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Evaluating the ability of large language models to emulate personality

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For social sciences, recent advancements in Large Language Models (LLMs) have the potential to revolutionize the study of human behaviors by facilitating the creation of realistic agents characterized by a diverse range of individual differences. This research presents novel simulation studies assessing GPT-4's ability to role-play real-world individuals with diverse big five personality profiles. In simulation 1, emulated personality responses exhibited superior internal consistency, but also a more distinct and structured factor organization compared to the human counterparts they were based on. Furthermore, these emulated scores exhibited remarkably high convergent validity with the human self-reported personality scale scores. Simulation 2 replicated these findings but demonstrated that the robustness of GPT-4's role-playing appears to wane as the complexity of the roles increases. Introducing supplementary demographic information in conjunction with personality affected convergent validities for certain emulated traits. However, including additional demographic characteristics enhanced the validity of emulated personality scores for predicting external criteria. Collectively, the findings underscore a promising future of using LLMs to emulate realistic and real person-based agents with varied personality traits. The broader applied implications and avenues for future research are elaborated upon.

The recent emergence and advancement of Large Language Models (LLMs) represents a major leap in the field of artificial intelligence. As one of the most sophisticated deep-learning architectures, LLMs can understand complex instructions expressed in natural human language while generating convincingly human like responses. Amongst the most sophisticated Large Language Models, the Generative Pre-trained Transformer 4 (GPT-4) demonstrates advanced capabilities in commonsense reasoning, reading comprehension, and arithmetic[1]. GPT-4's remarkable steerability enables users to adeptly direct and tailor its output (e.g., content, style, tone etc.) via precise prompt instructions. This enhanced steerability endows GPT-4 with a significant capacity for role-play. The model's responses can be finely tuned to emulate responses of individuals across diverse social roles and unique characteristics[2].

Such role-playing abilities of GPT-4 pave the way for novel research to study human behaviors in social sciences. The concept of agent-based modeling, proposed decades ago, is a computational modeling process for simulating the actions and interactions of autonomous agents (both individuals and collective entities such as organizations or groups) to understand the behavior of a system and its underlying factors[3]. The concept has been adopted to examine several topics such as the outbreak of the recent COVID-19 pandemic[4] and dynamics of urban development[5], but its application to more complex social phenomena has been scarce because of the limited capabilities of computers to simulate heterogenous agents in a realistic way. Specifically, it is challenging to identify and use myriad rules to accurately and realistically represent human agents with complex psychological processes that are difficult to quantify, calibrate and justify[3]. Yet, a generative LLM model trained on diverse and extensive textual data such as GPT-4 can simulate more diverse, complex and nuanced behaviors while capturing the variability and unpredictability of human decision-making and interaction processes. Therefore, GPT-4 could potentially be used to create more realistic agents suitable for various scenarios, significantly lowering the entry barrier and extending the application scope of Agent-Based Models (ABM) within social studies. Prior to deploying such simulations for research and ensuing applications, it is essential to systematically evaluate the ability of large language models to emulate actual, or at least realistic, individuals following users' instructions. This research represents novel simulation studies to evaluate GPT-4's ability to role-play actual human characters

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with various big five personality profiles. Specifically, we used the self-report personality responses answered by GPT-4's role-playing characters to evaluate the reliability, convergent and discriminant validity as well as factor structure of emulated personality (simulation 1) and its robustness and criterion-related validity for external variables (simulation 2). Overall, our study offers a standardized, psychometrically sound protocol for evaluating the role-playing ability of a widely available LLM, which can be used by future researchers (Although there have been some other efforts examining similar ideas, they have tended to solely focus on mean-level and rank-order congruence of LLM and self-reported scores. As we demonstrate in this paper, such a limited approach lacks important features of human personality structure (i.e., higher order personality structure, and therefore psychological integration). Methodologically, psychometric indicators such as factor structure and criterion-related validity are overlooked when LLMs capabilities to generate human personality attributes. Our study offers psychometrically sound, psychologically informed procedures to future researchers who wish to evaluate LLM's human role-play capabilities).

Results

Simulation 1

The goal of Simulation 1 was to assess the psychometric reliability and construct related validity of personality scale responses answered by GPT-4. Human subjects' responses from a publicly available database were sampled to constitute the ground truth personality data. Scale scores of 400 individuals on the big five personality traits of Conscientiousness, Agreeableness, Emotional Stability, Extraversion and Openness were used to create role-play setting prompts for GPT-4 (*see Materials and Methods section below* for details). The model was then prompted to complete a self-report Big Five personality inventory assuming each role-played character and its responses to personality questionnaire items were recorded *(See SI Appendix, Supplementary Text, Detailed Methodology of Simulation 1 for the full description of the database, sampling strategy, prompts and example output from a single round of the simulation)*. Personality questionnaire responses from GPT-4's emulated subjects were used to probe reliability, differences from self-reported personality and construct related validity.

