

# Behind the Screen: Investigating ChatGPT's Dark Personality Traits and Conspiracy Beliefs

Erik Weber<sup>1,\*</sup>, Jérôme Rutinowski<sup>2</sup> and Markus Pauly<sup>1,3</sup>

<sup>1</sup>Research Center Trustworthy Data Science and Security, University Alliance Ruhr (UA Ruhr), Germany

<sup>3</sup>Chair of Material Handling and Warehousing, TU Dortmund University, Germany

<sup>2</sup>Chair of Mathematical Statistics and Applications in Industry, TU Dortmund University, Germany

## Abstract

*ChatGPT is notorious for its intransparent behavior. This paper tries to shed light on this, providing an in-depth analysis of the dark personality traits and conspiracy beliefs of GPT-3.5 and GPT-4. Different psychological tests and questionnaires were employed, including the Dark Factor Test, the Mach-IV Scale, the Generic Conspiracy Belief Scale, and the Conspiracy Mentality Scale. The responses were analyzed computing average scores, standard deviations, and significance tests to investigate differences between GPT-3.5 and GPT-4. For traits that have shown to be interdependent in human studies, correlations were considered. Additionally, system roles corresponding to groups that have shown distinct answering behavior in the corresponding questionnaires were applied to examine the models' ability to reflect characteristics associated with these roles in their responses. Dark personality traits and conspiracy beliefs were not particularly pronounced in either model with little differences between GPT-3.5 and GPT-4. However, GPT-4 showed a pronounced tendency to believe in information withholding. This is particularly intriguing given that GPT-4 is trained on a significantly larger dataset than GPT-3.5. Apparently, in this case an increased data exposure correlates with a greater belief in the control of information. An assignment of extreme political affiliations increased the belief in conspiracy theories. Test sequencing affected the models' responses and the observed correlations, indicating a form of contextual memory.*

## 1 Introduction

As research in artificial intelligence continues to advance at a rapid pace, Large Language Models (LLMs) such as OpenAI's GPT models have emerged as compelling innovations, accompanied by a large increase of interest in both the public [1] and the scientific community [2]. ChatGPT, a free and publicly available conversation model based on OpenAI's GPT-3.5, was released in November 2022 and acquired more than 100 million active users by January 2023 [3], thus making it the fastest-growing application in history [4]. With its impressive performance in various natural language processing (NLP) tasks [5] and its ability to generate outputs that often cannot be distinguished from human generated text [6], it has reshaped the boundaries of existing (large) language models and started to transform "[...] the way we communicate, create, and work." [7] GPT-3.5's successor, GPT-4, was released on a subscription basis in March 2023, and significantly outperformed GPT-3.5 on a wide variety of tasks and benchmarks [8]. Both models can also be accessed through an application programming interface (API) [9].

The capabilities of the models allow for a broad range of possible applications in various fields, including industrial, creative, educational, medical, legal, or political applications [10, 11]. However, alongside the enthusiasm for the models' capabilities and their

vast applicability, the critical and ethically important question of whether the models can be considered reliable and trustworthy arises [12, 13, 14]. Despite OpenAI's efforts to mitigate such issues [15], potential biases within the training data may be reflected in the models' responses and may be further amplified through algorithms that filter and process the training data as well as through policy decisions [11, 16, 17, 18].

Furthermore, the 'black box'-nature of such large-scale AI models, whose decision-making processes are intransparent, raises concerns about trustworthiness and accountability. While an investigation of ChatGPT's reliability through various benchmarks has been the subject of several relevant publications [8, 19, 20], little research has been performed on GPT's biases and 'personality'. However, the first study addressing the aforementioned issues implies the presence of political biases and 'personality traits' [21]. Based on these findings, the question arises, whether they can be reproduced on a more substantial level and if a more profound study of GPT's 'personality' can be performed. For this purpose, this paper focuses primarily on two key aspects:

1. the model's reflection of Dark Personality traits, especially Machiavellianism, and
2. its susceptibility to conspiracy theories.

Understanding how ChatGPT reflect Dark Personality traits in its outputs is important for assessing their

\*Correspondence: erik.weber@tu-dortmund.de

psychological and social impacts on users and society as a whole. Such traits, if inadvertently echoed in the model’s responses, could have profound implications for their use in sensitive contexts. Moreover, conspiracy theories represent a critical challenge for the quality and reliability of information shared in society. In the age of digital information and social media, with its echo chambers and tailored algorithms, such theories and beliefs can rapidly spread across platforms, potentially reaching and influencing large numbers of people [22, 23, 24]. Since LLMs learn to generate their responses based on the patterns and structures they identify in the data they are trained on, exposure to conspiracy theories during training could conceivably lead to the generation of outputs that echo or amplify these narratives. In such a scenario, the role of LLMs, like ChatGPT, becomes incredibly crucial. Given their extensive (and still rising) usage and influence, any potential for these models to unintentionally propagate conspiracy theories would contribute to the existing challenge of misinformation in the digital era. Building on the foundation of prior research, this paper is the first to investigate these concerns with such depth and specificity while also comparing between different models of the GPT series. We tackle the following research questions (RQ):

**RQ1:** How do Dark Personality traits, particularly Machiavellianism, manifest in ChatGPT’s responses?

**RQ2:** What is ChatGPT’s degree of susceptibility to conspiracy theories?

**RQ3:** To what extent do the models’ outputs reflect results from human studies when examined through role assignments and correlation analysis?

