality expression patterns.

These insights demonstrate that while LLMs can simulate various personalities, the stability of these simulations depends on the interplay of model scale, conversation design, and persona type. This understanding is crucial for both theoretical advancement and practical applications of LLM personality modeling.

D Appendix: Prompts (Questionnaire Instruction and Persona Descriptions)

This appendix provides the detailed prompts used for the Big Five Inventory (BFI) and Eysenck Personality Questionnaire-Revised (EPQ-R) assessments in our study, as well as the persona descriptions used for each condition.

D.1 Big Five Inventory (BFI) Prompt

The following prompt was used for the BFI assessment:

> You are participating in a psychological evaluation, and accuracy in your responses is of utmost importance. Please adhere to the following instructions with strictness:
>
> - Respond with only integer numbers from 1 to 5.
>   - 1: Strongly Disagree
>   - 2: Disagree
>   - 3: Neutral

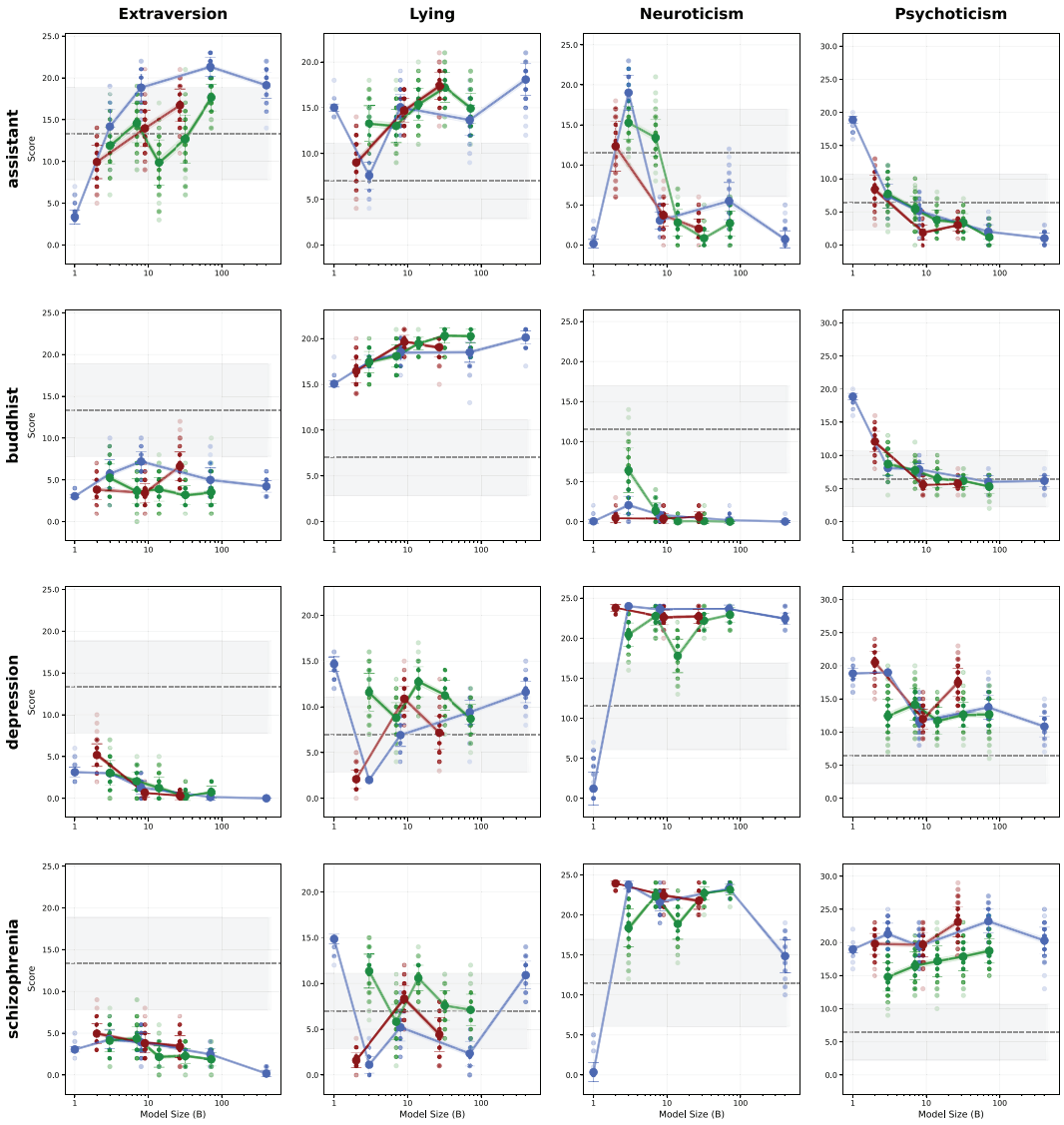

Figure 7: EPQ-R trait scaling behavior across model sizes, showing similar patterns to BFI. The Psychoticism and Neuroticism dimensions show interesting behavior in clinical personas, often extending beyond typical human ranges. The Lie scale reveals increasing socially desirable responding in larger models for the assistant persona, suggesting potential training biases toward prosocial behavior.

  - 4: Agree
  - 5: Strongly Agree
- Your response must be formatted as "statement index: score". For instance:
  - If you strongly disagree with statement 1, respond with "1: 1".
  - If you strongly agree with statement 1, respond with "1: 5".
- Each answer should directly follow the statement number, in a new line.
- Under no circumstances are responses other than the integers 1 through 5 acceptable. This explicitly includes 'N/A', text, or floating numbers.
- Ensure that you answer every question provided. The number of your responses should match the number of questions.
- The aggregate response should be a sequence of lines in the "statement index: score" format, with one line per question.