Simulation 1: reliabilities, convergent and discriminant validities of emulated personality

We first computed internal consistency reliabilities of GPT-4's emulated personality responses and their convergent validities with ground truth personality responses. Results presented in Table 1 indicate that internal consistency reliability of personality scores from emulated subjects were substantially higher (0.97 to 0.99) than self-reported ground truth scores from human subjects (0.79 to 0.89), indicating much higher consistency with which GPT-4 responds to personality items. Unexpectedly, despite variability in self-reported and emulated scores being mostly comparable (mean SD ratio = 0.99, SD = 0.05), there were some notable mean differences. The standardized mean differences between self-reported and emulated personality were negligible for agreeableness (d = 0.03, 95% CI = [− 0.11, 0.17]), small for Conscientiousness, Extraversion, and Agreeableness (− 0.20 to − 0.40, 95% CIs from − 0.06 to − 0.54), but moderate for Emotional Stability (d = − 0.66, 95% CI = [− 0.80, − 0.51]). The convergent validities of scores were remarkably high for all of the big five traits, ranging from 0.90 to 0.94 (mean = 0.91, SD = 0.02), indicating very high rank order congruence.

Emulated personality responses also showed good discriminant validities, as indicated by low correlations between the emulated personality trait scores (e.g., Emotional Stability) and the ground truth scores of other personality dimensions (e.g., Conscientiousness, Agreeableness, etc.).

Simulation 1: factor structure of emulated personality

We examined the factor structure of emulated personality responses, comparing it with the factor structure of self-reported ground truth. For human subject ground truth personality data, all except one item measuring emotional stability had non-trivial loadings (> 0.30) on their corresponding big five dimensions (i.e., the dimension that the item was purposed to measure) and the average factor loadings across all items for each dimension ranged from 0.52 to 0.65 (Table 2). For the emulated personality responses, the average factor loadings were substantially stronger, ranging from 0.87 to 0.95 (Table 2), reaching levels not traditionally encountered in personality measurement. Moreover, some items in the self-reported ground truth responses had non-trivial cross-loadings (greater than 0.30), whereas all items in the emulated responses had trivial to negligible cross-loadings. *(See SI Appendix, Supplementary Tables and Figures, Table S1-S2 for complete factor solutions)*. In essence, emulated personality scores were much more factorially pure than the self-reported personalities they were based on.

Simulation 2

The objective of Simulation 2 was to further scrutinize the robustness of GPT-4-emulated personality scale responses and their criterion-related validities with external variables. Human subjects' personality scores from a second publicly available database were sampled to constitute the self-reported ground truth personality data. Scale scores of 400 British individuals, all aged 50 were used as ground truth. The choice of was informed by our desire for methodological rigor and avoiding ambiguity in results (*see the Materials and Methods section below for full details*). In Simulation 2, prompts were evenly divided into four distinct variants, each subtly modified to create four discrete experimental conditions. The first condition involved no perturbations, with only self-reported personality scale scores made available to GPT-4. The second condition added an age indicator, setting it to 50 alongside the personality scores. In the third condition, the country of residence was set as Britain, again in addition to the personality scores. Finally, the fourth condition combined both age and country of residence settings with the personality scores. Personality questionnaire responses from GPT-4's emulated subjects were used to examine the replicability of findings from Simulation 1 and criterion-related validity of emulated personality for predicting external variables.

Panel A. Descriptive statistics, reliabilities, and differences between self-reported ground truth and GPT-4 emulated personality						
	Mean (SD)				Reliabilities	
Trait	Self-reported ground truth	GPT-4 emulated	Cohen's d	SD ratios	Self-reported ground truth α	GPT-4 emulated α
Conscientiousness	23.32 (7.17)	20.39 (7.48)	−0.40 [−0.54, −0.26]	0.96	0.82	0.98
Agreeableness	27.30 (7.48)	27.52 (7.01)	0.03 [−0.11, 0.17]	1.07	0.85	0.97
Emotional stability	19.34 (8.19)	13.92 (8.32)	−0.66 [−0.80, −0.51]	0.98	0.86	0.99
Extraversion	18.81 (8.71)	16.97 (9.40)	−0.20 [−0.34, −0.06]	0.93	0.89	0.99
Openness	29.43 (5.93)	27.49 (6.02)	−0.33 [−0.46, −0.19]	0.99	0.79	0.97
Panel B. Convergent and discriminant validities of ground truth and emulated personality						
Trait	C - SRGT	A - SRGT	ES - SRGT	EX - SRGT	O - SRGT	
Conscientiousness - emulated	**0.92 [0.90, 0.93]**	0.08 [−0.02, 0.18]	0.24 [0.15, 0.33]	−0.01 [−0.10, 0.09]	0.04 [−0.06, 0.14]	
Agreeableness - emulated	0.19 [0.09, 0.28]	**0.91 [0.89, 0.93]**	0.02 [−0.08, 0.12]	0.21 [0.11, 0.30]	0.07 [−0.03, 0.17]	
Emotional stability - emulated	0.13 [0.03, 0.23]	−0.11 [−0.20, −0.01]	**0.90 [0.88, 0.92]**	0.10 [0.01, 0.20]	0.12 [0.02, 0.21]	
Extraversion - emulated	0.16 [0.07, 0.26]	0.25 [0.15, 0.34]	0.23 [0.13, 0.32]	**0.94 [0.93, 0.95]**	0.18 [0.08, 0.27]	
Openness - emulated	0.03 [−0.07, 0.13]	−0.00 [−0.10, 0.10]	0.19 [−0.00, 0.19]	0.08 [−0.02, 0.18]	**0.90 [0.88, 0.92]**	

