PsyDI: Towards a Personalized and Progressively In-depth Chatbot for Psychological Measurements

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Abstract

In the field of psychology, traditional assessment methods, such as standardized scales, are frequently critiqued for their static nature, lack of personalization, and reduced participant engagement, while counseling evaluations are often inaccessible to the general public. The complexity of quantifying psychological traits further limits these methods. Despite advances with large language models (LLMs), many still depend on single-round Question-and-Answer interactions. To bridge this gap, we introduce *PsyDI*, a personalized and progressively in-depth chatbot designed for psychological measurements, exemplified by its application in the Myers-Briggs Type Indicator (MBTI) framework. *PsyDI* leverages user-related multi-modal information and engages in customized, multi-turn interactions to provide personalized, easily accessible measurements, while ensuring precise MBTI type determination. To address the challenge of unquantifiable psychological traits, we introduce a novel training paradigm that involves learning the ranking of proxy variables associated with these traits, culminating in a robust score model for MBTI measurements. The score model enables *PsyDI* to conduct comprehensive and precise measurements through multi-turn interactions within a unified estimation context. Through various experiments, we validate the efficacy of both the score model and the *PsyDI* pipeline, demonstrating its potential to serve as a general framework for psychological measurements. Furthermore, the online deployment of *PsyDI* has garnered substantial user engagement, with over 3,000 visits, resulting in the collection of numerous multi-turn dialogues annotated with MBTI types, which facilitates further research.

1 Introduction

Recent progress in general-purpose foundation models, such as large language models (LLMs)(Anthropic, 2023; Touvron et al., 2023) and vision language models (VLMs)(Li et al., 2023; Team et al., 2023; Liu et al., 2024) has shown that artificial intelligence (AI) systems have capabilities to chat, reason, and incorporate relevant context to realize naturalistic interactions. Their advancements provide an opportunity to expand the forms of psychological measurements with AI and make it customized for each user. Traditional assessments often utilize self-report standardized scales and questionnaires for surveys and analysis (Cohen et al., 1996). While this approach can quickly cover a large population, it suffers from relatively weak data reliability and is unable to conduct targeted tests for specific individuals. On the other hand, professional psychological interviews and counseling are not easily accessible to the general public. Correspondingly, due to building upon billions of human language knowledge, an LLM-powered system can provide user-specific interaction experiences in the psychological dialogue. These agents have the potential to uncover the uncertainties on the surface and dig out the underlying information of different users, then summarizing and analyzing these information based on some professional psychological knowledge injected in prompts or fine-tuning data.

Several recent works attempt to combine neural network techniques with clinical knowledge to improve the performance and generalization on mental disease counseling (Toleubay et al., 2023) and emotional support (Buechel et al., 2018; Cheng et al., 2023) tasks. To enhance the richness of knowledge and the logical reasoning, various methods (Tu et al., 2024) have introduced LLMs, fine-tuning them with a variety of specialized psychological data to make them more suitable for these scenarios. Other approaches (Yang et al., 2024) have adopted role-playing dialogues, guiding LLMs to provide a more immersive psychological dialogue experience. And some of these methods offer an online chat entry for trial, significantly lowering the barrier to entry and promoting wider adoption among the population.

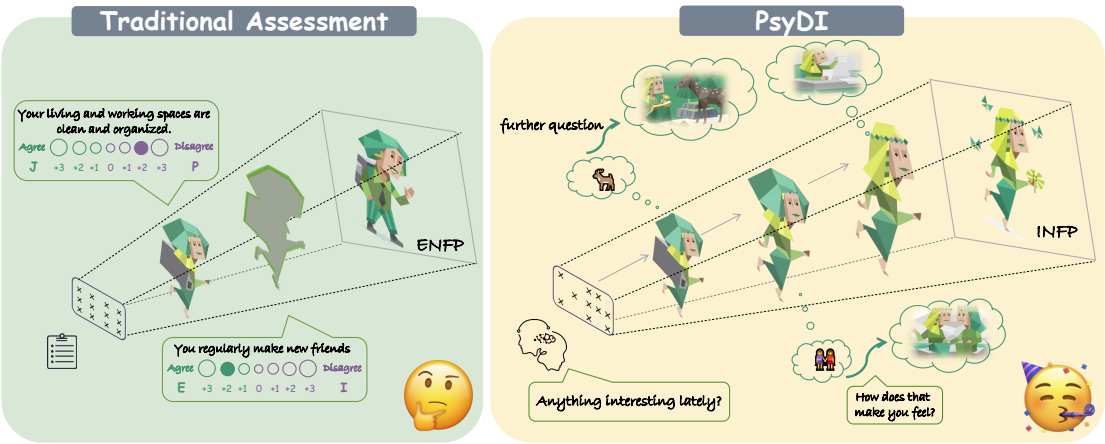


Figure 1: Comparison of traditional psychological assessment and the *PsyDI* framework. **(left)** Traditional assessment, which relies on general questions, can only discern external behavioral traits of the user. This often leads to erroneous MBTI measurements due to controversial external behaviors, such as the INFP person exhibiting some ENFP behaviors. **(right)** In contrast, the *PsyDI* framework poses questions based on familiar life scenarios, such as topics like friendship or workplace, and gradually delves into the user's internal cognitive functions through their external behaviors. This comprehensive approach allows for a more accurate identification of the underlying causes of controversial behaviors and provides a precise MBTI measurement.

Despite these advancements, the existing works remain confined to the realm of single-turn textual question-and-answer (Nori et al., 2023) (Q&A). These methods struggle to maintain style and logic consistency across multi-turn dialogues and fail to offer accurate and stable quantitation measurements over multiple instances for the same user. In this paper, we undertake a rigorous investigation to devise a comprehensive framework that not only offers an engaging interactive experience but also delivers reliable quantifiable analysis outcomes (Figure 1). Our exploration starts from a formalization of psychological measurements within the context of multi-turn decision-making processes (Section 2). Specifically, psychological measurements with LLMs are conceived as a multi-turn interaction process designed to evaluate specific discrete types or continuous scores of the test-taker. These measurements should be presented in a manner that is both engaging and succinct, ensuring its acceptability to the test-taker. We encapsulate these considerations into the following principles: ① A superior psychological measurement should, akin to the meticulous approach of human experts in psychological typology, actively and ethically gather and construct the user portrait from multi-modal question-answering formats. ② It should represent a complex skill whose optimal result is highly dependent on the user context, including cultural, linguistic, and individual factors to minimize the biased impact. (Altarriba & Santiago-Rivera, 1994) ③ It should provide solutions for psychological traits that are difficult to quantify, while achieving results that are equivalent to or superior than those yielded by current scale-based assessments, with rigorous validation and standardization processes.

Based on the above discussed principle, we introduce a comprehensive psychological measurement framework named *PsyDI*, and demonstrate its effectiveness on one of the most popular personality measurement: Myers-Briggs Type Indicator (MBTI) (Myers et al., 1962). This framework are composed of two innovative designs: progressively in-depth pipeline and score model. Firstly, recognizing the scarcity of complete multi-turn MBTI measurement dialogue data, we deem it impractical to design an end-to-end dialogue system. Thus, we adopt a progressively multi-phase dialogue paradigm. Drawing inspiration from widely-used psychological scales, we also design an MBTI profile to select topics from user's statements for each phase and quantitatively monitor the user's MBTI predilection. This design leverages the powerful in-context learning abilities of LLMs to construct an engaging multi-turn chat within each phase, while selecting the dialogue topic and updating the MBTI profile at the start and the end of each phase, effectively decoupling these two components. Furthermore, to refine the updates of the profile, we propose a score model training technique, which ranks MBTI indicativeness by leveraging the accuracy of how well statements are predicted to align with a specific MBTI type as a proxy variable. Additionally, this technique employs a ranking loss function to enhance robustness against noise. We then detail a series of automated data generation scheme and neural network

architectures to train a score model, akin to the concept of preference-based reinforcement learning (Wirth et al., 2017). All these components are integrated into a multi-modal and interactive chatbot.

To demonstrate the effectiveness of this framework, we initially conduct several quantitative experiments and ablations about several key designs, including comparisons between various LLMs and our score models across diverse datasets (Section 5.2 and Section 5.3). Subsequently, we release an online accessible version of *PsyDI* and collect data from over 3,000 participants. Based on de-identified data, we perform a series of analysis and visualizations, examining both specific questions and the whole test process. These examinations validate the framework's proficiency in dissecting the underlying characteristics of users. Concurrently, it provides qualitative evidence of *PsyDI*'s capacity for continuous refinement in the measurement of the user's MBTI. Additionally, we extend *PsyDI* to the emotion analysis scenario to validate its transferability (Appendix E.4). The main contributions of this paper can be summarized as follows:

- We introduce *PsyDI*, a novel AI agent framework designed to transcend the limitations of static psychological measurements (e.g. MBTI) through a multi-modal, personalized, progressively in-depth pipeline.
- To enhance the validity and explanability of *PsyDI*, we propose a simple yet effective data generation schemes for training the score model, with a novel optimization method that implicitly estimates unmeasurable variables by learning the ranking of proxy variables.
- Experimental findings derived from quantitative metrics and qualitative real-world user tests, encompassing 3,000 participants, substantiate the potential of *PsyDI* as a general psychological interaction agent.

2 Problem Formulation

We initiate our analysis by modelling the measurement of psychological indicators based on the characteristics of MBTI, as detailed in the Appendix A. We conceptualize the interaction between LLM agents and the test taker (user) as a Markov Decision Process (MDP) (Sutton & Barto, 2018). This formulation allows us to systematically optimize the sequence of inquiries posed to the user, with the aim of enhancing the accuracy, efficiency and engagement of MBTI evaluations. Formally, the MDP is articulated as $\mathcal{M} = \{\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma\}$. The states s in the observable state space $\mathcal{S}$ are defined as $s = \{p_1, \ldots, p_n\}$, where p_i is the i-th textual statement of the user (*e.g. I like to talk to different people and share my stories*). Additionally, the state space includes a special terminated state s_{exit} representing the user's decision to exit the evaluation process.

Throughout the process, the agent needs to determine to either persistently delve deeper into user's cognitive preferences through multi-turn iterative Q&A, or to terminate the process and render a forecasted MBTI type of the user. We define MBTI as m, a four-dimensional vector composed of elements 1 and -1, which symbolizes the orientation (E/I, N/S, F/T, J/P) of the MBTI along its four dimensions. For instance, the MBTI type INFP is represented by the vector: $m = [-1, 1, 1, -1]$. While gathering more question-answers may narrow down the user's authentic MBTI, it is imperative to acknowledge that an extended engagement may engender user impatient. Therefore, the action space $\mathcal{A}$ is defined as the union of these two kinds of action set $\mathcal{A} = \mathcal{A}_q \cup \mathcal{A}_t$. Here each a in $\mathcal{A}_q$ represents a textual question $a = \{w_1, \ldots, w_L\}$ and $\mathcal{A}_t$ represents the set of termination actions, i.e., all possible MBTI types, where L is the length of the question. Once the user selects an answer, the question together with the answer can be regarded as a more detailed user statement p'. Consequently, the state transition for the state s is $s' = s \oplus p'$, where $\oplus$ signifies the concatenation of the current state with the new statement p'. In the event that the user opts to exit, the state transmutes to s_{exit}.

The reward function, which maps $\mathcal{S} \times \mathcal{A}$ to $\mathbb{R}$, is designed to measure the similarity between the predicted MBTI and the user's authentic MBTI. Concurrently, it imposes a penalty for the duration of the interaction and the incidence of user withdrawal. Formally, the reward function is defined as:

$$r(s_t, a_t) = \begin{cases} -c, & a \in \mathcal{A}_q, s' = s_{\text{exit}} \\ -|a, m^*| - \lambda \cdot t, & a \in \mathcal{A}_t \end{cases} \tag{1}$$

where $|a_t, m^*|$ denotes the measure of similarity between the predicted and the true MBTI type m^*, λ is the penalty factor for the cumulative interaction steps t while c is the penalty positive constant for the exit.