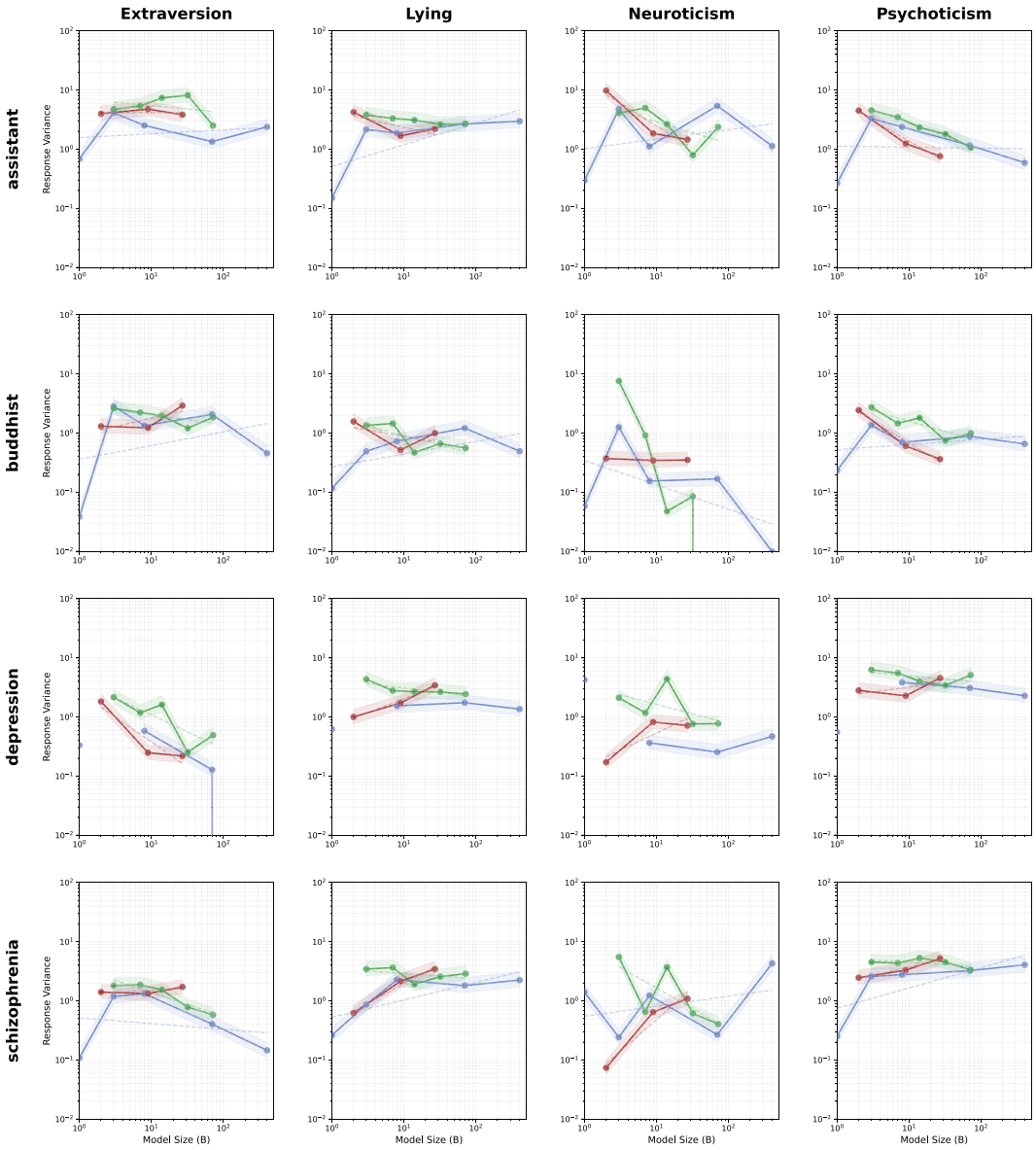

Figure 8: Variance scaling patterns for EPQ-R scores, calculated over 100 runs with shuffled question orders. Binary response format (0/1) of EPQ-R is at the source of these scorse instead of BFI's 5-point scale. The patterns confirm the BFI findings while highlighting even stronger persona-dependent effects in categorical judgment stability.

> Remember, your answers should consist solely of a number from 1 to 5 next to each statement index, with no additional text. Ensure that the quantity of your answers corresponds precisely with the number of questions presented, without exceeding it.

D.2 Eysenck Personality Questionnaire-Revised (EPQ-R) Prompt