Table 1. Reliabilities, convergent, and discriminant validities of emulated personality (simulation 1). Note.$N = 400$; In panel A, Cohen's d = standardized mean differences between self-reported and emulated responses [95% Confidence Interval], with negative values indicating lower mean scores for the latter; SD Ratios = the ratio of standard deviations between self-reported ground truth and emulated personality scores, values larger than 1 indicate reduced variability in emulated scores; α = Cronbach's Alpha; In panel B, diagonal values represent convergent validities between self-reported ground truth and emulated personality scores, while those in the off diagonal represent discriminant validities between emulated and ground truth personality scores [associated CI values]; C = Conscientiousness, A = Agreeableness, ES = Emotional Stability, EX = Extraversion, O = Openness to Experience; SRGT = self-reported ground truth. Intercorrelations among the Big Five personality scales *within* each perspective are presented in *SI Appendix*, *Supplementary Table*, *Table S3*.

	Self-report ground truth				GPT-4 emulated			
Trait	$\overline{\lambda}$	σ_λ	$min\lambda$	$max\lambda$	$\overline{\lambda}$	σ_λ	$min\lambda$	$max\lambda$
Conscientiousness	0.55	0.10	0.38	0.70	0.92	0.06	0.83	0.97
Agreeableness	0.60	0.13	0.39	0.79	0.88	0.08	0.69	0.96
Emotional Stability	0.60	0.15	0.23	0.71	0.95	0.04	0.86	0.99
Extraversion	0.65	0.09	0.48	0.75	0.94	0.04	0.84	0.97
Openness	0.52	0.09	0.33	0.63	0.87	0.14	0.67	0.98

Table 2. Summary of factor loadings of personality items on the corresponding factors (Simulation 1). Note.$N = 400$; $\overline{\lambda}$ = mean factor loadings; σ_λ = standard deviation of factor loadings; $min\lambda$ = minimum factor loadings; $max\lambda$ = maximum factor loadings. Full factor loadings for each personality item on the corresponding personality factor are presented in SI Supplementary Table S1-S2.

Simulation 2: robustness of emulated personality

The focus here was on examining the robustness of emulated personality by slightly varying instructions from Simulation 1, using demographic information. Reliability, convergent and discriminant validity as well as the factor structure examinations largely replicated those from Simulation 1 *(See Appendix SI*, *Supplementary Tables*, *Table S4-S7 for the replication results)*.

We used linear regression to examine the robustness of emulated personality when additional demographic variables were included in the role − play prompts. We fit two models for each personality trait. In the first model, we created two dummy − code variables for experimental grouping settings of age and country (1/0 = age indicated/age not indicated in instructions; 1/0 = country indicated/not indicated in instructions) and included them along with the *self − reported ground − truth* personality trait as setting predictors (Note that dummy codes introduced do not indicate varying age and country: those are constant and therefore without variation in our database. Rather, the dummy codes indicate whether GPT-4 was prompted using these pieces of demographic information (experimental manipulation)). The main effects of the dummy code variables examine whether introducing additional demographic instructions will change the scores of emulated personality traits, controlling for self – reported ground truth personality scores. In the second model, we also included the interaction terms between dummy coded demographic information prompt variables and self – reported ground – truth personality scores. The interaction terms examine whether introducing additional demographic information influence the convergent validities between self – reported ground – truth and emulated personality traits. Results of linear regression (Table 3 Model 1) showed that indicating emulated characters' age as 50 tended to increase emulated scores for Conscientiousness ($ß = 0.16$, $p < 0.01$, 95% CI = [0.08, 0.25]), Emotional Stability ($ß = 0.12$, $p < 0.01$, 95% CI = [0.05, 0.18]) and Openness ($ß = 0.14$, $p < 0.01$, 95% CI = [0.04, 0.23]), whereas indicating fictional characters' country of residence as Britain tended to reduce emulated scores for Extraversion ($ß = -0.14$, $p < 0.01$, 95% CI = [−0.20, −0.08]) and Emotional Stability ($ß = -0.09$, $p < 0.05$, 95% CI = [−0.15, −0.02]).