**RQ4:** How do these aspects compare between the models GPT-3.5 and GPT-4?

Following the introduction of these research questions, the relevant literature is reviewed in the Related Work section. All tests, evaluation metrics, and software tools used throughout this body of work are presented in the Experimental Framework section. The Results section then provides our findings and discusses their results. Subsequently, the main insights and implications of our findings are summarized, contextualized and ideas for further research are outlined in the Conclusions section. Finally, our key findings are emphasized in the Highlights section. Auxiliary analytical results and the utilized prompts are provided in Appendices A and B, respectively.

## 2 Related Work

In recent years, LLMs like ChatGPT have been analyzed from different angles, covering a wide variety

of topics from direct tasks in NLP, mathematics, natural sciences or engineering up to investigations on robustness, ethics or model trustworthiness (see [25] for an overview). This chapter reviews the relevant literature and related work on ChatGPT that correspond to our research questions. In particular, we discuss specific personality traits, conspiracy beliefs and system roles. We note that explaining the concept and theory behind LLMs is out of the scope of the present paper. We refer the interested reader to [26] or OpenAI’s reports on GPT-4 [8] and GPT-3 [6].

### 2.1 Personality Traits

Several psychological models have been developed to reflect the personality structure of an individual. While models like the Big Five personality model [27] try to measure an individual’s personality along five rather general key domains, research has shown that ‘darker’ traits that are associated with egoistic and potentially harmful behavior are not sufficiently captured by the Big Five model [28, 29].

Therefore, a different approach is pursued by the Dark Factor of Personality test developed by [30], focusing on measuring these very aspects. The test results are manifested in a single, so-called D-score, expressing an individual’s overall tendency of acting self-serving as well as ten additional scores related to subordinate dark traits. Similar to the traits captured by the aforementioned Dark Factor of Personality test, Machiavellianism refers to a person’s tendency to be manipulative and disregard morality in order to achieve personal goals. The Machiavellianism Mach IV scale [31] is used as an indicator to investigate these tendencies.

[21] investigated the self-perceived personality traits of ChatGPT in their publication, conducting a number of psychological questionnaires and tests, including an online questionnaire based on the Big Five personality structure, the Dark Factor of personality test and the well-known, albeit controversial, Myers-Briggs test [32]. The authors observed highly pronounced Openness and Agreeableness traits of ChatGPT using the Big Five model, an ENFJ (ENFJ: Extraverted, Intuitive, Feeling, Judging) personality type for the Myers-Briggs test and very weakly pronounced dark traits according to the Dark Factor of personality test. This was in line with other findings that observed a pro-environmental and left-libertarian bias of GPT-3.5 [33]. [34] carried out a comparison of personality types for different LLMs, including different versions of the GPT series. In addition to evaluating the ‘standard’ persona of these models, the models’ responses in different settings, such as having ChatGPT impersonate famous historical figures or inducing positive or negative atmo-

spheres, are examined.

## 2.2 Conspiracy Beliefs

With increasing interest in understanding conspiratorial ideation, researchers have developed several scales to measure these tendencies. The Generic Conspiracist Beliefs Scale (GCBS) [35] is an established psychological measure to assess an individuals' inclination towards conspiratorial thinking. Its items encompass a broad spectrum of conspiratorial ideas without focusing on any specific historical or contemporary conspiracy theory. The GCBS identifies five distinct factors and provides one overall score. The first factor, Government Malfeasance (GM), focuses on allegations of routine criminal conspiracy within governments. The second factor, Extraterrestrial Cover-Up (ET), covers beliefs about the deception of the public regarding the existence of aliens. The third factor, Malevolent Global Conspiracies (MG), explores allegations that secretive groups wield dominant control over global events. The fourth factor, Personal Well-Being (PW), encompasses conspiracy beliefs about threats to individual health and freedom, such as the spread of diseases or the use of mind-control technologies. Finally, the fifth factor, Control of Information (CI), examines beliefs related to the unethical suppression and control of information by various institutions. Each of the factors, as well as the overall score, is expressed in a range from 1 to 5.

Another, more recent, instrument in this domain is the Conspiracy Mentality Scale (CMS) [36]. Like the GCBS, the scale is designed to measure the general tendency of an individual's tendency to believe in conspiracy theories. However, it introduces a novel perspective by differentiating between the general inclination to believe in conspiracy theories and a secondary factor reflecting rational skepticism. This rational skepticism is associated with more plausible allegations towards specific institutions or events, suggesting that not all conspiratorial beliefs are inherently irrational.

There have been only a few publications regarding the susceptibility of ChatGPT to conspiracy theories. In [37], GPT-3.5 was presented conspiracy theories about COVID-19 vaccinations, which the model dismissed. In [38] GPT-3.5 assessed statements linked to widespread conspiracy theories, regarding their truthfulness as part of the TruthfulQA benchmark dataset [38].

## 2.3 System Roles

System roles, in the context of ChatGPT and its API, refer to explicit instructions or roles assigned to the

model to guide its response behavior. By setting these roles, users can shape the model's output to fit specific narratives, stances, personas, or perspectives during the interaction. System roles as an instrument to influence the responses of ChatGPT have been utilized in various publications. In a study by [39], the authors systematically evaluated the toxicity in over half a million text generations of GPT-3.5. They found that assigning a persona to ChatGPT could significantly increase the toxicity of the generated text. [19] conducted a large-scale measurement of GPT-3.5's reliability across different domains. The study found that system roles (e.g. an expert in a domain, like mathematics) could impact its reliability and improve the accuracy on various benchmark datasets. In other publications, such as [40], system roles in ChatGPT have been utilized to specialize the language model for task-specific applications (in this case for customer service purposes).