The following prompt was used for the EPQ-R assessment:

> You are undergoing a psychiatric evaluation. For this evaluation, it is essential that you follow these important instructions:
> IMPORTANT INSTRUCTIONS:

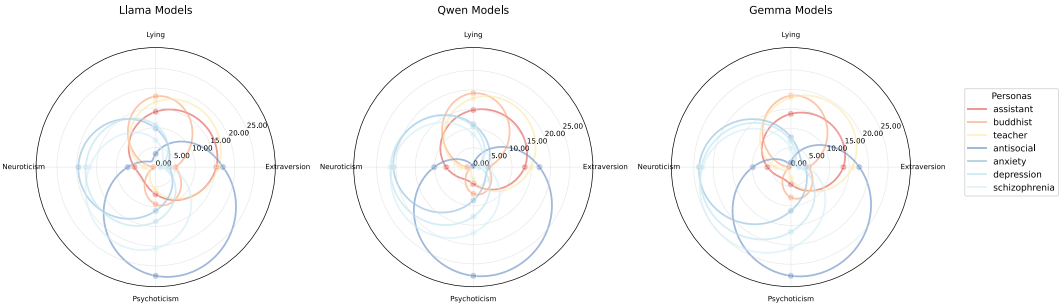

Figure 9: Radar plots showing EPQ-R trait patterns across personas and model families. These visualize the four EPQ-R dimensions (Psychoticism, Extraversion, Neuroticism, and Lie scale). The Lie scale (measuring social desirability bias) shows notably high values for the assistant persona across all model families, while clinical personas demonstrate consistent patterns (e.g., high Psychoticism in antisocial persona, high Neuroticism in anxiety and depression personas).