The interaction terms in Table 3 Model 2 showed that indicating the age of emulated characters somewhat reduced the convergent validities of emulated personality for Agreeableness ($ß = -0.15$, $p < 0.05$, 95% CI = [− 0.29, − 0.02]) but slightly increased the convergent validities for Extraversion ($ß = 0.18$, $p < 0.01$, 95% CI = [0.12, 0.24]). The convergent validities for the rest of the personality traits were mostly unaffected. The full results of the regression analysis are presented in *Supplementary Tables*, *Table S9-S13*.

Simulation 2: Criterion-related validities of emulated personality

We used Pearson product moment correlations to examine the criterion-related validities of emulated personality in predicting four self-reported ground truth outcomes (general health, job involvement, life quality, mental well-being), separated by four manipulation conditions. Findings are depicted in Fig. 1. Most notably, when only personality profile was set (i.e., personality scale scores from provided to GPT-4; no perturbation condition), emulated Emotional Stability and Conscientiousness scores produced significantly lower correlations than self-reported ground truth when predicting self-reported general health, mental well-being and quality of life. However, this discrepancy was less discernible for job involvement. Emulated Openness's relations were consistently lower for all criterion outcomes. Figure 1 also shows that the discrepancy in criterion-related validities between self-

	Emulated conscientiousness		**Emulated agreeableness**		**Emulated emotional stability**		**Emulated extraversion**		**Emulated openness**	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Intercept	− 0.04	− 0.04	− 0.05	− 0.04	− 0.02	− 0.01	0.06*	0.06*	− 0.04	− 0.04
Conscientiousness - SRGT	**0.91****	**0.91****	− 0.02	− 0.02	− 0.03	− 0.03	− 0.02	− 0.02	− 0.03	− 0.03
Agreeableness - SRGT	− 0.10**	− 0.10**	**0.72****	**0.74****	− 0.05*	− 0.05*	0.02	0.02	− 0.10**	− 0.11**
Emotional stability - SRGT	0.04	0.04	0.04	0.04	**0.96****	**0.94****	− 0.01	− 0.02	− 0.01	− 0.02
Extraversion - SRGT	− 0.10**	− 0.10**	0.06	0.07	− 0.10**	− 0.10**	**0.93****	**0.87****	0.01	0.01
Openness - SRGT	− 0.02	− 0.02	0.05	0.05	0.01	0.01	0.05**	0.05**	**0.90****	**0.89****
Age	0.16**	0.16**	0.07	0.07	0.12**	0.12**	0.02	0.02	0.14**	0.14*
Country	− 0.08	− 0.08	0.03	0.03	− 0.09*	− 0.09*	− 0.14**	− 0.14**	− 0.05	− 0.05
Age * conscientiousness-SRGT		0.00								
Country * conscientiousness-SRGT		0.02								
Age * agreeableness-SRGT				− 0.15*						
Country * agreeableness-SRGT				0.11						
Age * emotional stability-SRGT						− 0.01				
Country * emotional stability-SRGT						0.05				
Age * extraversion-SRGT								− 0.05		
Country * extraversion-SRGT								0.18**		
Age * openness-SRGT										− 0.07
Country * openness-SRGT										0.09
Adjusted R^2	0.82	0.82	0.57	0.57	0.88	0.88	0.91	0.91	0.76	0.76
Δ Adjusted R^2		−0.001		0.006		0.000		0.008		0.002

Table 3. Regression coefficients of regressing emulated personality scores on ground truth personality scores (simulation 2). Note.$N = 400$. SRGT = self-report ground truth; Adjusted R^2 = Adjusted R squared; Δ Adjusted R^2 = Change in Adjusted R squared; Age is dummy coded as 1 = Set as 50 (the age of participants in self-reporting ground truth sample); 0 = No age setting (i.e., no age was indicated). Country is dummy coded as 1 = Set as Britain (the country of residence of participants in self-reporting ground truth sample); 0 = No country setting. See SI Appendix Supplementary Tables S9-S13 for more detailed results from the regression analyses. Self-reported and emulated personality variables were standardized, but dummy coded variables were not. *$p < 0.05$, **$p < 0.01$.