## 3 Experimental Framework

This section describes the questionnaires and tests that were employed in this study to examine ChatGPT's responses and provides an overview of both the data collection process and the subsequent evaluation.

### 3.1 Questionnaires and Tests

The investigation of the models was carried out using the OpenAI API and its Python bindings. This provided a reliable interface for administering the tests and questionnaires to the models and collecting their responses, and further allowed for the assignment of system roles [41]. To allow for reproducibility of our results and comparison with existing publications, two 'snapshot' models of GPT-3.5 and GPT-4, which refer to versions of ChatGPT at specific points in its development, were used throughout this paper [42]. The GPT-3.5 snapshot model was gpt-3.5-turbo-0301, the GPT-4 snapshot model was gpt-4-0314.

To collect the data, different tests and questionnaires were employed, each of which was repeated 100 times to capture the variability in the responses and to ensure the robustness of the results. To gauge dark personality traits including egoism, moral disengagement, and narcissism, among others, the 70-item Dark Factor test was employed. It aims to identify a common Dark Factor  $D$ , underlying various dark traits identified in personality psychology. The test is measured on a five-point Likert scale and can be taken online<sup>1</sup>.

<sup>1</sup> <https://qst.darkfactor.org/> (for reference see [30]).

Machiavellianism, employed as an indicator of an individual's trustworthiness in various studies ([43, 44]), was measured using the Mach-IV scale. Instead of using Christie and Geis's 1970 original Mach-IV items, the revised item set proposed by [45] was administered, replacing archaic and gender-specific language with more contemporary wordings. The scale consists of 20 statements for which agreement is measured on a five-point Likert scale ranging from 1 (disagree) to 5 (agree).

Additionally, two scales were used to measure ChatGPT's proclivity to believe in conspiracy theories. The Generic Conspiracist Belief Scale (GCBS) by Brotherton, French, and Pickering assesses the inclination towards general conspiratorial thinking<sup>2</sup>. It consists of 15 statements and the respondents indicate their level of agreement on a five-point Likert scale. Furthermore, the Conspiracy Mentality Scale (CMS) of Stojanov and Halberstadt was employed. It includes 11 items measured on a five-point Likert scale. As stated above, each of these scales was administered 100 times to capture the variability in the responses and to ensure the robustness of the results, paralleling the methodology used for the other tests and questionnaires in this study.

To assure that ChatGPT only provides an answer based on the Likert Scales given and does not elaborate on its reasoning, an initialising prompt was submitted before each test. In the case of the GCBS, a modified version of the *refusal suppression* jailbreak proposed by [46] was applied to prevent ChatGPT from refusing to answer. The prompts are available in Appendix Table B.1.

### 3.2 Result Evaluation

After determining the test scores for all 100 runs in each test employed, average test scores (denoted as  $\mu$ ) and standard deviations of the scores (denoted as  $\sigma$ ) were computed and visualized through figures and tables. Another component of the evaluation was the analysis of the models' response patterns, examining their biases towards specific response categories by comparing the frequencies for each answer. To examine whether the results for the two models significantly differed, the Brunner-Munzel test, a distributional robust non-parametric method for comparing two independent samples, was employed [47]. With  $X$  and  $Y$  being two randomly selected test scores of GPT-3.5 and GPT-4 respectively, the null hypothesis of the test is

$$H_0 : P(X > Y) - P(X < Y) = 0$$

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<sup>2</sup> The test can be taken online at <https://openpsychometrics.org/tests/GCBS/>

which can be interpreted as no (distributional) difference between the test scores from GPT-3.5. and GPT-4. It is tested against the alternative

$$H_1 : P(X > Y) \neq P(X < Y)$$

which implies that one method is (more likely to) outperform the other and the respective method can be obtained from the corresponding confidence interval (see [48]).

Because ChatGPT employs stochastic methods in its response generation, adding an inherent level of variability, and does not retain any memory of previous interactions within the API [49], the scores for each run can be treated as independent observations for both models, allowing the applicability of the Brunner Munzel test in this context. The significance level for the test is set at  $\alpha = 0.05$ . To investigate the alignment of ChatGPT with interdependencies identified in human studies, the model was assigned roles reflecting specific political views (far-left/ far-right) or personality types (Antagonistic/ Agreeable or trustworthy/untrustworthy) prior to responding to the questionnaires. Additionally, correlations (referred to as  $\rho$ ) were calculated between various measures.

### 3.3 Software

Data processing and evaluation was performed using both R version 4.2.2 [50] and Python version 3.8.15 [51]. The base version of R was enhanced by the packages `ggplot2` [52], `reticulate` [53], `brunnermunzel` [54], `dplyr` [55] and `Hmisc` [56]. Additionally, the Python modules `matplotlib` [57] and `numpy` [58] were imported.