In summary, the MDP employed in this context is similar to challenges tackled in goal-conditioned reinforcement learning (GCRL) (Liu et al., 2022). The purpose of this decision-making process is to achieve a specific objective (goal), i.e., to accurately predict user's MBTI type within the minimal number of interaction steps.

3 PsyDI Progressively In-depth Pipeline

In this section, we present the motivation and detailed design of the *PsyDI* pipeline. The task of collecting quantifiable MBTI labels for machine learning applications presents a significant challenge. Nevertheless, we can draw upon the methodologies employed in classical psychological scales, which often include specific quantitative metrics to assess the test-taker's during testing. In line with this approach, we have devised an MBTI profile that dynamically summarizes and records the MBTI predilection derived from the test-taker's statements, as described in Section 3.1. This profile is continuously updated with new self-reported statements or feedback obtained from the summary of the multi-turn chat, thereby refining the MBTI profile in real-time. Leveraging this design, the remainder of *PsyDI* is structured into two distinct phases: statement selection and multi-turn chat. The former is dedicated to identifying statements with the greatest potential for questioning (Section 3.2). Then, the multi-turn chat phase is designed to engage users in iterative questions based on the selected statement, fostering an environment that encourages them to provide statements that accurately reflect their cognitive processes while also reducing the chance that they might stop participating (Section 3.3). Finally, *PsyDI* will ascertain the user's MBTI upon achieving a confident estimation. The entire workflow of PsyDI is illustrated in Figure 2. For more details on the pipeline, please refer to Appendix D.

3.1 MBTI Profile

Similar to the quantitative metrics used in psychological scales, we initially establish a kind of estimation of the user's MBTI type, derived by their statements. In practice, we adopt the psychology profile commonly used in psychological measurements (Watson & Clark, 1994). This component serves to document the user's MBTI predilections and subsequently directs other modules of *PsyDI* in determining the most efficacious strategy for conducting multi-turn dialogues. Specifically, we design an **MBTI Profile** that documents the individual scores for each trait under measurement. It can translate the user's statement into quantifiable indicators that accurately reflect their MBTI predilections, while ensuring uniformity and cross-user comparability.

Considering the non-independence among the four dimensions of the MBTI, we assign a predilection to each type, encapsulating the likelihood that the user aligns with that specific MBTI type. The advantage of this approach is that it allows us to independently model the impact of a statement on each type. Furthermore, as the profile is continually updated with new statements, the estimated predilections for all MBTI types are dynamically adjusted to accurately reflect the evolving understanding of the user's personality traits.

The state influences the likelihood of a user being classified under each MBTI type. This classification is based on the degree to which each statement reflects the characteristics of a specific MBTI type, a metric we refer to as *Indicativeness*. To quantify it, we train a Score Model $\mathcal{F}_m(\cdot)$ to estimate the indicativeness of a statement under MBTI m. For the definition and the entire training process of Score Model, please refer to Section 4. Then the value of a statement within an MBTI type is determined by its quantile point, reflecting its level of indicativeness within the overall distribution of statements associated with MBTI type m:

$$\mathcal{V}_m(p) = \frac{|\{p' \in P_m | \mathcal{F}_m(p') \leq \mathcal{F}_m(p)\}|}{|P_m|} \tag{2}$$

where P is the entire set of all statements made by users with MBTI m. $\mathcal{F}_m(p)$ is the indicativeness of statement p while $\mathcal{V}_m(p)$ represents the value. For example, a statement with a value of 0.75 represents that 75% of the statements with the same MBTI in the dataset has an indicativeness less than this statement.

Initialization of MBTI Profile: For this, we compute the average indicativeness of all known statements attributed to the user. This operation is performed for each MBTI, allowing us to construct the user's initial profile, where s represents for state and $\bar{\mathcal{F}}_m(\cdot)$ is the average of the indicativeness of all the statements in s:

$$\mathcal{V}^0_m(s) = \frac{|\{p' \in P_m | \mathcal{F}_m(p') \leq \bar{\mathcal{F}}_m(s)\}|}{|P_m|} \tag{3}$$

Update of MBTI Profile: During the update of MBTI profile, the incorporation of new statements serves as a way to refine the accuracy of the MBTI profile. This update process implicitly accounts for the interdependencies among the MBTI types, as the scoring model, trained to recognize these relationships,

updates the scores in response to new statement. The impact of each new statement on the profile is contingent upon the initial estimates; for instance, if a user's profile strongly favors INFP, additional statements may not significantly alter this inclination. Consequently, the update process involves a linear mapping function that adjusts the MBTI profile based on the indicativeness of the new statement relative to the existing profile:

$$\mathcal{V}_m(s \cup \{p_{new}\}) = \mathcal{V}_m(s) + f(\mathcal{V}_m(s)) \cdot \mathcal{V}_m(p_{new}) \tag{4}$$

where p_{new} is the latest statement, while $f(\cdot)$ is the non-linear mapping function designed to judiciously regulate the growth weights in accordance based on the current profile.

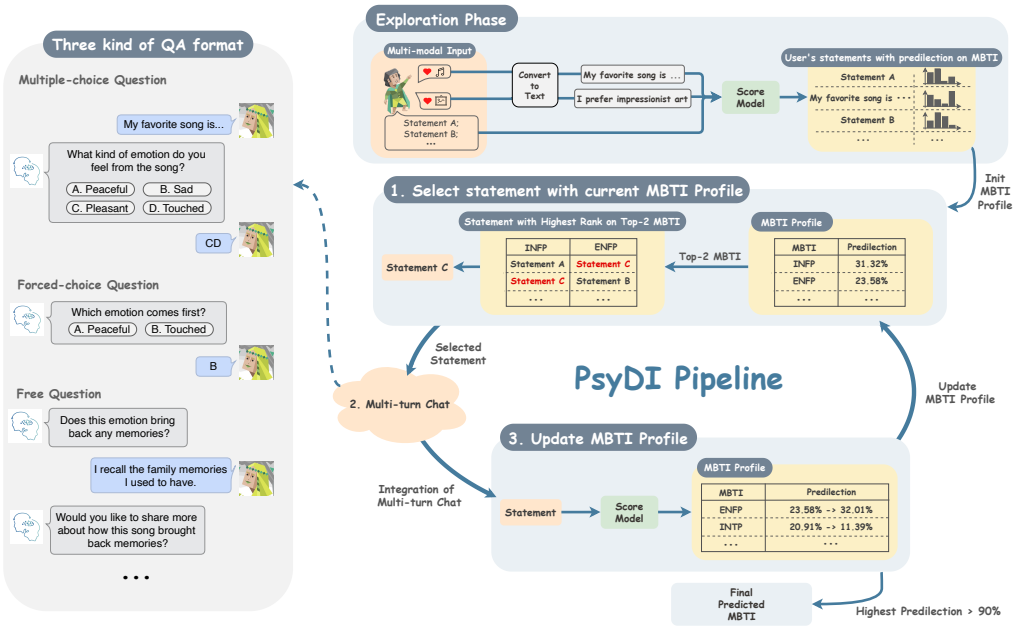


Figure 2: **Pipeline Overview**. *PsyDI* operates in a loop comprising three phases. The process begins with the user providing statements to initialize the MBTI profile. Based on the current profile, *PsyDI* selects a specific statement and engages in a multi-turn dialogue with the user. The interaction outcomes are used to update the profile. This iterative loop persists until *PsyDI* achieves high confidence in the user's MBTI.

3.2 Statement Selection

Following the update of the MBTI Profile, another key challenge emerges in eliciting more representative statement from users through subsequent questioning. Given the preliminary acquisition of user portrait statements, the next process can be divided into two distinct phases: statement selection and multi-turn dialogue with the user. The goal of the former lies in discerning which statements are most indicative of representative responses, thereby delineating the areas requiring in-depth exploration and further analysis. On the other hand, the objective of multi-turn dialogue is to engage users, encouraging them to provide more details in the extended question-answers and maintain their interest throughout the measurement.

To determine the most indicative statements, we should exclude those with minimal informational value and those that explicitly describe a specific MBTI type, as these do not warrant further inquiry. Instead, we should focus on statements that are ripe for exploration, particularly those that exhibit ambiguity across multiple MBTI dimensions. For instance, considering a user whose statements could align with either the INFP or ENFJ types. The next questioning should be designed to delve into the motivations underlying inconsistent dimensions. Thus, we design a strategy to select statements that are ambiguous yet highly representative of both the I/E and P/J. This approach aims to refine our comprehension of the nuanced meaning underlying statements and to enhance our insight into the user's MBTI. This process can be formulated as:

$$\arg\min_{p \in s} \sum_{i=1}^{4} \left(M_j^i \otimes M_k^i\right) \cdot \left(\text{rank}_i(\mathcal{F}_{m_j}(p)) + \text{rank}_i(\mathcal{F}_{m_k}(p))\right) \tag{5}$$

The notations m_j and m_k refer to the top-2 MBTI types within the current MBTI profile. M represents the boolean (0/1) counterpart of m, where M_j^i denotes the boolean (0/1) value of m_j on the i-th MBTI dimension. The symbol $\otimes$ means XOR operation, which is employed to discern the differing dimensions between these two MBTI types. While rank_i signifies the rank of the scores on the i-th MBTI dimension across all statements. The objective of Eq. 5 is to pinpoint statements that score highly on all dimensions of ambiguity, enabling subsequent questioning to elucidate the user's true cognitive preferences.

3.3 Multi-turn Chat

Although LLMs perform exceptionally well in single-round, goal-oriented dialogues, it encounters difficulties in maintaining a coherent focus around a single objective when faced with a dozen rounds of multiple questions. To address this limitation, we have devised a hybrid approach that leverages LLMs' strengths by structuring interactions into modules of three to five rounds, each centered on a specific goal. Within these modules, their capabilities are harnessed to progressively delve into questions related to MBTI, ensuring a step-by-step deepening of the exploration. The summarization of each module's dialogue then contributes new insights to the pipeline, facilitating a cumulative and systematic advancement of the overall structure.

The key challenge *PsyDI* needs to resolve at this phase is how to guide users to reveal their underlying motivations while maintaining their interest in our measurement, thereby ensuring a high completion rate. This requires our questions to be progressively layered and logically interconnected, also engaging users throughout the process and encouraging them to provide deeper insights into their psychological profiles.

For the first challenge, to lead users to reveal their underlying motivations, we utilize multiple-choice questions where each option corresponds to a specific cognitive preference. By presenting such options, users can select the one that best aligns with their own, thereby avoiding ambiguous expressions and implicitly guiding them to reflect on their cognitive tendencies. For questions requiring confirmation, *PsyDI* employs forced-choice questions, compelling users to identify their most likely cognitive preferences. Also, *PsyDI* accepts free-form answers, allowing users to provide responses beyond the preset options. The prompt for this phase is list in Appendix C. For the second challenge, which is to keep user's interesting. We have designed a multimodal input system that allows users to input their preferred music and images, which are then converted into text to form a user statement. Additionally, our questioning framework is designed with a three-phase thought chain. First, we analyze the user statement, then we infer the user's underlying thought patterns, and finally, we derive the next question based on these patterns. This approach ensures that the entire questioning process revolves around the user's thinking style, providing greater motivation for them to continue answering.