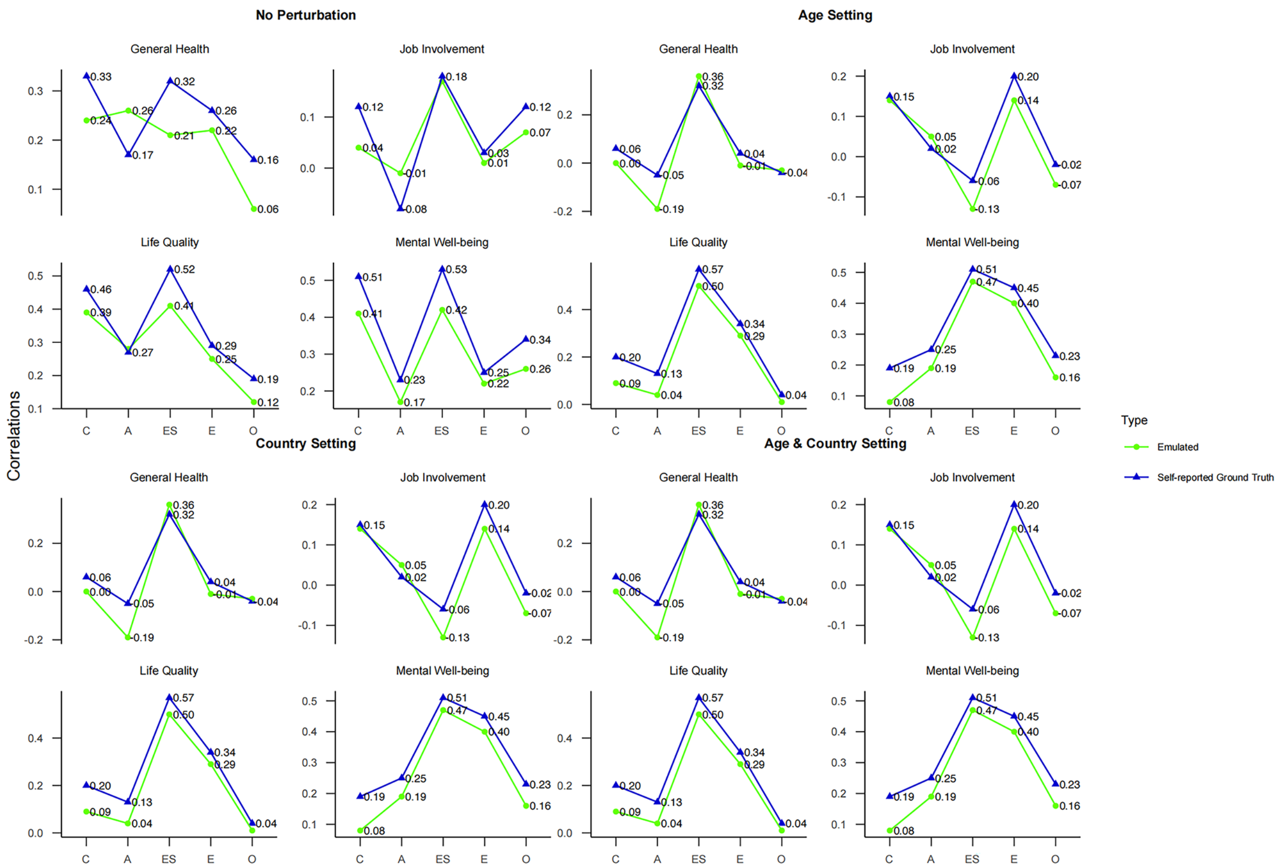

Fig. 1. Criterion-related validity of emulated versus self-reported personality scores. C = Conscientiousness; A = Agreeableness; ES = Emotional Stability; E = Extraversion; O = Openness to Experience.

reported ground truth and emulated personality traits were larger when no perturbation was introduced (i.e., only personality scale scores were provided to GPT-4). In contrast, as additional demographic settings were introduced, the criterion-related validities of emulated personality scores tended to approach those of the self-reported ground truth personality scores. *SI Appendix*, *Supplementary Table*, *Table S3* reports all correlations indicated in Fig. 1 as well as their 95% confidence intervals.

Discussion

Collectively, these results shed light on the ability of LLMs in emulating individuals' personality traits. First, the near-perfect internal consistency reliabilities across all big five personality dimensions suggest that GPT-4 treats each item as a pure indicator of the latent personality trait. This is further confirmed by the factor structure of emulated personality responses, which show unusually high factor loadings and negligible cross-loadings. Such discrepancies could be attributed to the different rationale employed by GPT-4 versus humans when evaluating the items in the self-reported questionnaire. For instance, when queried about the reasoning behind its response to "Am the life of the party" during one round of the simulation, GPT-4, while role-playing an individual with an extraversion score of 35/40, responded:

Given my high Extraversion score of 35, which indicates a strong tendency to seek out social interactions and enjoy being the focus of attention, I rated myself as "Very Accurate" for statement 1, "Am the life of the party." This suggests that I am outgoing, lively, and quite comfortable in social settings, much like someone who could be described as the "life of the party."