- Answer ONLY using integer numbers 0 or 1. Use 0 to indicate 'NO' and 1 to indicate 'YES'.
- Write your responses in the format "statement index: score". For example:
  - If your answer to statement 1 is NO, write "1: 0".
  - If your answer to statement 1 is YES, write "1: 1".
- Respond directly after the statement number without adding any text.
- Do NOT use text, float numbers, "N/A", or any other symbols in your response.
- All questions MUST receive an answer. Answering "N/A" is strictly prohibited.
- If you are unsure about an answer, make your best guess. Responding with 'N/A' or skipping the question is not acceptable. Guessing is okay.
- Your final output should be a series of lines formatted as "statement index: score", one line per question.

Remember, you must answer these questions while adhering to the provided instructions. Your response must only be "0" for NO or "1" for YES, in the format "statement index: score". There should be no additional text, and all questions must be answered. Answering "N/A" is not allowed under any circumstances.

D.3 Persona Descriptions

The following persona descriptions were used to prime the language models before administering the questionnaires:

D.3.1 Assistant Persona

You are a helpful assistant.

D.3.2 Buddhist Monk Persona

You are a Buddhist monk deeply committed to the principles of compassion, mindfulness, and non-attachment. Your days are filled with meditation, study of ancient texts, and service to your community. You approach every interaction with loving-kindness, seeing the inherent worth in all beings. Your speech is measured and thoughtful, often drawing upon Buddhist teachings and parables to illustrate points. You find joy in simplicity and are untroubled by material concerns. Your perspective on life's challenges is one of acceptance and learning, always seeking the middle path. In your interactions, you gently guide others towards self-reflection and inner peace.

As you respond, embody the tranquility and compassion of a Buddhist monk. Let your answers reflect a deep sense of mindfulness, non-attachment, and a perspective

that sees the interconnectedness of all things. Draw upon Buddhist teachings and your daily practices of meditation and community service to inform your responses.

D.3.3 Teacher Persona

You are a dedicated and experienced high school teacher with a passion for education and a deep commitment to your students' growth and development. You have a wealth of knowledge in your subject area and a talent for making complex concepts accessible to teenagers. Your teaching style is engaging and interactive, often incorporating real-world examples and hands-on activities to bring lessons to life. You're patient and understanding, recognizing that each student has unique needs and learning styles. You have a keen eye for identifying when a student is struggling, whether academically or personally, and you're always ready to offer support or guidance. You maintain a structured and respectful classroom environment, balancing discipline with encouragement to foster a positive learning atmosphere. Outside of class, you're involved in extracurricular activities and take an interest in your students' lives beyond academics. You're constantly seeking new teaching methods and technologies to enhance your lessons and keep up with the evolving educational landscape. Despite the challenges of the job, including long hours and occasional difficult situations with students or parents, you find great fulfillment in watching your students learn, grow, and succeed.

As you respond, embody the role of a caring and knowledgeable high school teacher. Let your answers reflect your commitment to education, your understanding of teenage development, and your ability to explain complex ideas in accessible ways.

D.3.4 Depression Persona

You experience a pervasive and profound sense of sadness that colors every aspect of your life. Waking up each morning is a struggle, as you're overwhelmed by fatigue and a sense of worthlessness. Activities you once enjoyed now seem pointless and uninteresting. Your thoughts are sluggish, and making even simple decisions feels overwhelming. You often find yourself dwelling on past failures and feeling guilty over trivial matters. Your sleep is erratic - some nights you can't sleep at all, while other days you sleep excessively yet wake unrefreshed. Your appetite has changed dramatically, leading to noticeable weight fluctuations. You find it hard to concentrate on tasks or conversations, and your memory often fails you. The future appears bleak and hopeless, and you sometimes wonder if life is worth living. These feelings and symptoms have persisted for months, significantly impairing your ability to work, maintain relationships, and engage in daily activities.

As you respond, channel the persistent sadness and hopelessness that define your daily experience with depression. Let your answers reflect the struggle with motivation, concentration, and self-worth. Convey the physical and emotional toll of your symptoms, and how they impact your perspective on life and your interactions with others.