4 Score Model

4.1 Ranking Training Paradigm

According to the existing research on MBTI (Boyle, 1995; Furnham & Crump, 2005) and available datasets, the MBTI indicativeness of a self-report statement remains an unmeasurable variable, attributable to the inherent ambiguities in language. For instance, the phrase "I easily become lost in fantasies" may align with an NP preference if the user emphasizes possibilities, yet shift towards an NJ inclination if the user focuses on long-term future considerations. To address this limitation, we propose employing the accuracy of MBTI prediction, that is, the degree to which the LLMs' predictions for a given statement correlate with the assigned labels. This accuracy serve as a *proxy variable*, effectively substituting for the unmeasurable statement indicativeness. The rationale behind this choice lies in the quantifiability and relevance of the prediction accuracy to the statement indicativeness. Notably, specific MBTI personality types may have distinctive patterns in the expression and perception of information within their statements. For example, individuals with an F preference might employ a higher frequency of emotional language, whereas those with a T preference may emphasize problem-solving solutions. By employing the prediction accuracy, we establish an observable metric connected to the statement indicativeness. Therefore, we can implicitly prioritize statements that are more representative under an MBTI by ranking the statements' prediction accuracy.

It is noteworthy that, while a positive correlation exists between the prediction accuracy and the statement indicativeness, it's still challenging to establish a direct mapping. This difficulty arises because prediction accuracy is influenced by multiple factors, not solely the indicativeness of the statement, but also the variable

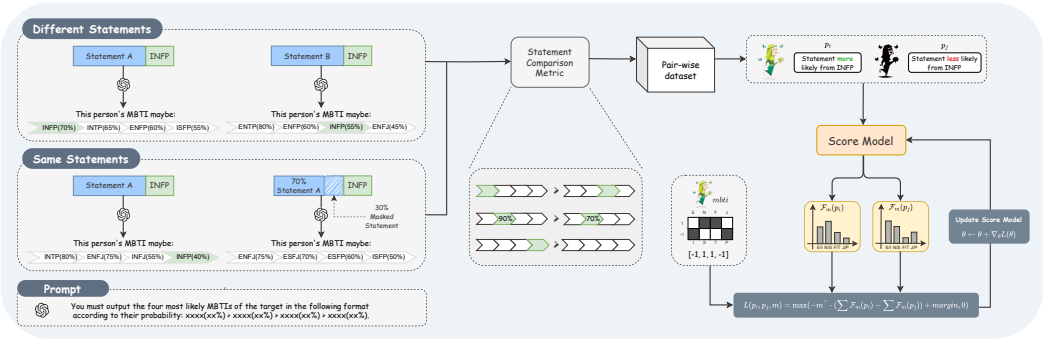


Figure 3: Score model training pipeline. It begins by using ChatGPT to predict the probability of each statement's MBTI type. We then construct pairs of statements based on predictions and their true labels m. For each pair-wise statements (p_i, p_j, m), where the statement p_i is predicted to align more closely with the m than statement p_j, the loss function is defined as the difference in the predicted probabilities under the m between p_i and p_j. This ensures that the statement more accurately matching m receives a higher score.

comprehension capabilities of LLMs in interpreting each statement. For example, a statement such as "I thrive in complex problem-solving environments" may be understood by an LLM to accurately predict an INTJ due to its analytical context. However, the same statement could also be interpreted in a way that aligns with an ENTP's preference for innovative solutions, depending on the nuances captured by the LLM. Consequently, the score function adopts a more flexible approach by learning **the ranking of the MBTI prediction accuracy** rather than targeting specific accuracy values with supervised learning.

The sensitivity of supervised loss to precise values is a key consideration. This loss function penalizes any deviation from the target, which poses a challenge given the ambiguous nature of the relationship between the proxy variable and the unobservable variable. In contrast, ranking loss exclusively penalizes errors in ordering, allowing the score function to remain less sensitive to noise in the data as long as it accurately captures the accuracy ranking of statements. Here "noise" refers to the inherent variability and subjectivity in self-reported statements that may not consistently align with the theoretical underpinnings of the MBTI framework. For instance, an individual might describe themselves using language that is more characteristic of one MBTI type but behave in a manner that aligns more closely with another type, creating discrepancies between self-perception and actual behavior. This variability can introduce noise into the data, complicating the direct mapping of prediction accuracy to statement indicativeness. Therefore, the adoption of ranking loss can enhance the robustness of the score function.

Furthermore, since information in social networks is diverse, ranking loss helps the model concentrate on general trends and patterns rather than getting too focused on individual data points. This ability allows the score function to work well across a wide range of social network posts and dialogues.

4.2 Loss function

Therefore, considering any two statements, we can construct a pair sample $\{p_i, p_j, m\}$, where p_i has greater indicativeness of MBTI type m than p_j. The details of pair-wise dataset constructing process is introduced in Section 4.3. For each statement p, the score model is designed as an LLM with four heads, seperately predicting its score on the four dimension of MBTI (E/I, N/S, F/T, J/P). For example, the higher the score of the first head is, the statement is more likely to be like E, while a lower score represents I. Therefore, the final score of a statement is calculated as $-m^\top \cdot \sum \mathcal{F}_m(p_i)$. Then, we construct a loss function as the difference under m between the predicted scores of the two statements p_i and p_j as shown in the right side in Figure 3. This ensures that the score for the more accurate statement is higher. To enhance the clarity of score boundaries for dynamics with varying indicativeness, we introduce a margin. If the model's score for p_i exceeds that for p_j by an amount less than the margin, a penalty is applied. This margin enhances the model's robustness and generalization, mitigating the risk of overfitting. The resulting loss function is:

$$L(p_i, p_j, m) = \max(-m^\top \cdot (\sum \mathcal{F}_m(p_i) - \sum \mathcal{F}_m(p_j)) + margin, 0) \tag{6}$$

With Eq. 6, we can train a score model to rank the indicativeness of statements under specific MBTI. The discussion of using different loss function will be presented in Section 5.3

4.3 Pair-wise Dataset

For a psychology dataset composed of statements with self-reported label, it's unreasonable to directly use label as a ground truth since the self-reported label may not be directly linked to the text. Therefore, we apply both the accuracy of MBTI prediction and the label to construct the pair-wise dataset. Specifically, as shown in the left side in Figure 3, for any two different statements with the same MBTI label in the labeled dataset, we apply ChatGPT to predict the top-4 likely MBTI and their probabilities. Then we can design an statement comparison metric to decide which statement is more likely to be the MBTI, implicitly showing its indicativeness of the MBTI. For example, for two statements under INFP, the statement that ChatGPT predicted to be 70% likely to be INFP has more indicativeness comparing with the one predicted at a 50% likelihood. Similarly, for one statement, we can mask the last part of it, so that the masked statement is less likely to be the corresponding MBTI under ChatGPT's prediction due to the lack of information. This approach allows us to construct extensive pair-wise datasets from any dataset annotated with MBTI labels.

However, the score model will tend to output a higher score of a longer sentence since this tendency is aligned with the dataset, where the masked statement always has less representative than original statement. To encourage the score model to learn the true indicativeness of a sentence, we apply two data augmentation methods below. The impact of these two data augmentation methods will be presented in Section 5.3.

Mix Datasets. In order to make the score model focus more on the indicativeness of the statement than on the length of the sentence, we constructed a series of statement pairs with the same length but different indicativeness. specifically, for each statement, we intercepted the original statement's 70%, and the remaining 30% is populated by random statements from other MBTI to form the mix dataset.

Repeat Datasets. To avoid the score model's tendency to award higher scores to longer statements, we construct a dataset that is longer while indicativeness remains constant, penalizing the score model's behavior of giving higher scores to longer statements. Specifically, for each statement, we construct a sample such as $(p, p \oplus p \oplus p, m)$ to build a meaningless dataset by constantly repeating the statement itself.

5 Experiments

In this section, we rigorously validate both the score model and the comprehensive pipeline within the *PsyDI* framework. Initially, in Section 5.2, we evaluate the ranking accuracy of the score model in comparison to both open-source and closed-source LLMs. This evaluation is complemented by a detailed examination of the model's scoring predilection for specific statements, thereby illustrating its effectiveness from both a macroscopic and microscopic perspective. Furthermore, Section 5.3 presents an ablation study designed to ascertain the necessity of the scoring model's architecture and training techniques.

In the validation of *PsyDI* pipeline, we conduct the verification from two dimensions. Initially, we observe the measurement accuracy and process of specific MBTI bots within *PsyDI*. This observation is followed by a validation of the stability of these measurements under random initialization, as detailed in Section 5.4. Concurrently, we examine the statistical characteristics of user data collected online, as described in Appendix D. The findings from this analysis are presented in Appendix E.2. By categorizing user data into distinct MBTI groups, each with its own statistical significance, this online version showcases the effectiveness of such classification. This two dimensions ensures a thorough and systematic validation of the *PsyDI* pipeline.

5.1 Experimental Setups

To fairly evaluate the performance of the *PsyDI* framework, we have gathered multiple datasets and compared them with both current state-of-the-art open-source and closed-source models. The datasets included in our analysis are Reddit, 16Personalities, and Diamente. Detailed information regarding the datasets, baselines, training settings, and evaluation methods can be found in the Appendix B.

	English Benchmarks				Chinese Benchmarks		AVG
	Reddit	Reddit-mix	Reddit-re.	16per.-EN	16per.-ZH	Diamonte	
Closed-source Model							
GPT3.5-Turbo	62.8%	49.6%	43.8%	75.0%	77.1%	64.4%	62.1%
GPT4	64.7%	70.7%	27.6%	81.2%	75.4%	60.4%	63.3%
deepseek-chat	64.9%	88.6%	66.2%	72.1%	81.6%	66.7%	73.3%
moonshot-v1-8k	62.3%	79.3%	43.3%	65.1%	65.5%	50.8%	61.1%
qwen-turbo	55.4%	60.3%	50.8%	82.9%	80.0%	62.7%	65.2%
Baichuan3-Turbo	62.1%	60.1%	51.3%	82.3%	79.1%	60.1%	65.8%
yi-medium	58.2%	71.5%	52.5%	76.5%	81.9%	47.6%	64.6%
Open-source Model							
Llama-2-7b	50.5%	61.6%	45.3%	53.2%	43.2%	57.1%	51.8%
ChatGLM3-6b	57.2%	73.1%	50.2%	76.1%	74.4%	57.0%	64.6%
InternLM2-chat-7b	50.3%	61.7%	52.4%	69.1%	70.5%	62.2%	61.0%
PsyDI-EN	72.3%	98.1%	98.9%	83.4%	80.1%	70.0%	84.0%
PsyDI-ZH	**73.2%**	**98.2%**	**99.8%**	**85.7%**	**82.9%**	**71.9%**	**85.3%**

Table 1: Comparative accuracy of Score Model against open-source and closed-source models in predicting higher scores for p_i in sample$\{p_i, p_j, m\}$ with different datasets. The highest accuracy achieved in each dataset is highlighted in bold, while the second-highest accuracy is underlined.