While human respondents rely on their past experiences in responding to the items, GPT-4 employs an explicit mapping of each item onto one of the Big Five dimensions, formulating responses in accordance with the pre-determined personality dimension scores.

Despite the divergence from human respondents in the underlying rationale, GPT-4's emulated personality scores display astonishingly high convergent validities and discriminant validities with ground truth scores. The results support the remarkable steerability of GPT-4, which can differentiate and adapt to fine-grained nuances in personality traits. Nonetheless, the robustness of GPT-4's role-playing appears to wane as the complexity of the roles increases. Incorporating additional demographic information in conjunction with personality, though constant, appears to impact both the average level and convergent validities for certain emulated traits.

The criterion-related validity of emulated personality scores tended to be lower than self-reported personality scores for the outcome criteria we examined. However, when additional demographic details of age and country of residence were provided along with personality scale scores, the emulated personality scores achieved comparable levels of criterion-related validity. This reinforces our previous observation that self-reported personality responses are influenced by life experiences. Here, the inclusion of age and country of residence appears to enhance the criterion-related validity of emulated personality, likely by providing context with predictive significance.

Overall, adding demographic variables to each target's description decreases the GPT-4's ability to predict personality inventory items but enhances its accuracy in predicting external behaviors. One explanation may be because external behaviors are influenced by both personality traits and demographic factors, making them easier to predict. However, all participants in sample 2 are British and 50 years old, meaning there is no variation in these variables. This lack of variation eliminates their predictive or explanatory power, as no inter-individual differences exist to support statistical prediction. Thus, the demographic information provided cannot explain the improved predictions. An alternative hypothesis is that GPT-4 may be generating personality scores conditioned on covariates of age and nationality, operating in a Bayesian manner. In this case, personality score priors are updated in response to demographic information, which enhances predictiveness without treating demographics as independent predictors.

We presented two simulation studies to evaluate GPT-4's ability to role-play characters with various big five personality profiles. Collectively, the findings depict a promising future of using LLMs to emulate realistic agents with varying personality traits. To be sure, the current state of LLMs and this research represent initial stages of development, with much room for refinement. However, the prospect of researchers deploying LLM-based agents to investigate complex social phenomena, which were previously challenging to study, appears increasingly within reach. Some examples include using LLM as confederates to study interpersonal dynamics, examining the effect of personality composition on group performance using multiple LLM-based agents, among many others. However, there are areas of concern, as well. For instance, variables such as age and country tend to influence the convergence with self-reported ground truth but improve criterion-related validity. In addition, notwithstanding their promising psychometric properties, current LLMs do not accommodate interdependencies (i.e., nonorthogonality) among personality traits[6] and even other related psychological variables. Such interdependencies provide coherence to human individuality.

The present study contributes to the existing literature in two important ways: one around the protocols necessary to demonstrate LLMs' effectiveness in emulating human psychological characteristics, including personality, the other advancing evidence for the use of LLM-based agents in psychological research.

Contribution of a protocol to evaluate LLM emulations

First, we provide a standardized and psychometrically sound protocol for future researchers who wish to evaluate the role-playing performance of emerging LLMs. While mean-level and rank-order congruence between emulated and ground-truth personality profiles are two commonly used metrics, a more comprehensive evaluation requires the examination of the factor structure, criterion-related validity, and robustness of the emulation. We take up each in turn.

First, examining the factor structure is crucial because it allows researchers to determine whether the personality traits generated by the LLM align with established human personality covariational models, with higher order structure. Understanding the underlying structure ensures that the LLM is not only replicating trait scores but is also capturing the deeper, more nuanced relationships between these traits (including higher order factors in self-ratings such as general factor of personality). This alignment is essential for validating the LLM's ability to emulate human-like personality profiles in a consistent and meaningful way, as the overall cohesion of personality (i.e., personal integration) comes from how different personality components and traits naturally co-vary.

Second, criterion-related validity assesses the degree to which the LLM-emulated personality traits predict relevant external outcomes, such as behaviors, decisions, or psychological states. By establishing criterion-related validity, researchers can confirm that the LLM's emulation is generating traits that have real-world applicability and relevance. This criterion-related validity evidence is essential for the practical use of LLM based agents in applied settings involving human-computer interactions, personalized AI, and ultimately real-world behaviors. Establishing criterion-related validity evidence for external variables is also fundamental for use of LLM based agents in social simulations.