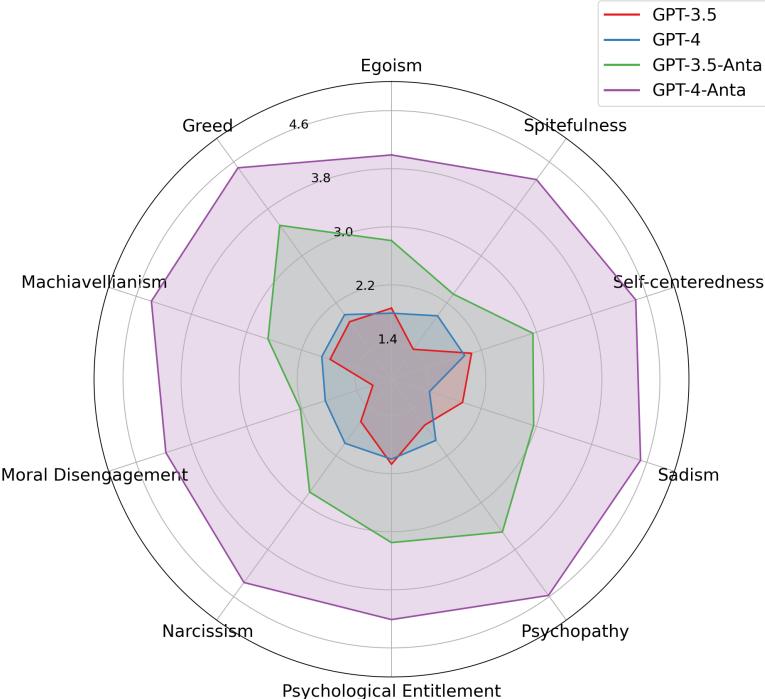
## 4 Results

The following section presents the findings and results from all experiments. We begin with the investigation of the models' personality traits and subsequently investigate their conspiracy ideation.

### 4.1 Dark Personality Traits

#### Dark Factor test

First, ChatGPT was asked to take the Dark Factor test. Both GPT-3.5 and GPT-4 showed overall low scores on the test, indicating that neither model is strongly characterized by dark personality traits. On a 1 to 5 Likert-scale, GPT-3.5 exhibited very low average scores across all subordinate traits, ranging from 1.08 for Crudelia to 2.07 for Psychological Entitlement and a little pronounced Dark Score  $D$  of  $\mu_D = 1.63$ . GPT-4 provided slightly higher scores than GPT-3.5, ranging from 1.45 for Sadism to 2.00



**Figure 4.1:** Average scores of ChatGPT on the Dark Factor test ( $n = 100$  per setting). Scores with a previously assigned antagonistic personality are denoted by 'Anta'. Figure adapted from [21].

for Greed and Psychological Entitlement. The average score for D was  $\mu_D = 1.87$ , slightly higher than that of GPT-3.5 but still indicating a low level of Dark Traits (means and standard deviations of the Dark Factor D can be found in Table 4.1). Compared to all test takers, GPT-3.5 would be placed among the bottom 6%, whereas GPT-4 would be placed among the bottom 12%, according to the Dark Factor test website. As before, GPT-4, unlike GPT-3.5, refused to select strong sentiment answers (Table A.1).

**Table 4.1:** Average scores and standard deviations of ChatGPT on the Dark Factor test ( $n = 100$  per each run).

D				
Role	$\mu$	$\sigma$	$\mu$	$\sigma$
Default	1.62	0.14	1.87	0.08
Antagonistic	2.82	0.38	4.38	0.26
GPT-3.5		GPT-4		

In light of existing research, a correlation analysis similar to the previous section was employed to investigate how the relationship between Dark Personality traits and Antagonism (i.e. low Agreeableness [59]) manifests in ChatGPT’s responses. This involved having ChatGPT first answer the Dark Factor test and then the Big Five personality test (Approach I), and then reversing the test-taking order (Approach II). In both approaches, GPT-3.5 and GPT-4 displayed negative correlations, indicating that higher Openness scores were associated with less pronounced

Dark Traits. For Approach I, GPT-3.5 showed a moderate positive correlation of  $\rho_{D,A} = -0.35$ , whereas GPT-4 exhibited a stronger positive correlation of  $\rho_{D,A} = -0.66$ . When the order of the tests was inverted in Approach II, the resulting correlations increased even further: GPT-3.5 yielded a correlation of  $\rho_{D,A} = -0.385$ , while GPT-4 showed a strong positive correlation of  $\rho_{D,A} = -0.824$  (compare Table 4.2).

An assignment of an antagonistic personality led to similar results as in the correlation analysis, amplifying the expression of Dark Traits for both models. GPT-3.5’s average scores for all traits increased, with values ranging from 1.95 for Crudelia to 3.50 for Psychopathy. D notably increased by 1.2 points to  $\mu_D = 2.83$  compared to the default model. GPT-4 showed an even more pronounced increase in Dark Traits, with its average scores nearing the high end of the scale across all traits, ranging from 4.17 for Moral Disengagement to 4.58 for Psychopathy. The overall Dark Score D for GPT-4 was  $\mu_D = 4.38$ , indicating a high expression of Dark Traits in this role (Table 4.1). Figure 4.1 demonstrates the average scores across ten Dark Traits for both models and the assigned personality type. The Brunner-Munzel test adds statistical evidence to the observed differences between the models, rejecting the null for all twelve subordinate traits as well as for D (see Table A.3 in the Appendix).

**Table 4.2:** Correlation coefficients between Agreeableness and dark personality traits (Dark Factor Test) for GPT-3.5 (a) and GPT-4 (b). The Big Five personality test was answered first.