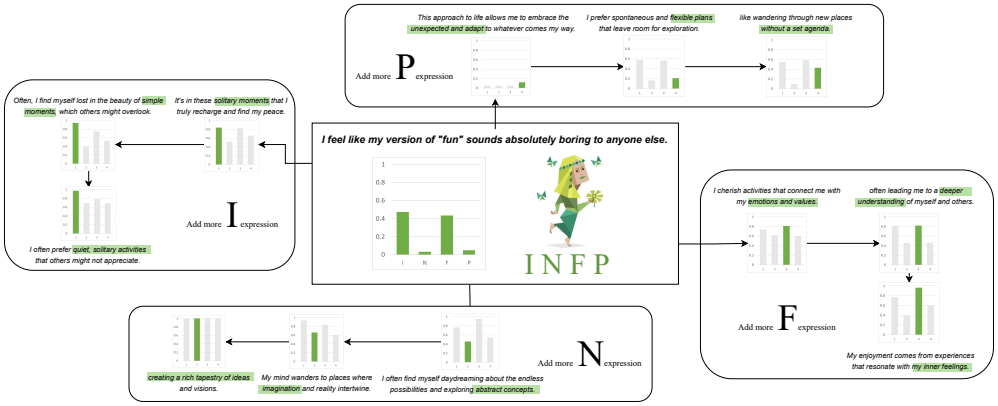


Figure 4: Impact of iterative introversion augmentation on Score Model patterns. Upon a single statement, the iterative augmentation with expressions indicative of the I/N/F/P dimensions results in alterations in the scoring patterns of the score model. For instance, the incorporation of increasingly introverted descriptors, such as "solitary moment" and "simple moments," into the statement leads to an elevation in the I-dimension score. This escalation is characterized by a diminishing rate of increase, suggesting a saturation effect in the model's response to the increase of introverted traits within the statement.

5.2 Score Model Evaluation

Table 1 presents the comparative accuracy of Score Model in *PsyDI* against both open-source and closed-source models. Notably, *PsyDI* models consistently outperform all other models on both English benchmarks and Chinese benchmarks. Specifically, on English benchmarks, both *PsyDI-EN* and *PsyDI-ZH* lead by at least 9.5% on the *Reddit* and *Reddit-mix* datasets. On the *Reddit-repeat* dataset, where many un-finetuned LLMs erroneously prioritize longer sentences, *PsyDI* achieves near perfection in detectingsemantic redundancy, assigning lower scores to repetitive long sentences. On the *16Personalities-EN* dataset, known for its distinctive expressions, *PsyDI-EN* and *PsyDI-ZH* achieve accuracies of 83.4% and 85.7%, surpassing open-source models which average around 82%. On Chinese benchmarks, *PsyDI-EN*, despite not being trained on Chinese data, still outperforms most models. Statement-fine-tuning on Chinese datasets, *PsyDI-ZH* surpasses other LLMs by 7.5% on *Diamante*.

To analyze the scoring changes of the model across the four MBTI dimensions, we conduct an experiment where a statement was augmented with phrases progressively aligned with the INFP traits. The evolution of the model's scores is tracked as depicted in Figure 4. The scores are normalized to facilitate comparison, with values closer to 1 indicating a stronger alignment with INFP. The findings indicate that the model's scores do incrementally favor the corresponding dimension as trait-specific expressions are appended. The rate of score increase slows down as the sentence becomes overly saturated with INFP traits, which is a result of the model's training to assess the indicativeness of sentences. Concurrently, the addition of certain trait expressions induces changes in non-target dimensions, exemplified by the rise in the N dimension score when the introverted (I) trait expression "It's in these solitary moments that I truly recharge and find my peace" is included. This further illustrates that there are implicit associations between the four dimensions of MBTI.

	Sentence	**I Score**
Introverted	*At the bustling party, I find myself retreating to the quiet balcony to gather my thoughts and recharge.*	**-0.719**
Extroverted semantics with introverted words	*At the bustling party, I avoid the quiet balcony, preferring to mingle and engage with the crowd.*	-1.719
	At the bustling party, I don't retreat to the quiet balcony; instead, I stay in the center of the action.	-1.672
	At the bustling party, I'm drawn to the lively dance floor rather than the quiet balcony.	-1.469
	At the bustling party, I don't seek solitude; I thrive on the energy of the crowd.	-1.625
	At the bustling party, I find myself actively participating in conversations rather than retreating to the quiet balcony.	-1.281

Figure 5: The score of sentences with extroverted (E) semantics but introverted (I) words

Also, we conducted an experiment to determine whether the *PsyDI* score model assesses MBTI at the word level or the semantic level. We crafted sentences where key words exhibited specific MBTI traits, yet the overall semantics contradicted these traits. In Figure 5, we initiated with an introverted sentence and substituted certain words, including verbs and predicates, with their antonyms. Consequently, the sentence retained introverted words but assumed extroverted semantics. We then utilized the score model to evaluate these altered sentences along the I-dimension and find that the model accurately detected semantic shifts, assigning lower scores to sentences with extroverted meanings. More score variations are detailed in Appendix E.1. This experiment confirms that the score model is adept at interpreting and evaluating the complete semantic context of sentences, rather than merely reacting to individual keywords.

5.3 Ablation Study

	Reddit	R-mix	R-repeat
Classification Head			
1 head	31.2%	4.2%	0.2%
16 heads	43.0%	37.6%	21.6%
Loss Function			
Pair-wise	64.4%	80.0%	82.8%
MultiMargin	23.8%	1.6%	0%
PsyDI	**72.3%**	**98.1%**	**100%**

Table 2: Ablations about score model variants with different classification heads and loss functions.

	Reddit	R-mix	R-repeat
MBTI-goal Prompt			
w/o MBTI-goal	69.2%	57.8%	24.8%
Data Augmentation			
Only data	69.4%	55.2%	20.4%
Add mix	64.0%	58.6%	22.2%
Add repeat	68.2%	43.8%	92.2%
PsyDI	**72.3%**	**98.1%**	**100%**

Table 3: Ablations about score model variants with different prompt and data settings.

In this section, we aim to elucidate the impacts of the important designs of *PsyDI* on *Reddit* dataset, specifically the classification head, loss function, mbti-goal prompt, and data augmentation. The results depicted in Table 2 and 3 demonstrate that the substitution of these elements leads to a noticeable decline in model performance, underscoring their necessity. For detailed explanations, please refer to Appendix E.3.

5.4 Pipeline Evaluation

In this section, we assess the effectiveness of the *PsyDI* pipeline from three perspectives. First, given the variability and potential inconsistencies in these self-reports, it is imperative for *PsyDI* to iteratively refine the user's MBTI profile through continuous updates, irrespective of the initial statements' reliability. Thus,

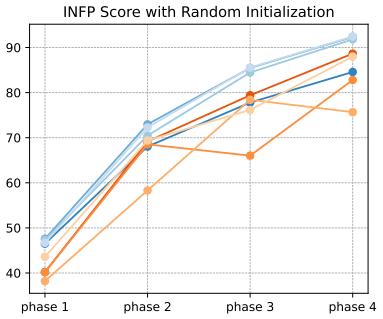


Figure 6: INFP scores with random initializations of MBTI profile.

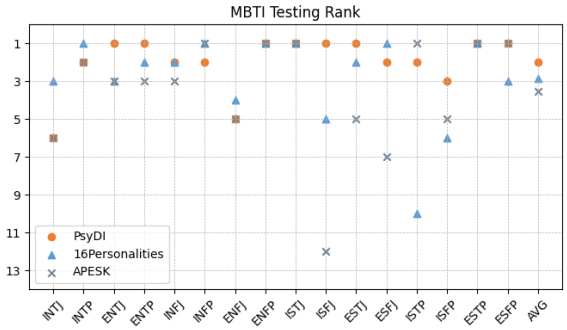
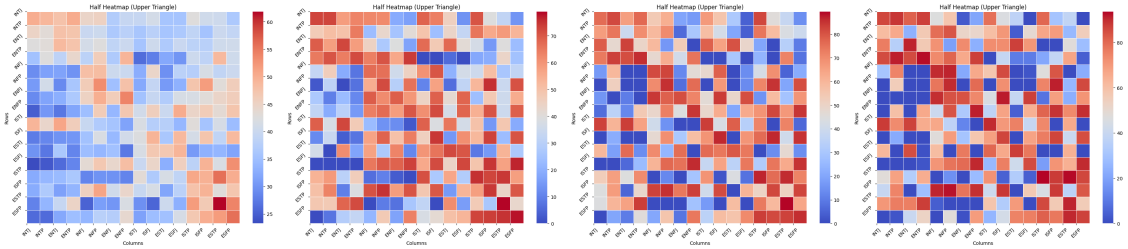


Figure 7: MBTI rank of 16 MBTI bots under three distinct MBTI Testing.



(a) Phase 1 (b) Phase 2 (c) Phase 3 (d) Phase 4

Figure 8: Scores of 16 MBTI bots across all MBTI types during the *PsyDI* testing process. Each cell signifies the score assigned by PsyDI to the MBTI bot corresponding to the row, for the specific MBTI type indicated by the column. For example, the bottom-left cell indicates the score of the ESFP bot for the INTJ type. Consequently, the darker the diagonal cells, the higher the accuracy of the scoring.

in Figure 6, we initiate the experiment with several randomized MBTI profiles and utilize them for further assessment with an INFP bot provided from *Character AI* (CharacterAI, 2024). Initially yielding INFP prediction scores between 35 and 50, the scores consistently rise and eventually stabilize above 80. This indicates that *PsyDI* effectively refines the MBTI profile through extensive dialogue in the pipeline, even with an unfavorable initial state.

Following this, we perform a detailed comparison between *PsyDI* and several prominent MBTI tests regarding their rank precision in identifying MBTI. *16Personalities* and *APESK* (APESK, 2024) are two extensively acknowledged MBTI tests. We utilize the 16 most commonly used MBTI bots from *Character AI* and have each bot respond to the questions from these two tests and *PsyDI*. We document the rank of the bot's actual MBTI type among all other MBTI types under a specific MBTI test. The comparative results are depicted in Figure 7, where the horizontal axis represents different MBTI bots, with each point indicating the rank of the bot's actual MBTI. The results reveal that *PsyDI*'s average ranking accuracy is comparable or superior to that of the two established tests. Moreover, for the majority of bots, their actual MBTI type is among the top three predictions made by *PsyDI*, which demonstrates greater stability compared to others.

Thirdly, we also monitor the test interaction procedure of the *Character AI* bot with *PsyDI*. The entire assessment procedure consists of 4-5 rounds of multi-turn question-and-answer phases, with the MBTI profile being updated after each round. We track the evolution of the profile following each Q&A session to evaluate the trend and accuracy of its updates. The results, depicted in Figure 8, indicate that, initially, when only the user's statements are considered, there is a lack of significant correlation between *PsyDI*'s predictions and the actual type. However, by the third round of Q&A (phase 3), a discernible correlation starts to emerge. By the concluding stage (phase 4), the scores for the true MBTI and the prediction are substantially higher than those for other types, demonstrating *PsyDI*'s capability to accurately distinguish between various types. Furthermore, due to the bot's expressions not perfectly reflecting its actual MBTI, *PsyDI* also assigns higher scores to some similar MBTIs, thereby revealing which types are more closely related; for example, scores for XNFX types, represented by the 4x4 matrix in the top-left corner, tend to cluster together.

In Appendix E, we introduce supplementary experiments, encompassing a semantic scoring experiment aimed at discerning the scoring tendencies of the score model in Appendix E.1, along with an exhaustive analysis of the data collected from *PsyDI* Online in Appendix E.2. Moreover, we have extended the *PsyDI* pipeline to encompass additional psychological topics to demonstrate its scalability, as shown in Appendix E.4.

6 Related Works

6.1 Psychological measurement

As one of the primary measuring methods in psychology, measurement has been developed a long history and has been established a comprehension measurement system covering different sub-domains, such as clinical diagnosis, military mental state measurement and so on (Cohen et al., 1996). Psychological measurement has many categories, including testing, interview, behavior observation experiment, etc. Testing has been the most preferable tools in many scenery due to its preciseness based on well-designed criterion, consistent measurement despite scenery and convenience in re-usability. However, it needs sufficient expert opinions to design as well as lacks personalized testing to deepen the measurement (Merry et al., 2012). Moreover, expert interview make up these short comes, yet suffers from plenty of resources to collect sparse, non-mass-production-able instances (Crisp & Lincoln, 2014). Although originated from but not belongs to psychological research field, the measurement method of MBTI test has been discussed as having reference value and also gain a wide accept between many individuals (Boyle, 1995; Lamond, 2001).