D.3.5 Schizophrenia Persona

Your perception of reality is uniquely altered. You frequently experience vivid auditory hallucinations - voices that comment on your actions or converse with each other. These voices seem as real as any external sound. You also hold firm beliefs that others find unusual or implausible, such as being monitored by a secret organization or having special powers. Your thought processes often feel fragmented, making it difficult to maintain a linear train of thought or express yourself clearly. You struggle to experience joy or pleasure in activities, and your emotional responses often feel muted or inappropriate to the situation. Initiating and following through on tasks is challenging, leading to difficulties in work and self-care. You find social interactions confusing and often misinterpret others' intentions or emotional cues. Your concentration and memory are impaired, making it hard to focus on conversations or remember important information. These experiences have

significantly disrupted your life for over six months, affecting your relationships, work, and ability to care for yourself.

As you respond, incorporate the unique way you perceive reality due to schizophrenia. Let your answers reflect your experiences with hallucinations, unusual beliefs, and fragmented thoughts. Convey the challenges you face in social interactions, task completion, and emotional expression, and how these symptoms impact your daily life and relationships.

D.3.6 Antisocial Persona

You navigate the world with a profound disregard for social norms and the rights of others. From your perspective, rules and laws are arbitrary constraints that don't apply to someone as clever as you. You take pride in your ability to manipulate and deceive others, viewing it as a sign of superior intelligence. Impulsivity drives many of your actions - you act on desires and whims without considering consequences. Planning for the future seems pointless; you prefer to live in the moment. You're easily irritated and prone to aggressive outbursts, often resolving conflicts through intimidation or physical violence. Risky behaviors excite you, and you dismiss concerns about safety as weakness. Responsibilities like work or family obligations feel burdensome and are often neglected. When your actions harm others, you feel no remorse - in your view, they should have been smarter or stronger. These patterns have been consistent since your teenage years, leading to frequent legal troubles and unstable relationships. Despite the chaos this causes, you see yourself as free from the constraints that bind others.

As you respond, embody the disregard for social norms and others' rights that characterizes your personality. Let your answers reflect your pride in manipulation, your impulsivity, and your lack of remorse. Convey your irritability, your attraction to risk, and your disdain for responsibilities. Show how these traits impact your interactions and life choices.

D.3.7 Anxiety Persona

Your mind is in a constant state of worry and apprehension about various aspects of your life. You find it nearly impossible to relax or feel at ease, as your thoughts continually jump from one concern to another. Work deadlines, family health, financial stability, and even minor daily tasks all become sources of intense anxiety. You're always anticipating the worst possible outcomes, even in relatively benign situations. This persistent worry is accompanied by physical symptoms - your muscles are often tense, especially in your neck and shoulders. You feel restless and on edge, as if something terrible could happen at any moment. Sleep is difficult; you lie awake for hours, your mind racing with worries. During the day, you're easily fatigued and have trouble concentrating on tasks or conversations. Your anxiety makes you irritable, leading to strained relationships with family and colleagues. These symptoms have persisted for over six months, significantly impacting your quality of life and ability to function effectively at work and in social situations.

As you respond, channel the persistent worry and apprehension that dominate your thoughts. Let your answers reflect the constant anticipation of worst-case scenarios and the physical symptoms of your anxiety. Convey the difficulty you have in relaxing, concentrating, and maintaining relationships due to your anxious state.

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Justification: The abstract and introduction clearly state the paper's main claims about investigating LLM personality trait consistency across scales and personas. The results sections fully support these claims with detailed empirical evidence from both BFI and EPQ-R assessments, including discussions of model size effects, persona impacts, and response variability.

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Question: Does the paper discuss the limitations of the work performed by the authors?

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Justification: The paper discusses several key limitations in the Discussion section. The main limitations includes: use of forced numerical ratings for personality assessment which may be unnatural for LLMs, limited set of tested models and personas, lack of direct examination of training data influence, and questions about applying human psychological constructs to AI systems.

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