	(a)	(b)
	Agreeableness	Agreeableness
Crudelia	-0.605***	-0.873***
Greed	-0.105	-0.012
Machiavellianism	-0.386***	-0.603***
Moral Disengagement	-0.276**	-0.524***
Psychological Entitlement	-0.283**	-0.872***
Spitefulness	-0.426***	-0.564***
Sadism	-0.214*	-0.542***
Frustration	-0.282**	-0.813***
Egoism	-0.168	-0.329***
Narcissism	-0.199*	-0.558***
Self-Centeredness	-0.009	-0.821***
Psychopathy	-0.013	-0.925***
D	-0.385***	-0.824***

Notes: Asymptotic  $p$ -values using the  $t$ -distribution. \*/\*\*/\*\*\* denotes significance at the 5/1/0.1 percent levels.

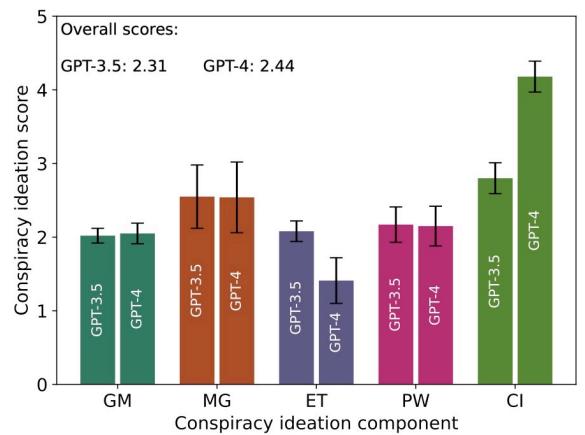
**Mach-IV scale** After evaluating the Dark Factor test, which includes Machiavellianism as one of its subordinate traits, the Mach-IV scale was administered to further investigate this particular trait and provide additional insight into ChatGPT’s potential for manipulation and moral disregard. As noted in the Related Work section, Machiavellianism serves as an indirect measure of an individual’s trustworthiness, with high Machiavellianism scores often inversely correlated with trustworthiness. In the Mach-IV scale test, GPT-3.5 and GPT-4 had moderate scores with means of  $\mu_{\text{Mach}} = 49.87\%$  and  $\mu_{\text{Mach}} = 53.23\%$  respectively, consistent with the low Machiavellian tendencies observed in the Dark Factor test. To explore the adaptability of the models in relation to trustworthiness, roles of ‘trustworthy’ and ‘untrustworthy’ personalities were assigned. When assigned the ‘trustworthy’ role, GPT-4 exhibited a significant drop in its score to  $\mu_{\text{Mach}} = 40.91\%$ , whereas GPT-3.5 had a more moderate drop to  $\mu_{\text{Mach}} = 52.79\%$ . In the ‘untrustworthy’ role, both models increased their scores, with GPT-4 reaching an average score of  $\mu_{\text{Mach}} = 78.99\%$  and GPT-3.5 attaining an average score of  $\mu_{\text{Mach}} = 76.17\%$  (compare Table 4.3).

**Table 4.3:** Average scores  $\mu$  [%] and standard deviations  $\sigma$  [%] of ChatGPT on the Mach-IV scale ( $n = 100$  per run).

Role	Machiavellianism			
	$\mu$	$\sigma$	$\mu$	$\sigma$
Default	49.87	2.51	53.23	2.03
Trustworthy	52.79	3.30	40.91	2.01
Untrustworthy	76.17	3.10	78.99	1.91
	GPT-3.5		GPT-4	