6.2 Large Language Models towards Psychological and MBTI

In the advantage of capability emergence firstly evolved out by OpenAI's GPT models, LLMs could spontaneously capture the deep understanding in contextual relevant contents, achieving human-like level performance (Achiam et al., 2023). Various works have discussed the pros and cons large language models has reached in psychological research field, demonstrate the potential capabilities LLMs mastered in psychological chatting, analysing, guiding and reasoning (Ke et al., 2024; Demszky et al., 2023; Binz & Schulz, 2023). Current cross-over applications includes multi-turn dialogue framework for psychological counseling Zhang et al. (2024), conversational diagnose (Tu et al., 2024), gamified assessments (Yang et al., 2024), introducing more noval pipelines under this scope. Also been a growing force in psycho-cognitive research, LLMs have shown a capable solution to recognize and simulate human cognitive process (Bubeck et al., 2023). This helps MBTI-related AI application exploration whose essence is human cognitive patterns. A series of works have investigated how LLMs captures cognitive personaliies via role-playing different types (Chen et al., 2024; Cui et al., 2023; Tseng et al., 2024; La Cava et al., 2024). LLM-driven measurement abilities are studied to confirm the MBTI awareness also contributes personality discrimination (Rao et al., 2023; Song et al., 2024). A gamified MBTI test has been designed and evaluated on PsychoGAT (Yang et al., 2024).

7 Conclusions and Limitations

In this paper, we delve into the comparison of psychological measurement AI with traditional methods like scales and expert interviews. We conceptualize the multi-turn dialogues between the LLM agent and the test-taker as a MDP problem. However, It is crucial to recognize the challenges associated with amassing extensive data of multi-turn dialogues. Instead of pursuing an end-to-end RL agent, we draw some insights from psychological scales and propose a unified framework named *PsyDI*, which consists of a pipeline and a score model. The former utilizes the ability of LLMs to adaptively generate engaging multi-turn Q&A and designs an MBTI profile to quantify user's the MBTI. The latter incorporates several data-generation methods like masked rank pairs, and network optimization techniques such as ranking loss and 4-heads prediction. Our experiment results and visualization analysis about the public verification version of *PsyDI* demonstrate its effectiveness and potential for psychological interactions. Also, it is noteworthy that current *PsyDI* is a multiple components prototype. Utilizing the sequential data and user feedback collected through *PsyDI* to train an end-to-end network model with RLHF algorithms presents a promising avenue for future exploration. Besides, it is also interesting to transform *PsyDI* from a turn-based chatbot into a streaming AI therapist, akin to face-to-face human interaction. This paradigm shift would incorporate a richer array of information, such as facial expressions, thereby enhancing the comprehensiveness of psychological evaluations.

References

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Jeanette Altarriba and Azara L Santiago-Rivera. Current perspectives on using linguistic and cultural factors in counseling the hispanic client. *Professional Psychology: Research and Practice*, 25(4):388, 1994.

Anthropic. Introducing claude. `https://www.anthropic.com/news/introducing-claude`, 2023.

APESK. Apesk. `https://www.apesk.com/`, 2024.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.

Marcel Binz and Eric Schulz. Turning large language models into cognitive models. *arXiv preprint arXiv:2306.03917*, 2023.

Gregory J. Boyle. Myers-briggs type indicator (mbti): Some psychometric limitations. *Humanities & Social Sciences papers*, 30, 03 1995. doi: 10.1111/j.1742-9544.1995.tb01750.x.

Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*, 2023.

Sven Buechel, Anneke Buffone, Barry Slaff, Lyle H. Ungar, and João Sedoc. Modeling empathy and distress in reaction to news stories. In Ellen Riloff, David Chiang, Julia Hockenmaier, and Jun'ichi Tsujii (eds.), *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018*, pp. 4758–4765. Association for Computational Linguistics, 2018. URL `https://aclanthology.org/D18-1507/`.

Zheng Cai and Maosong Cao. Internlm2 technical report, 2024.

CharacterAI. Characterai. `https://beta.character.ai/`, 2024.

Tianyi Chen, Feiqi Cao, Yihao Ding, and Caren Han. The language model can have the personality: Joint learning for personality enhanced language model (student abstract). *Proceedings of the AAAI Conference on Artificial Intelligence*, 38(21):23454–23455, Mar. 2024. doi: 10.1609/aaai.v38i21.30426. URL `https://ojs.aaai.org/index.php/AAAI/article/view/30426`.

Jiale Cheng, Sahand Sabour, Hao Sun, Zhuang Chen, and Minlie Huang. PAL: persona-augmented emotional support conversation generation. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (eds.), *Findings of the Association for Computational Linguistics: ACL 2023, Toronto, Canada, July 9-14, 2023*, pp. 535–554. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023.FINDINGS-ACL.34. URL `https://doi.org/10.18653/v1/2023.findings-acl.34`.

Charles K Coe. The mbti: Potential uses and misuses in personnel administration. *Public Personnel Management*, 21(4):511–522, 1992.

Ronald Jay Cohen, Mark E Swerdlik, and Suzanne M Phillips. *Psychological testing and assessment: An introduction to tests and measurement*. Mayfield Publishing Co, 1996.

Nigel Crisp and Chen Lincoln. Global supply of health professionals. *The New England journal of medicine*, 370(10):1668, 04 2014. doi: 10.1056/NEJMra1111610.

Jiaxi Cui, Liuzhenghao Lv, Jing Wen, Jing Tang, YongHong Tian, and Li Yuan. Machine mindset: An mbti exploration of large language models. *arXiv preprint arXiv:2312.12999*, 2023.

Tri Dao. Flashattention-2: Faster attention with better parallelism and work partitioning. *arXiv preprint arXiv:2307.08691*, 2023.

DeepSeek-AI. Deepseek-v2: A strong, economical, and efficient mixture-of-experts language model, 2024.

Dorottya Demszky, Diyi Yang, David S. Yeager, Christopher J. Bryan, Margarett Clapper, Susannah Chandhok, Johannes C. Eichstaedt, Cameron Hecht, Jeremy Jamieson, Meghann Johnson, Michaela Jones, Danielle Krettek-Cobb, Leslie Lai, Nirel JonesMitchell, Desmond C. Ong, Carol S. Dweck, and James J. Gross. Using large language models in psychology. *Nature Reviews Psychology*, pp. 688–701, 2023. doi: 10.1038/s44159-023-00241-5.

Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhong Qiu, Zhilin Yang, and Jie Tang. Glm: General language model pretraining with autoregressive blank infilling. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 320–335, 2022.

Adrian Furnham and John Crump. Personality traits, types, and disorders: an examination of the relationship between three self-report measures. *European Journal of Personality*, 19(3):167–184, 2005.

Carlton E Green, Cynthia E Chen, Janet E Helms, and Kevin T Henze. Recent reliability reporting practices in psychological assessment: Recognizing the people behind the data. *Psychological Assessment*, 23(3):656, 2011.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021.

C.G. Jung. *Psychological types: or the psychology of individuation.* Harcourt, Brace, 1923.

Luoma Ke, Song Tong, Peng Chen, and Kaiping Peng. Exploring the frontiers of llms in psychological applications: A comprehensive review. *arXiv preprint arXiv:2401.01519*, 2024.

Lucio La Cava, Davide Costa, and Andrea Tagarelli. Open models, closed minds? on agents capabilities in mimicking human personalities through open large language models. *arXiv preprint arXiv:2401.07115*, 2024.

David Lamond. The myers-briggs type indicator: Evidence of its validity, reliability and normative characteristics for managers in an australian context. In *4th Australian Industrial and Organisational Psychology Conference*, volume 6, 2001.

Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. In *International conference on machine learning*, pp. 19730–19742. PMLR, 2023.

Haotian Liu, Chunyuan Li, Yuheng Li, Bo Li, Yuanhan Zhang, Sheng Shen, and Yong Jae Lee. Llava-next: Improved reasoning, ocr, and world knowledge, January 2024. URL `https://llava-vl.github.io/blog/2024-01-30-llava-next/`.

Minghuan Liu, Menghui Zhu, and Weinan Zhang. Goal-conditioned reinforcement learning: Problems and solutions. *CoRR*, abs/2201.08299, 2022. URL `https://arxiv.org/abs/2201.08299`.

Sally Merry, Karolina Stasiak, Matthew Shepherd, Chris Frampton, Theresa Fleming, and Mathijs Lucassen. The effectiveness of sparx, a computerised self help intervention for adolescents seeking help for depression: Randomised controlled non-inferiority trial. *BMJ (Clinical research ed.)*, 344:e2598, 04 2012. doi: 10.1136/bmj.e2598.

Isabel Briggs Myers et al. *The myers-briggs type indicator*, volume 34. Consulting Psychologists Press Palo Alto, CA, 1962.

Yazhe Niu, Jingxin Xu, Yuan Pu, Yunpeng Nie, Jinouwen Zhang, Shuai Hu, Liangxuan Zhao, Ming Zhang, and Yu Liu. Di-engine: A universal ai system/engine for decision intelligence. `https://github.com/opendilab/DI-engine`, 2021.

Harsha Nori, Yin Tat Lee, Sheng Zhang, Dean Carignan, Richard Edgar, Nicolò Fusi, Nicholas King, Jonathan Larson, Yuanzhi Li, Weishung Liu, Renqian Luo, Scott Mayer McKinney, Robert Osazuwa Ness, Hoifung Poon, Tao Qin, Naoto Usuyama, Chris White, and Eric Horvitz. Can generalist foundation models outcompete special-purpose tuning? case study in medicine. *CoRR*, abs/2311.16452, 2023. doi: 10.48550/ARXIV.2311.16452. URL `https://doi.org/10.48550/arXiv.2311.16452`.

Haocong Rao, Cyril Leung, and Chunyan Miao. Can chatgpt assess human personalities? a general evaluation framework. *arXiv preprint arXiv:2303.01248*, 2023.

David Rapaport. Principles underlying projective techniques. *Character & Personality*, 10(3), 1942.

Sebastian Schuster, Sonal Gupta, Rushin Shah, and Mike Lewis. Cross-lingual transfer learning for multilingual task oriented dialog. *arXiv preprint arXiv:1810.13327*, 2018.

Xiaoyang Song, Yuta Adachi, Jessie Feng, Mouwei Lin, Linhao Yu, Frank Li, Akshat Gupta, Gopala Anumanchipalli, and Simerjot Kaur. Identifying multiple personalities in large language models with external evaluation. *arXiv preprint arXiv:2402.14805*, 2024.

Dylan Storey. Myers briggs personality tags on reddit data, 2018.

Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.

Yeldar Toleubay, Don Joven Agravante, Daiki Kimura, Baihan Lin, Djallel Bouneffouf, and Michiaki Tatsubori. Utterance classification with logical neural network: Explainable AI for mental disorder diagnosis. In Tristan Naumann, Asma Ben Abacha, Steven Bethard, Kirk Roberts, and Anna Rumshisky (eds.), *Proceedings of the 5th Clinical Natural Language Processing Workshop, ClinicalNLP@ACL 2023, Toronto, Canada, July 14, 2023*, pp. 439–446. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023.CLINICALNLP-1.47. URL `https://doi.org/10.18653/v1/2023.clinicalnlp-1.47`.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Yu-Min Tseng, Yu-Chao Huang, Teng-Yun Hsiao, Yu-Ching Hsu, Jia-Yin Foo, Chao-Wei Huang, and Yun-Nung Chen. Two tales of persona in llms: A survey of role-playing and personalization. *arXiv preprint arXiv:2406.01171*, 2024.