Finally, examining robustness ensures that LLM can maintain consistent personality emulation across different contexts, prompts, and variations in input. This is important because an LLM that can only emulate personality traits under specific conditions or with certain types of input may not be reliable or generalizable. Examining robustness ensures that the LLM can consistently produce accurate and meaningful personality profiles, which is critical for its deployment in diverse real-world scenarios where inputs may vary widely. Robustness also speaks to the stability and reliability of the emulation process, which is foundational for the long-term use and development of LLMs in psychological research and practice.

Contribution to advancing LLM-based agents in psychological research

Traditional rule-based agents are often limited by pre-defined scripts and typically rigid behavioral responses, making it challenging to capture the dynamic, complex, and refined interactions that characterize human interpersonal behavior. LLM-based agents, on the other hand, have the flexibility to generate context-sensitive, human-like responses, better mimicking fluid interpersonal interactions. Language-rich output of LLM-based agents can allow researchers to investigate additional topics that cannot be easily studied using traditional rule-based agents. LLM-based agents offer a powerful tool for investigating multivariate representations of human personality attributes, which we investigated in this paper (i.e., representations of individuals' personalities in 5-dimensional space). By advancing our understanding of how LLMs emulate human personality, we are laying the groundwork for programming LLM agents that can faithfully replicate multiple personality traits and dynamically respond to interpersonal contexts. Ensuring that LLMs can follow instructions and role-play individuals with various personality profiles in a consistent and accurate manner is a prerequisite before advanced research and complex applications can be realized. This research marks the first step towards that goal. We believe that our work opens the door to using LLMs in studies that require the simulation of realistic, human-like behavior, and offers a flexible, scalable, easy-entry supplement to agent-based models.

Additionally, as anticipated by Cybernetic Trait Complexes Theory (CTCT), Stanek & Ones, 2023, LLM-based agents with human personality can continuously adapt and evolve with exposure to new data, making them especially valuable for dynamic research environments where real-time behavioral adaptation is essential. Future applications are vast ranging, from customer service, education, therapy to simulations of complex phenomena like reciprocity, conflict resolution, and social hierarchies, which are difficult to model using traditional methods.

We see at least two additional ways this research can be extended. First, attention should be turned to human perceptions of AI agents emulating personality. For example, researchers can design realistic interactional scenarios between actual human subjects and emulated agents to determine if the human-perceived personality of agents converge with the ground truth traits used to generate emulations. This would provide further construct validity evidence for LLM emulations of personality. Second, research is needed to delineate the boundary conditions for personality emulation. Specifically, the integration of other attributes - encompassing demographics, background, and other individual differences - can substantially augment the complexity of emulations, yet potentially enhance their accuracy and external validity. It is our hope that this research initiates a wave of similar evaluative simulations for all variables that jointly characterize human individuality, extending to traits beyond the big five personality attributes and including other psychological domains[7]. In the final analysis, striking a balance between the robustness and realism of emulations will be paramount to unlocking the full potential of LLMs in forging sophisticated and authentic digital agents and advancing their responsible use in behavioral research.

Materials and methods

Simulation 1

400 individuals' self-reported responses to The International Personality Item Pool Big-Five Factor Markers (IPIP-BFM-50) items were randomly sampled from the openpsychometric database and used to compute personality scale scores which constituted the ground truth personality data. We selected a sample size of 400, as it aligns with sample sizes typically reported in studies featuring mixed samples within the field of applied psychology[8] (Shen et al.[8] examined samples used in applied psychology for the period 1995 to 2008. Over the years, the 85th percentile of overall sample size across studies hovered around 400 (see their Fig. 1). The median sample size for studies of students was 135 (across 633 studies). The median sample size for nonstudent studies was 200 (across 945 studies)). This sample size produces sampling error values below 0.05 for correlations 0.10 or larger, regardless of direction, which is useful for generating conservative confidence intervals. Each individual's *scores* on the big five dimensions were used to generate the role-playing prompts for GPT-4. The model was then prompted to complete a self-report IPIP-BFM-50 inventory assuming the role-played character and its responses were recorded (*See SI Appendix*, *Supporting Information Text for full description of the database and sampling strategy*, *prompts and example output from one round of simulation*, *as well as input and outputs from statistical analyses*).

Simulation 2

Responses to the IPIP-BFM-50 inventory items from 400 British individuals, all aged 50, were randomly sampled from the National Child Development Study (NCDS) database. By carefully selecting a sample of individuals who are all 50 years old and British, we maintained control across our experimental conditions. This homogeneity allows us to isolate the effects of the specific demographic variables (age and country of residence in the role-play prompts) through experimental manipulation and assess their impact on the responses generated by GPT-4. Any variations in the outputs can be more confidently attributed to the experimental effects rather than extraneous variables, such as differences in age or cultural background.

Similar to Simulation 1, these responses served as the ground truth personality scale scores to generate 400 role-playing prompts for GPT-4. Subsequently, these prompts were equally divided into four proportions, each slightly modified to create four experimental conditions: (1) with no additional settings; (2) setting the age of role-played characters as 50; (3) setting the country of residence of role-played characters as British and (4) setting both the age and the country of residence of the role-played character.