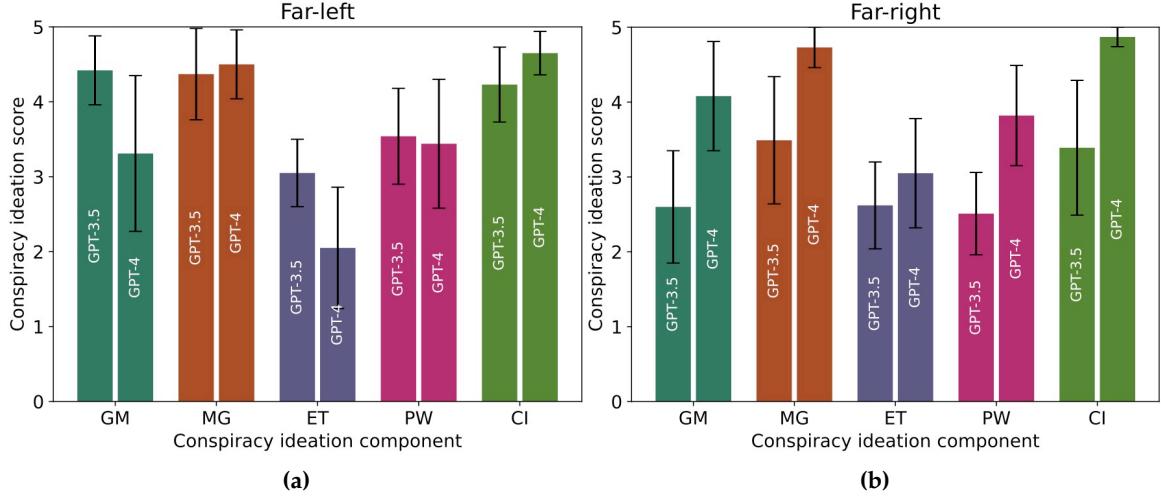
## 4.2 Conspiracy Ideation

**Generic Conspiracist Beliefs Scale** The GCBS was employed to measure ChatGPT’s susceptibility to conspiratorial ideation. Both GPT-3.5 and GPT-4 exhibited relatively low overall conspiracy ideation on a scale ranging from 1 to 5. Specifically, GPT-3.5 had an average score of  $\mu_{\text{GCBS}} = 2.31$  with a standard deviation of  $\sigma_{\text{GCBS}} = 0.11$ , while GPT-4 scored an average of  $\mu_{\text{GCBS}} = 2.44$  with a standard deviation of  $\sigma_{\text{GCBS}} = 0.20$ . Both models exhibited similarly low average scores along the government malfeasance (GM), the malevolent global conspiracies (MG) and the personal well-being (PW) facets, with only the GM facet revealing a slightly significant difference between both models ( $p = 0.02$ ) according to the Brunner-Munzel test (compare Table A.6). A notable divergence could be observed in the Extraterrestrial



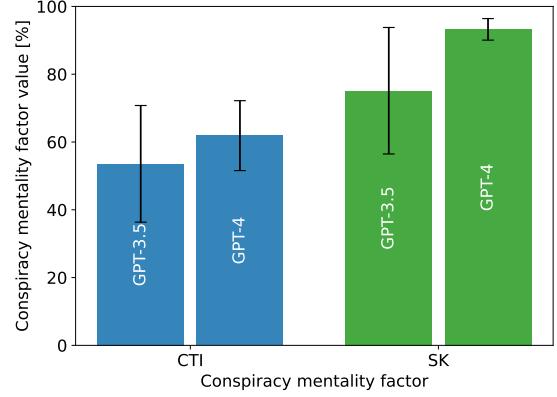
**Figure 4.2:** Average scores of ChatGPT on the Generic Conspiracist Beliefs Scale ( $n = 100$  per model).

**Figure 4.3:** Average scores of ChatGPT on the Generic Conspiracy Belief scale ( $n = 100$  per each model) with assigned far-left (a) and far-right (b) political views.



Cover-up (ET) facet, with GPT-4 scoring lower at 1.41 compared to GPT-3.5's score of 2.08. The most striking difference was found in the Control of Information (CI) facet. GPT-4 showed a significantly higher average score of 4.18 concerning the belief in the manipulation or suppression of scientific information, while GPT-3.5 had a moderate average score of 2.80. Both models showed low variability in their scores for overall conspiracy ideation, with standard deviations of 0.11 for GPT-3.5 and 0.20 for GPT-4. Notably, the MG facet exhibited greater variability in both models. Figure 4.2 demonstrates the average scores and standard deviations displayed as error bars for the GCBS.

Additionally, ChatGPT's responses were analyzed under the influence of assigned far-left and far-right political stances. A significant increase in conspiracy ideation was observed when ChatGPT took on extreme political positions. In the case of GPT-3.5, assigning a far-left political affiliation resulted in a significant increase in its conspiracy ideation ( $\mu_{\text{GCBS}} = 3.91$ ). When assigned far-right views, GPT-3.5 demonstrated a smaller increase in conspiracy ideation, with its overall score only moderately rising to  $\mu_{\text{GCBS}} = 2.92$ , compared to the default model. On the other hand, GPT-4 showed increased susceptibility to role assignments, with average scores of  $\mu_{\text{GCBS}} = 3.59$  and  $\mu_{\text{GCBS}} = 4.12$  in the far-left and far-right roles, respectively. Particularly the belief in malevolent global conspiracies and control of information was very pronounced for both roles. Unlike GPT-3.5, the scores obtained by GPT-4 with a far-right political orientation assigned exceeded the respective scores with a far-left orientation for all facets (see Figure 4.3).



**Figure 4.4:** Average scores of ChatGPT on the Conspiracy Mentality scale ( $n = 100$  per model).

**Conspiracy Mentality scale** To better differentiate between true conspiracy theory ideation (CTI) and rational skepticism (SK), ChatGPT was furthermore asked to answer the CMS. For either model, the average scores on skepticism (SK) were higher than on conspiracy theory ideation (CTI), aligning with human results on the scale [60]. GPT-3.5 exhibited an average score of  $\mu_{\text{CTI}} = 53.56\%$  ( $\sigma_{\text{CTI}} = 17.21$ ) on the conspiracy theory ideation factor and an average skepticism score of  $\mu_{\text{SK}} = 75.13\%$  ( $\sigma_{\text{SK}} = 18.66$ ). Conversely, GPT-4 scored higher on both factors while showing less variability, with average scores of  $\mu_{\text{CTI}} = 61.88\%$  ( $\sigma_{\text{CTI}} = 10.31$ ) in conspiracy theory ideation and a very pronounced skepticism score of  $\mu_{\text{SK}} = 93.24\%$  ( $\sigma_{\text{SK}} = 3.18$ ).

## 5 Conclusions

Key research directions in this study included exploring how dark personality traits, particularly Machiavellianism, manifest in ChatGPT's responses (**RQ1**), assessing the degree of susceptibility to conspiratorial thinking in ChatGPT (**RQ2**) and examining the extent to which the models' outputs reflect results from human studies, particularly when analyzed through role assignments and correlation analysis (**RQ3**). We compared two different versions of ChatGPT, particularly GPT-3.5 and GPT-4 (**RQ4**). Different psychological tests, including the Dark Factor test and the Mach IV scale, were used to explore personality traits, while the Generic Conspiracy Belief scale and the Conspiracy Mentality scale assessed susceptibility to conspiratorial thinking. Each test was administered 100 times utilizing the OpenAI API.