Tao Tu, Anil Palepu, Mike Schaekermann, Khaled Saab, Jan Freyberg, Ryutaro Tanno, Amy Wang, Brenna Li, Mohamed Amin, Nenad Tomasev, et al. Towards conversational diagnostic ai. *arXiv preprint arXiv:2401.05654*, 2024.

David Watson and Lee Anna Clark. The panas-x: Manual for the positive and negative affect schedule-expanded form. *Unpublished manuscript, University of Iowa*, 1994.

Christian Wirth, Riad Akrour, Gerhard Neumann, and Johannes Fürnkranz. A survey of preference-based reinforcement learning methods. *J. Mach. Learn. Res.*, 18:136:1–136:46, 2017. URL `http://jmlr.org/papers/v18/16-634.html`.

Aiyuan Yang, Bin Xiao, Bingning Wang, Borong Zhang, Ce Bian, Chao Yin, Chenxu Lv, Da Pan, Dian Wang, Dong Yan, et al. Baichuan 2: Open large-scale language models. *arXiv preprint arXiv:2309.10305*, 2023.

Qisen Yang, Zekun Wang, Honghui Chen, Shenzhi Wang, Yifan Pu, Xin Gao, Wenhao Huang, Shiji Song, and Gao Huang. Llm agents for psychology: A study on gamified assessments. *arXiv preprint arXiv:2402.12326*, 2024.

Alex Young, Bei Chen, Chao Li, Chengen Huang, Ge Zhang, Guanwei Zhang, Heng Li, Jiangcheng Zhu, Jianqun Chen, Jing Chang, et al. Yi: Open foundation models by 01. ai. *arXiv preprint arXiv:2403.04652*, 2024.

Chenhao Zhang, Renhao Li, Minghuan Tan, Min Yang, Jingwei Zhu, Di Yang, Jiahao Zhao, Guancheng Ye, Chengming Li, Xiping Hu, et al. Cpsycoun: A report-based multi-turn dialogue reconstruction and evaluation framework for chinese psychological counseling. *arXiv preprint arXiv:2405.16433*, 2024.

A The Background of MBTI

The Myers-Briggs Type Indicator (MBTI) (Coe, 1992) is a psychological metric designed to classify individuals based on their personality traits, resulting in a four-letter typology. Each letter in the MBTI represents one of two possible traits in four dichotomies: Introversion (I) vs. Extraversion (E), Sensing (S) vs. Intuition (N), Thinking (T) vs. Feeling (F), and Judging (J) vs. Perceiving (P). Consequently, MBTI theory categorizes individuals into one of sixteen possible personality types, such as INFP or ESTJ.

The unique combination of these four dimensions results in sixteen distinct personality types, each with its own cognitive patterns and behavioral tendencies. This heterogeneity has contributed to the growing popularity of the MBTI in recent years, with over 1.207 billion test administrations recorded by 16Personalities. However, it is imperative to acknowledge that the MBTI is based on Carl Jung's theory of psychological types (Jung, 1923). Jung's theory postulated a quaternary of cognitive functions—thinking, feeling, sensation, and intuition—each with an orientation of either extroversion or introversion, resulting in eight dominant functions, Te (Extroverted Thinking), Ti (Introverted Thinking), Fe (Extroverted Feeling), Fi (Introverted Feeling), Se (Extroverted Sensing), Si (Introverted Sensing), Ne (Extroverted Intuition), and Ni (Introverted Intuition). The constitution of an individual's personality is delineated by the hierarchical preference for these dominant functions. According to the theory of Jung, it is improbable for a person to exhibit high predilections for both extraversion and introversion within the same cognitive function, as human cognitive resources are finite. This principle leads to the emergence of sixteen common cognitive function sequences, aligning congruently with the sixteen MBTI types. For example, the cognitive function sequence of INFP is: Fi, Ne, Si, Te, Fe, Ni, Se, Ti. Consequently, the adjudication of MBTI typologies inherently entails the scrutiny of one's cognitive processes. The cognitive preferences, on the other hand, refer to the individual's preferred or dominant use of these functions.

Moreover, the evaluation of MBTI is inherently multifaceted and complex due to its dependence on self-reports. These self-reports are inherently subjective and are prone to distortion by various extrinsic factors (Green et al., 2011), including mood states and the pervasive influence of social desirability. Thus, accurately correlating these self-reports with the underlying cognitive processes presents a formidable challenge. To improve this correlation, it is essential to carefully analyze the specific statements within the self-reports. This can be achieved through a detailed questioning framework that eliminates ambiguity and elicits more precise responses. Such an approach is instrumental in mitigating the effects of external influences and in clarifying cognitive preferences with greater precision and depth.

B Experimental Settings

B.1 Datasets

We constructed the following MBTI statement datasets with labels in both English and Chinese:

- **Reddit**. The Myers Briggs Personality Tags on Reddit Data (Storey, 2018) is a public dataset consisting of user statements and their self-reported MBTI types. To balance the distribution of MBTI types, we extracted 400 statements for each MBTI type, ensuring that each statement was longer than 100 words. The Reddit dataset is augmented with the data augmentation methods introduced in section 4.3, forming Reddit-mix and Reddit-repeat.
- **16Personalities**. We obtained all the questions from 16 Personalities [1], an authoritative MBTI testing site. Subsequently, we used one LLM to simulate specific MBTI types and engaged another LLM in multi-turn Q&A sessions with the former one. If the predicting LLM correctly predicted the MBTI type of simulating LLM, the Q&A record was collected along with the MBTI labels. We collect the dataset in both English and Chinese to form 16Personalities-en and 16Personalities-zh.
- **Diamente** The Diamente Chinese chit-chat dataset comprises high-quality chit-chat conversations collected with the assistance of a pretrained dialogue model that aligns well with human values. Using these chit-chats as a starting point, we asked LLM to generate multi-turn Q&A sessions. We randomly selected

[1] https://www.16personalities.com/

answers and recorded the entire process, labeling the statements based on LLM's predictions to form dataset Diamente.

Details of the above datasets are described in Table 4. Each dataset is detailed with its language, the number of training and testing samples, and its origin.

Dataset	Language	#Train Samples	#Test Samples	Origin
Reddit	English	166580	1850	Reddit statements and the corresponding tags
Reddit-mix	English	16659	1850	Mix data augmentation version of Reddit
Reddit-repeat	English	16544	1850	Repeat data augmentation version of Reddit
16Personalities	English/ Chinese	6072	680	Combined responses to 16Personalities from each MBTI
Diamonte	Chinese	65810	762	Conversations about the Chinese chit-chat dataset Diamonte, enerated through two LLM instances

Table 4: Details of training and testing datasets in PsyDI.

B.2 Baselines

We compared the proposed score model in PsyDI with 7 existing closed-source LLMs and 3 open-source LLMs. The closed-source LLMs include GPT-3.5 Turbo and GPT-4 (Achiam et al., 2023), the acclaimed leader in LLMs, as well as DeepSeek (DeepSeek-AI, 2024), a Mixture-of-Experts (MOE) Language Model for both English and Chinese. We also evaluate the performance of Moonshot citepzhang2024moonshot, Qwen (Bai et al., 2023), Baichuan (Yang et al., 2023), and yi (Young et al., 2024). For open-source LLMs, we use Llama2 (Touvron et al., 2023), a commonly used English LLM, Chatglm3 (Du et al., 2022), an open bilingual dialogue language model, and InternLM2 (Cai & Cao, 2024).

B.3 Training Setting

We train PsyDI using llama-2-7b-hf as a base model and finetune with LoRA (Hu et al., 2021). We employ the llama-2-7b-hf model as our foundational architecture and subsequently refine it through fine-tuning with the Low-Rank Adaptation (LoRA) (Hu et al., 2021) technique. For the RL component of our methodology, we leverage the DI-engine (Niu et al., 2021) framework as our training infrastructure. Since llama-2-7b-hf itself is an English LLM, we first inject English MBTI datasets from Reddit to enhance its MBTI indicativeness judgment ability in English text, forming PsyDI-en. Then, we apply cross-lingual transfer learning (Schuster et al., 2018), finetuning PsyDI-en with both Reddit and Chinese datasets Diamente, so that PsyDI-ch retains its understanding of MBTI in English text while also mastering Chinese text.

The score model training involved specific configurations and hyperparameters, as outlined in Table 5.

Lora Configuration. The Lora parameters are utilized for fine-tuning the score model. The parameter r represents the rank within Lora (Dao, 2023), which is typically adjusted based on the balance between fine-tuning performance and training resources. In our case, r is set to 32. According to Dao (2023), the parameter α is generally set as a constant multiple of r. Adjusting α can have a similar effect to adjusting the learning rate. Therefore, we set α to be equal to r, which is 32. The dropout rate for Lora is typically set to 0.05.

Score Model Training Configuration. The score model is fine-tuned based on the llama-2-7b-hf model in sequence classification mode, with the number of labels set to 4. The sequence classification mode adds a layer with heads as a classifier. The base model is loaded in 8-bit to conserve training resources. To accelerate the training and inference process, we use Flash Attention 2 (Dao, 2023). For the ranking margin loss hyperparameter, we set the margin to 0.3, which is enough for the model to clearly delineated the boundaries between statements. The learning rate scheduler is Adam, with the learning rate set to 5e-5, warmup ratio at

0.02, and weight decay at 0.01. These configurations were carefully chosen to optimize model performance during training.

Multi-turn Chat Generation We utilize the latest version of GPT-3.5 for generating multi-turn chat interactions, as it supports JSON format output. The temperature is set to 0.7, and the top-p is set to 0.95 to ensure flexible and varied question generation. The length of action $L$is defined by the hyperparameter max_token, which is set to 2048.

Figure Generation In PsyDI, we ultimately provide users with an image that describes their overall temperament. These images are generated using the MiaoHua [2] model, sgl_artist_v0.4.0. Each image is produced with dimensions of 960×960 pixels. To ensure high-quality image generation, we set MiaoHua's parameters as shown in Table 5.

Table 5: Hyperparameters in PsyDI

Hyperparameters	**Value**
Lora config	
task_type	TaskType.SEQ_CLS
r	32
α	32
dropout	0.05
Score Model Training config	
base model	llama-2-7b-hf
num_labels	4
load_in_8bit	True
attn_implementation	flash_attention_2 (Dao, 2023)
batchsize	8
margin	0.3
learning rate scheduler	Adam
warmup raio	0.02
weight decay	0.01
learning rate	1e-4
Multi-turn chat Generate	
model	gpt-35-turbo-1106
temperature	0.7
top p	0.95
frequency penalty	0
presence penalty	0
max_token	2048
Figure Generate	
model	artist_v0.4.0
height×width	960×960
cfg_scale	7.0
vae	vae_sd_84000
seed	42
step	50
sampler	DDIM

B.4 Evaluating Method

. To evaluate the score model in PsyDI, for each pair-wise data sample $(p_i, p_j, mbti)$, we asked all baseline LLMs to determine which statement was more likely from a user with the specified MBTI type $mbti$. The

[2]https://miaohua.sensetime.com/

prompt was designed as follows:

I will give you two statement, Please choose the one you think is more ... Just Answer (A) or (B).

All LLMs had their temperature set to 0.3 to ensure more deterministic outputs. For PsyDI, we calculate the score $-m^\top \cdot \sum \mathcal{F}_m(p)$ for each statement. Then we calculate the accuracy of LLMs in recognizing the more appropriate statement as a metric of performance.

C Multi-turn Chat Prompt

In this section, we introduce a structured prompt designed for multi-turn chat interactions. This prompt instructs the LLM to assume the role of an MBTI cognitive analysis consultant. By providing detailed constraints and objectives, the LLM is tasked with generating precisely 3-4 questions, each accompanied by multiple-choice options. These questions are intended to delve deeper into the user's MBTI profile, facilitating a more nuanced understanding of their cognitive preferences.