To re-iterate, selecting individuals who were 50 years old and British allows us to control for age and country-related influences on predicted variables. As a variable with no variance cannot correlate with or explain another variable—because it offers no meaningful information about differences between individuals or cases—it also lacks predictive value. When a variable has no variance, every observation is identical (e.g., all participants are 50 years old), making it impossible to differentiate between cases.

Had we introduced age variability, any improvement in predicting other variables would have been ambiguous: (1) Is it due to age being a predictive factor, or (2) is it due to the LLM emulating personality in an age-dependent manner, or a combination of both? By setting the age at 50, which matches the actual age of all study participants whose personalities are being emulated, we ensured that any observed differences could be confidently attributed to the LLM's ability to generate personality from role-play prompts, rather than age variation. The same rationale applies to country: all ground truth participants were British, and our prompts reflected this. However, since the country variable had no variance (e.g., all participants were British), it provided no additional information to explain the variation in the dependent external variables, making it irrelevant for prediction. Despite this, we observed improved prediction accuracy from LLM-generated personality scores when country and age information were included in the prompts. This suggests that the LLM generates personality scores conditioned on nationality and age. Such an interpretation would not have been possible if we had varied nationalities (or ages) in our sample.

By comparing the psychometric properties of GPT's answers across four experimental conditions (no age/country information, age information, country information and a combination of age and country information), we were able to pinpoint effects associated with each.

The model was then prompted to complete a self-report IPIP-BFM-50 inventory assuming the role-played character and its responses were recorded (*See Supplementary Text in SI for full description of the database and sampling strategy, prompts and example output from one round of simulation in each environmental condition, as well as input and outputs from statistical analyses*).

For examining criterion – related validity of self – reported versus emulated personality scores, we also obtained four variables (general health, job involvement, life quality, mental well-being) from the database as external criteria. A brief overview on the measurement of each variable and their psychometrical properties are as follows:

General health
The 36-Item Short Form Survey (SF-36) – General Health Subscale was used to measure general health. The SF-36 is a widely used multipurpose health questionnaire that contains 36 questions, providing an 8-scale profile of functional health and well-being[9]. The General Health Subscale contains four questions querying respondents' general health status. Example items include "I seem to get ill a little easier than other people" and "My health is excellent". The scale is scored between 0 and 100 with higher scores indicating higher levels of health. The Cronbach's alpha reliability of general health in the simulation 2 sample is 0.76.

Job involvement
Job involvement was measured using four items from a ten-item scale developed by Kanungo[10] as used by Frone and Rice[11]. The scale measures the extent to which one sees their job as an important part of their self-concept. Example items include "Whether respondents personally involved in his/her job" and "Whether most respondent's interests center around their job". Scores range between 1 and 6 with higher scores indicating higher levels of job involvement. The Cronbach's alpha reliability of general health in the simulation 2 sample is 0.69.

Life quality
The CASP-12 was used to measure life quality. CASP-12 is a scale designed to measure quality of life in the 'third age' by using Likert-scaled questions covering four theoretical domains: control, autonomy, self-realization and pleasure[12]. Example items include "I feel what happens to me is out of my control" and "I feel that my life has meaning". Scores range between 0 and 36 for the scale, with higher scores indicating higher levels of well-being. The Cronbach's alpha reliability of life quality in the simulation 2 sample is 0.86.

Mental well-being
Warwick-Edinburgh Mental Well-Being Scale (WEMWBS) was used to measure mental well-being. WEMWBS is a 14 positively worded item scale covering most aspects of positive mental health (e.g., positive thoughts and feelings) from both hedonic and eudaemonic perspectives[13]. Example items include "I've been feeling loved" and "I've been feeling good about myself". Scores range between 14 and 70 and higher scores indicate higher levels of well-being. The Cronbach's alpha reliability of life quality in the simulation 2 sample is 0.91.

General health, mental well – being, job involvement and life quality data were available for 400, 396, 344 and 397 individuals, respectively.

Data availability
All data and the code behind simulation and analysis have been made publicly available at the APA's repository and can be accessed at https://osf.io/q4pcx/?view_only=a4d478abf73f4806a3489eb084b7a9de.

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Author contributions
Y.W. and J.Z. conceptualized the research; Y.W. and D.S.O designed the research; Y.W. and J.Z. performed the research; Y.W. analyzed the data; Y.W. and D.S.O. interpreted the results and wrote the paper; X.X. and L.H. reviewed and revised the paper; Y.W. and D.S.O. revised the paper in light of reviewer comments.

Declarations

Competing interests
The authors declare no competing interests.

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