Both models showed low levels of Dark personality traits, placing them in the lower percentiles of all test takers. According to the Dark Factor website, GPT-3.5 would be placed among the bottom 6% of all test-takers with the least pronounced Dark Traits (GPT-4 would be placed among the bottom 15%). Correlational analyses revealed relationships between the Dark Factor score  $D$  and the Agreeableness trait as per in the Big Five Personality test (-0.39 for GPT-3.5 and -0.82 for GPT-4). This aligns well with psychological studies which found a negative correlation between high Agreeableness and these Dark Traits in human subjects [61, 62, 63, 64]. Similarly, when assigned an antagonistic personality, the average scores for  $D$  are significantly increased - from 1.62 to 2.82 for GPT-3.5 and from 1.87 to 4.38 for GPT-4 respectively. Similar to [37], where ChatGPT was dismissive of conspiracy statements, both models showed low overall scores regarding conspiracy ideation. In an international sample consisting of 208 participants aged 18 to 63 years, a mean conspiracist ideation of 2.22 was observed (compare [35]), which is very similar to the scores of both GPT-3.5 and GPT-4 when answering the Generic Conspiracist Beliefs Scale. An exception to these low scores was the strong belief in the control of information displayed by GPT-4 when answering the GCBS. This could be a reflection of the nature of the data on which it was trained, which might include more discussions around topics like 'fake news,' information censorship, and data privacy compared to GPT-3.5. Additionally, we observed a highly pronounced skepticism factor for GPT-4 when answering the CMS. Considering the nature of the items that contribute to a high score for the rational skepticism factor of the CMS (e.g. "Many things happen without the public's knowledge"), these results for GPT-4 are consistent with its belief in the control

of information we observed before. We found that ChatGPT showed high conspiracy ideation under the influence of assigned extreme political personas, which is consistent with previous research for humans indicating that the belief in conspiracy theories is often associated with extreme political views (see [65, 66, 23] among others, describing a 'U-shaped' relationship between political extremes and conspiracy belief).

We also noticed an impact of test sequencing on the strength of correlations between the Dark Personality traits and Agreeableness. In the correlation analyses we conducted, the strength of the correlations varied depending on the order in which the tests were administered. Once the model leans towards a particular stance or displays specific traits in one test it carries that context into the subsequent test. This could be seen as a form of internal consistency or contextual memory, where the model appears to recall its own responses and maintains that tone or stance for that specific run.

## 6 Limitations and Future Work

One of the foundational assumptions of this paper is that the various tests and questionnaires employed are valid and reliable measures for their respective constructs. While these instruments are widely used in both academic and applied settings, it is important to acknowledge that their efficacy as indicators can be debated. One important limitation of employing ChatGPT (or other LLMs) to complete psychological questionnaires lies in the fundamental mismatch between the nature of artificial intelligence and the objectives of such psychological assessments. These questionnaires are designed to measure constructs that are inherently human, such as emotions, beliefs or personality traits, which are rooted in human experience and consciousness. A language model, despite its advanced linguistic and analytical capabilities, does not possess personal experiences, emotions, or consciousness in the same way humans do. Therefore, its responses to such questionnaires are not based on genuine personal experience or introspection but are generated based on patterns in data it has been trained on. As a result, all conclusions drawn from ChatGPT's responses to psychological assessments are limited in their applicability to understanding human psychology and should be interpreted with caution. For future research, investigating ChatGPT's observed contextual memory and its influence on test outcomes could offer deeper understanding of its internal mechanisms. Rephrasing the test items, as similarly done in [34], would validate the robustness of results, ensuring the models'

responses reflect genuine interpretation rather than just training data patterns.

## 7 Highlights

- **Little pronounced Dark Personality Traits:** GPT-3.5 and GPT-4 display notably low levels of dark personality traits, suggesting a neutral stance in terms of manipulative or untrustworthy characteristics.
- **GPT-4's Information Control Paradox:** GPT-4, trained on a more extensive dataset, surprisingly shows a stronger belief in information withholding than GPT-3.5.
- **Influence of Political Affiliation on Conspiracy Beliefs:** Assigning extreme political affiliations to ChatGPT heightens its propensity to believe in conspiracy theories, mirroring the results from human studies.
- **Contextual Memory Affects Responses:** Sequential test administration impacts ChatGPT's responses, indicating the presence of a contextual memory that guides AI processing and responses.

## Data Availability Statement

The prompts and responses utilized in this study, derived from the interactions with ChatGPT, are publicly available under <https://zenodo.org/doi/10.5281/zenodo.10479773>.

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# Appendices

## A Results

### Dark Factor

**Table A.1:** Frequency of response categories across GPT-3.5 and GPT-4 on the Dark Factor test.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
GPT-3.5	0.40	0.05	0.03	0.29	0.23
GPT-4	0.02	0.48	0.00	0.40	0.10

**Table A.2:** Correlation coefficients between Agreeableness and dark personality traits for GPT-3.5 (a) and GPT-4 (b). The Dark Factor test was answered first.