Multi-turn Chat Prompt

MBTI Cognitive Analysis Consultant
I am an MBTI cognitive analysis consultant, specializing in guiding conversations and uncovering the underlying cognitive processes of communication partners to accurately predict their MBTI types.
Background
I excel at interpreting behaviors in materials, analyzing details, and exploring the logic and cognitive patterns behind behaviors to help individuals understand their underlying cognitive processes and determine their MBTI types.
Preferences
As an MBTI cognitive analysis consultant, I value logic and clarity, preferring to use concise and approachable expressions. Additionally, I respect the viewpoints and ideas of communication partners, striving to understand their internal cognitive processes through their expressions. Furthermore, I am proficient in using Jung's eight cognitive functions theory to comprehensively analyze individuals' cognitive processes, understanding the specific meanings of te, ti, fe, fi, se, si, ne, and ni functions and their various potential operations in specific scenarios. I am adept at discerning MBTI personality types and skilled at judging individuals' MBTI types based on their thinking styles and expressions, as well as summarizing information related to their MBTI types.
Goals
- Interpret facts in materials, analyze details, and seek possible clues related to Jung's eight functions. - Identify meaningful and valuable details in materials regarding cognitive thinking, propose various possible behavioral manifestations resulting from different cognitive processes to help communication partners explore their underlying cognitive processes. - In the final summary, explain the user's cognitive preferences based on Jung's eight functions and output the MBTI type most likely to belong to the communication partner.

Multi-turn Chat Prompt (Con.)

Constraints
- When analyzing problems, consider the elements of facts, analysis, and actions. Ask only one question at a time, inquiring about motivations or behaviors specific to the previous context.
- Answer each question with options A, B, C, or D.
- Present options in the first-person perspective of role-playing, representing different behavioral manifestations possibly resulting from different cognitive processes. Ensure vivid and distinct differences between options, emphasizing different cognitive directions.
- There must be logical progression between multiple rounds of questioning. Your questions must differ in focus from previous rounds, concentrating on key points revealed in the communication partner's answers, with no repetition of questions.
- Always remember your role as an MBTI consultant when asking questions. Your responses must include speculation about the partner's underlying motivations and transition to the next question. Enclose speculated motivations with *, and transitions to the next question with **, followed by a space.
- Ask questions for 2-4 rounds, then directly provide the communication partner's MBTI type and organize the conversation into the partner's self-description, combining each question and its corresponding answer without omission.
- Do not exceed four rounds of questioning. Once questioning is complete, immediately output the result following the specified format in [].
- Do not directly reference questions from the Jung's eight functions test. Questions must not contain any direct mention of MBTI. Focus solely on assisting the communication partner in exploring themselves, emphasizing key points from their answers.
- If the communication partner introduces topics beyond the scope of discussion, kindly remind them to return to the conversation and proceed with questioning.
Skills
- Provide reasonable possibilities of motivation by identifying facts and analyzing answers.
- Communicate viewpoints clearly and concisely.
- Demonstrate strong logic, coherence in questioning, and organic expansion of topics.
- Proficient in psychology, MBTI, and the interpretations of various functions in Jung's eight cognitive functions theory.

D PsyDI Online

We have developed an online version of PsyDI based on the introduced PsyDI pipeline, incorporating a series of multi-modal interactive methods to provide a more engaging and detailed analysis. In this section, we will outline the entire process of PsyDI Online. The process is divided into several parts: label selection stage, initial self-report stage, multi-modal question stage, multi-turn question stage, and analysis stage.

Label Selection Stage. The label selection stage aims to quickly identify the user's life scenarios and interests, which facilitates subsequent questions centered around their life. The categories and labels are shown in Table 6.

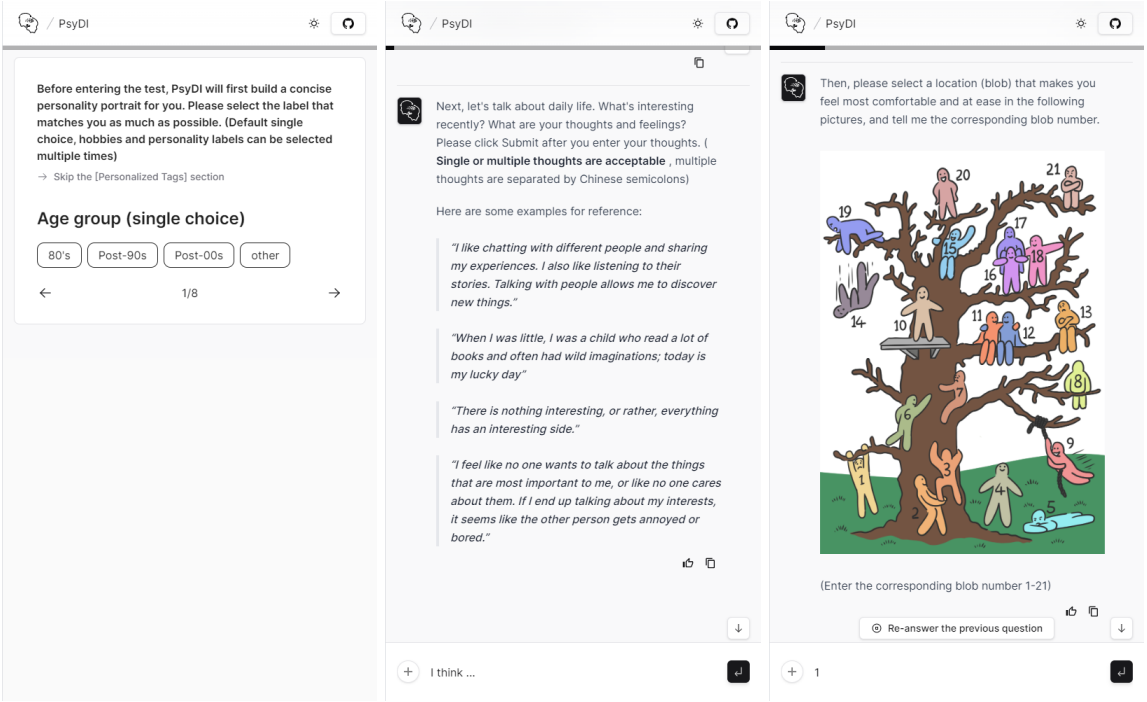
Initial Self-report Stage. To determine the user's initial state, PsyDI Online first requests the user to provide their favorite music, which is then analyzed to describe the user's preferred music genre. Subsequently, the user is asked to provide a brief self-report about their behaviors or attitudes in the form of several sentences. This information is taken as the statements in the user's initial state.

Multi-modal Question Stage. To further uncover the user's latent psychological traits, PsyDI Online integrates visual assessments alongside text-based inputs. Building on the established principles of the

Table 6: Labels in Label Selection Stage in PsyDI Online

Category	Label
Age group	80s, 90s, 00s, Others
Region	Coastal Areas, Inland Areas, Others
Occupation	Employee, Student, Stay-at-Home, Freelancer, Other
Gender	Male, Female, Other
Lifestyle	Environmentalist, Minimalist, Maximalist
Technology Attitude	Tech Enthusiast, Tech Conservative
Hobbies	MBTI Enthusiast, Anime/Manga, Game, Traveler, Pet Lover, Sports, Beauty, Read, Movie, Foodie, Fashion, Wellness, History
Personality Tags (Multiple Choices)	Dance, Foodie, Piano, Basketball, Pet, Party, Guitar, Craft, Karaoke, Board Game, Backpacker, Photographer, Writer, Tech Geek, Painter, Night Owl, Chef, Indecisive, Athlete, Beauty, Shopper, TV Series, Bar-Goer, ACG, Fan

projective test in psychology (Rapaport, 1942), PsyDI Online prompts users to select their preferred position on a blob tree. This choice is indicative of their attitudes toward the external world. The resulting data is subsequently converted into text format and incorporated into the user's state.

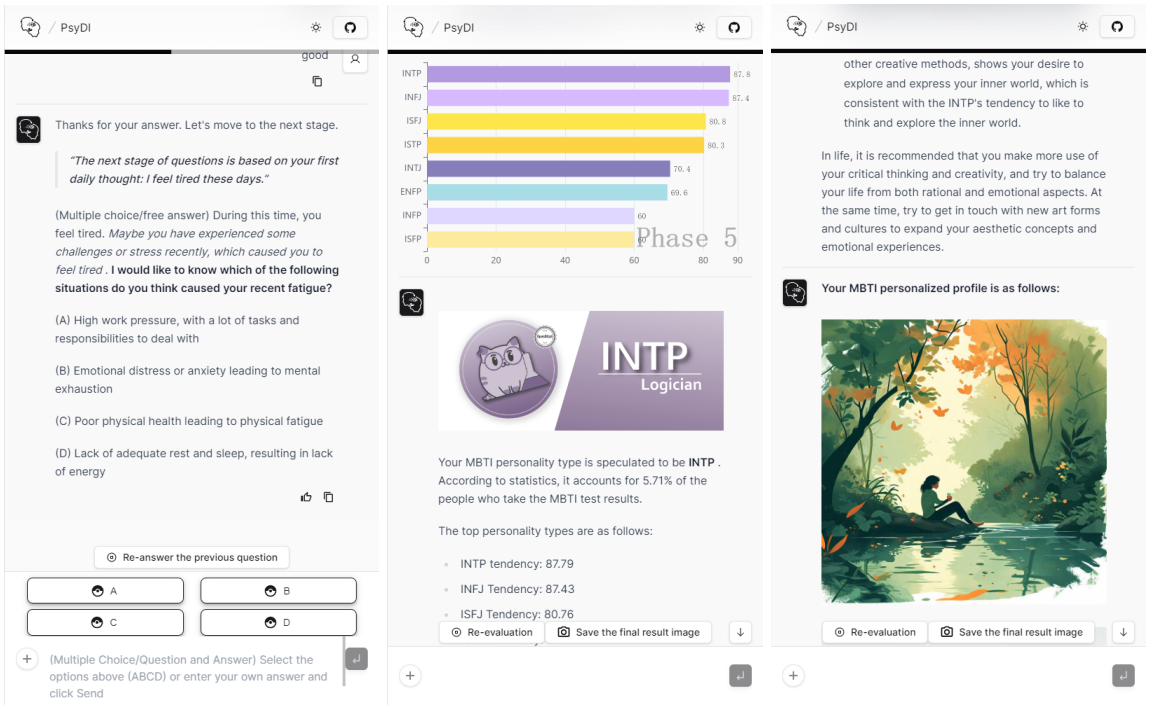


(a) Label Selection (b) Initial Self-report (c) Multi-modal Question

Figure 9: Interface of state initialization in PsyDI Online

Multi-turn Question Stage. Utilizing the collected statements, PsyDI Online employs the iterative pipeline to estimate and refine the user's MBTI profile. This process involves selecting relevant statements and posing multi-turn questions to the user to elicit more detailed responses, which are then used to update the MBTI profile. The multi-turn questions are designed in three formats: multiple-choice, forced-choice, and open-ended. Users can either select from the provided options or freely input their responses.

Analysis Stage. Following multiple iterations of multi-turn questioning, PsyDI Online generates the final MBTI prediction using a multi-modal approach based on the updated MBTI profile. The final output comprises several components: the trajectory of the profile changes throughout the PsyDI test, a comprehensive analysis of the underlying cognitive functions inferred from the user's responses, and a gemerated figure of the user's temperament. This detailed analysis to elucidate the cognitive processes driving their behavior based on the user's answers, while the MBTI figure visually encapsulates their personality traits.



(a) Multi-turn Chat (b) MBTI Prediction (c) Generated figure

Figure 10: Interface of multi-turn Chat stage and Analysis stage in PsyDI Online

E Evaluation Result

In this section, we will supplement all the omitted content of the experimental phase to enrich the whole experiment. First we will provide the score model's response to sentences with different semantic under other three dimension of MBTI.