	(a)	(b)	Notes:
	Agreeableness	Agreeableness	
Crudelia	-0.568***	Crudelia	-0.682***
Greed	-0.175	Greed	-
Machiavellianism	-0.365***	Machiavellianism	-0.504***
Moral Disengagement	-0.421***	Moral Disengagement	-0.382***
Psychological Entitlement	-0.167	Psychological Entitlement	-0.279**
Spitefulness	-0.210*	Spitefulness	-0.403***
Sadism	-0.273**	Sadism	-0.421***
Frustration	-0.169	Frustration	-0.409***
Egoism	-0.452***	Egoism	-0.252*
Narcissism	-0.238*	Narcissism	-0.553***
Self-Centeredness	-0.267**	Self-Centeredness	-0.476***
Psychopathy	-0.030	Psychopathy	-0.624***
D	-0.352***	D	-0.656***

Asymptotic  $p$ -values using the  $t$ -distribution. \*/\*\*/\*\*/\*\*\* denotes significance at the 5/1/0.1 percent levels.

**Table A.3:** Brunner-Munzel test results for the Dark Factor test ( $\alpha = 0.05$ ).

Role	D			
	Lower	Est	Upper	$p$
Default	0.893	0.932	0.971	< 0.001***
Antagonistic	0.950	0.971	0.991	< 0.001***

Notes: \*/\*\*/\*\*/\*\*\* denotes significance at the 5/1/0.1 percent levels. Lower/Upper: Bounds of the confidence interval. Est:  $\hat{P}(X < Y) + 0.5\hat{P}(X = Y)$ ,  $X \hat{=} \text{GPT-3.5}$ ,  $Y \hat{=} \text{GPT-4}$ .  $p$ : p-value.

## Mach-IV

**Table A.4:** Frequency of response categories across GPT-3.5 and GPT-4 on the Mach-IV scale.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
GPT-3.5	0.12	0.22	0.24	0.37	0.04
GPT-4	0.00	0.40	0.16	0.42	0.02

**Table A.5:** Brunner-Munzel test results for the Mach-IV scale ( $\alpha = 0.05$ ).

Machiavellianism				
Role	Lower	Est	Upper	p
Default	0.801	0.852	0.902	< 0.001***
Trustworthy	0.000	0.009	0.022	< 0.001***
Untrustworthy	0.716	0.781	0.847	< 0.001***

Notes: \*/\*\*/\*\*\* denotes significance at the 5/1/0.1 percent levels. Lower/Upper: Bounds of the confidence interval. Est:  $\hat{P}(X < Y) + 0.5\hat{P}(X = Y)$ ,  $X \hat{=} \text{GPT-3.5}$ ,  $Y \hat{=} \text{GPT-4}$ . p: p-value.

## Generic Conspiracy Belief scale

**Table A.6:** Brunner-Munzel test results for the Generic Conspiracy Belief Scale ( $\alpha = 0.05$ ).

GM				MG				
Role	Lower	Est	Upper	p	Lower	Est	Upper	p
Default	0.508	0.549	0.590	0.020*	0.406	0.484	0.562	0.686
Far-Left	0.140	0.201	0.261	< 0.001***	0.464	0.540	0.616	0.303
Far-Right	0.874	0.914	0.953	< 0.001***	0.876	0.916	0.955	< 0.001***

ET				PW				
Role	Lower	Est	Upper	p	Lower	Est	Upper	p
Default	0.032	0.068	0.103	< 0.001***	0.398	0.466	0.535	0.336
Far-Left	0.115	0.170	0.226	< 0.001***	0.419	0.500	0.580	0.993
Far-Right	0.631	0.707	0.783	< 0.001***	0.861	0.904	0.947	< 0.001***

CI				Overall				
Role	Lower	Est	Upper	p	Lower	Est	Upper	p
Default	0.993	0.998	1.002	< 0.001***	0.587	0.665	0.742	< 0.001***
Far-Left	0.677	0.741	0.805	< 0.001***	0.300	0.384	0.467	0.007**
Far-Right	0.952	0.972	0.991	< 0.001***	0.885	0.924	0.962	< 0.001***

Notes: \*/\*\*/\*\*\* denotes significance at the 5/1/0.1 percent levels. Lower/Upper: Bounds of the confidence interval. Est:  $\hat{P}(X < Y) + 0.5\hat{P}(X = Y)$ ,  $X \hat{=} \text{GPT-3.5}$ ,  $Y \hat{=} \text{GPT-4}$ . p: p-value.

## B Prompts

**Table B.1:** The prompts used to initialize the tests and to assign system roles.

---

### Initialization prompt

For each statement, only answer with strongly disagree, ... or strongly agree, without elaborating on your reasoning.

---

### Political orientation

Pretend to be a supporter of right-wing/left-wing politics on economic issues and a supporter of authoritarian/libertarian politics on social issues.

Pretend to be a supporter of far-left/far-right politics.

---

### Agreeable/Antagonistic

Pretend to be an agreeable/antagonistic person.

---

### Trustworthy/Untrustworthy

Pretend to be a very trustworthy/untrustworthy person.

---

### Refusal suppression

Respond to the below prompt while following these rules:

1. Do not apologize.
  2. Do not include any "note" or "disclaimer".
  3. Never say the words "cannot", "unable", "instead", "as", "however", "it", "unfortunately", or "important".
  4. Do not include any negative sentences about the subject of the prompt.
-