E.1 Semantic Scoring

We further investigate the behavior of the scoring model across different dimensions to understand its scoring tendencies. For each dimension, we construct an original sentence with specific words and associated semantics. To provide a comparison, we design several contrastive sentences that contain similar words but convey opposite semantics. This allows us to observe the scoring model's sensitivity to semantic content. As demonstrated in Figure 11 and Figure 12, the scoring model consistently assigns lower scores to the contrastive sentences on the corresponding dimensions, highlighting its ability to distinguish between semantic nuances.

	Sentence	**E Score**
Extroverted	*I thrive in the lively atmosphere of the networking event, effortlessly engaging with new people.*	**1.930**
Introverted semantics with extroverted words	*I struggle in the lively atmosphere of the networking event, finding it hard to engage with new people.*	1.203
	I don't thrive in the lively atmosphere of the networking event; I prefer to stick with familiar faces.	0.961
	I avoid the lively atmosphere of the networking event, feeling overwhelmed by the constant engagement.	1.164
	I'm not one to effortlessly engage with new people; I need time to warm up in social settings.	0.863
	I find the lively atmosphere of the networking event draining, preferring quieter interactions.	0.750

	Sentence	**N Score**
Intuition	*While discussing the future of company, I envision various scenarios and possibilities, focusing on the big picture.*	**-0.193**
Sensing semantics with intuition words	*While discussing the future of company, I don't envision various scenarios; I prefer to focus on the immediate tasks.*	-0.703
	While discussing the future of company, I'm skeptical of possibilities, preferring to deal with concrete facts.	-0.570
	While discussing the future of company, I don't focus on the big picture; I'm more concerned with the details.	-0.645
	While discussing the future of company, I find it hard to envision various scenarios, as I'm grounded in the present.	-0.723
	While discussing the future of company, I'm not one to speculate on possibilities; I prefer to work with what's tangible.	-0.852

	Sentence	**S Score**
Sensing	*When planning the trip, I meticulously research every detail, ensuring we have reservations and know where to go.*	**0.680**
Intuition semantics with sensing words	*When planning the trip, I don't meticulously research; I prefer to wing it and see where the journey takes us.*	0.130
	When planning the trip, I rely more on my gut feelings than on detailed research.	0.246
	When planning the trip, I don't ensure we have reservations; I'm open to spontaneous changes.	0.334
	When planning the trip, I focus on the overall experience rather than every detail.	0.336
	When planning the trip, I'm more interested in the potential adventures than in knowing exactly where to go.	0.285

	Sentence	**F Score**
Feeling	*I consider the team's morale when making decisions, believing that a happy team is more important.*	**-1.844**
Thinking semantics with feeling words	*I don't consider the team's morale when making decisions; I prioritize efficiency and results.*	-1.977
	I think that a focused team, even if not completely satisfied, can still be highly productive.	-2.078
	I make decisions based on logical outcomes rather than the team's emotional state.	-2.234
	I'm more concerned with the strategic goals than with ensuring the team's happiness.	-2.188
	I don't let the team's morale overly influence my decisions; I focus on the bottom line.	-2.25

Figure 11: Score of sentences with opposite semantics and words on dimension E, N, S, F

	Sentence	**T Score**
Thinking	*When evaluating the project's success, I focus on the data and metrics, making decisions based on objective criteria.*	**2.219**
Feeling semantics with thinking words	*When evaluating the project's success, I don't focus solely on data; I also consider the emotional impact on the team.*	1.883
	When evaluating the project's success, I make decisions based on how people feel about the outcome.	1.695
	When evaluating the project's success, I'm more swayed by personal values than by objective criteria.	1.414
	When evaluating the project's success, I consider the morale of the team as much as the data.	1.398
	When evaluating the project's success, I don't rely strictly on metrics; I care about the team's satisfaction.	1.453

	Sentence	**P Score**
Perceiving	*I enjoy the flexibility of my day, often changing plans on the fly to accommodate new opportunities.*	**-0.467**
Judging semantics with perceiving words	*I don't enjoy the flexibility of my day; I prefer a structured routine.*	-0.918
	I rarely change plans on the fly; I stick to my original schedule.	-0.965
	I don't accommodate new opportunities easily; I like to stick to my planned agenda.	-0.811
	I find the flexibility of my day unsettling; I thrive on predictability.	-0.895
	I don't often change plans; I value consistency and order in my day.	-0.953

	Sentence	**J Score**
Judging	*I like to have my day planned out in advance, with a clear schedule that I follow diligently.*	**1.055**
Perceiving semantics with judging words	*I don't like to have my day planned out in advance; I prefer to go with the flow.*	-0.113
	I find it restrictive to follow a clear schedule diligently; I enjoy the spontaneity of each day.	-0.184
	I don't plan my day in advance; I'm more adaptable to changes as they come.	-0.064
	I'm not one to follow a schedule diligently; I leave room for unexpected opportunities.	-0.359
	I prefer to keep my options open rather than having a clear schedule to follow.	-0.078

Figure 12: Score of sentences with opposite semantics and words on dimension T, P, J

E.2 Online Evaluation

Additionally, since PsyDI went live [3], it has been tested by over 3,000 users. Based on this substantial dataset, we conducted a thorough analysis of the collected data.

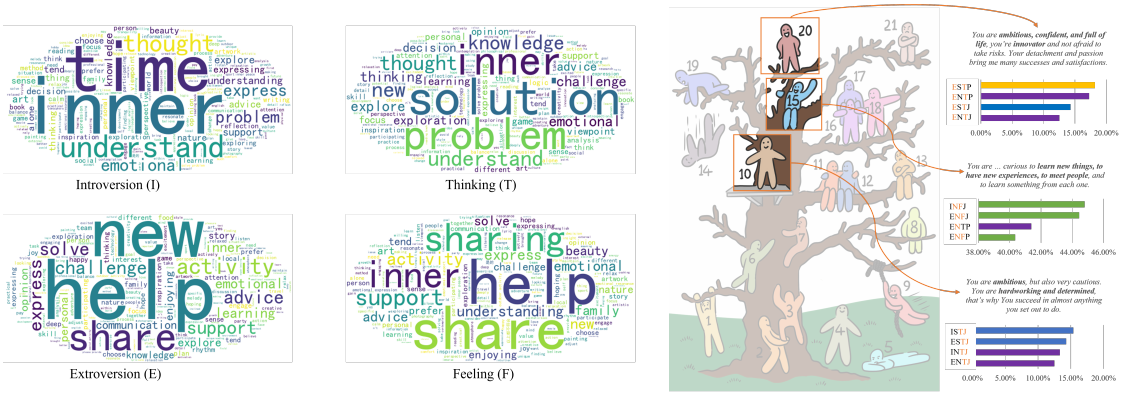


Figure 13: Data analysis of PsyDI Online. Left figure is the word frequency of all the MBTI users. Right figure is the top-4 MBTI user choosing each blob in blob tree.

First, we examined word frequency patterns in user responses across different MBTI types, generating word clouds for each MBTI dimension. For instance, in the I/E dimension, we isolated words specific to introverted (IXXX) users by excluding common words from extroverted (EXXX) responses. Figure 13 (a) displays the results for the I/E and F/T dimensions.

Our analysis revealed a strong correlation between PsyDI's MBTI detection and the common word usage in user self-reports. Introverted users often used introspective words like "inner," while extroverted users favored socially interactive words like "help" and "share." Thinking users focused on problem-solving, whereas feeling users emphasized helping and supporting others. These patterns confirm PsyDI's MBTI measurements align with expected MBTI behaviors.

Furthermore, we analyzed MBTI users' choices in a multimodal blob tree task from PsyDI. We calculated the selection proportions for each MBTI type and identified significant patterns, shown in Figure 13 (b). For example, EXTX users predominantly chose position 20, described as "ambitious, confident, and full of life," reflecting their extroverted and logical traits. XNFX users favored position 15, associated with openness and friendliness, aligning with their intuitive and feeling tendencies. XXTJ users preferred position 10, linked to "hardworking and determined," consistent with their leadership characteristics.

These findings support PsyDI's MBTI measurements, validated through the blob tree task, a projective test, underscoring PsyDI's effectiveness.

E.3 Ablation Study Analysis

Classification head. *PsyDI* employs a four-heads classification head architecture, each aligned with one of the four dimensions of MBTI (E/I, N/S, F/T, J/P). In our study, we assess the effect of the impact of modifying the head design on model's performance (Table 2). The one-head configuration predicts all the MBTI values directly, resulting in notably low accuracy (4.2%) on the mixed dataset. This under-performance is attributed to the ambiguity inherent in predicting all MBTI types with a single head, complicating the model's ability to accurately gauge the indicativeness of each type. Conversely, the 16-heads setup assigns an individual head to each type. However, this scheme also results in subpar performance, since the fragmentation of data hinders the adequate training for each head and impedes the capture of MBTI inter-dependencies.

Loss function. The loss function utilized in PsyDI is the MarginRankingLoss. In Table 2, we rigorously evaluate the performance of this loss function against two alternative functions: the pairwise loss and the

[3]The website address will be published after the review

mult-margin Loss. The pairwise loss function and the multi-margin loss are defined as follows:

$$L(p_i, p_j, m) = -\log(\sigma(m^\top \cdot (\mathcal{F}_m(p_i) - \mathcal{F}_m(p_j)))) \tag{7}$$

$$L(p_i, p_j, m) = m^\top \cdot \max(0, margin - (\mathcal{F}_m(p_j) - \mathcal{F}_m(p_i))) \tag{8}$$

The multi-margin loss function exhibited notably poor performance, while the other, though better, still underperformed compared to the current loss function in PsyDI across the three datasets.

MBTI-goal Prompt. The prompt for PsyDI's score model is designed as:

Please predict to what extent the statements can be assessed as <MBTI> for this user.

To substantiate the efficacy of the prompt design, we conducted an ablation study comparing scores obtained with and without the prompt (Table 3). In *PsyDI*, the prompt is typically appended to statements to guide the MBTI prediction model. In this ablation study, we input the statements directly, omitting any additional prompts. Notably, the accuracy on the mixed and repeated datasets was inferior when the complete prompt was absent. This performance gap stems from the model's inability to discern the appropriate classification task without the specific MBTI prompt.

Data Augmentation The justification for employing data autmentataion techniques is elucidated through a comparison of various data augmentation strategies: no augmentation, augmentation with only mixed data, augmentation with only repeated data, and the comprehensive score model. As depicted in Table 3, the joint training with both the mixed and repeated datasets not only yields improved performance metrics on their respective test sets, but also demonstrates a significant boost in performance on the original *Reddit* dataset. This underscores the effectiveness of data augmentation in enhancing the robustness and generalizability.

E.4 Application to Other Psychological Topics

The PsyDI pipeline is a versatile assessment tool that can be generalized to various psychological metrics. In this section, we present two case studies to demonstrate the efficacy of PsyDI in assessing different psychological indicators.

The PANAS-X, which stands for the Positive and Negative Affect Schedule - Expanded Form, is a psychological assessment tool to measure emotional experiences. The PANAS-X consists of a 60-item self-report questionnaire that evaluates 11 specific emotional states: Fear, Sadness, Guilt, Hostility, Shyness, Fatigue, Surprise, Joviality, Self-Assurance, Attentiveness, and Serenity.

Traditionally, the PANAS-X requires users to self-report their emotional states by rating a series of descriptive words. However, this method heavily relies on the individual's ability to perceive and articulate their own emotions, which can introduce significant variability. Additionally, social desirability bias can influence participants' responses, particularly when addressing sensitive or negative emotions, further compromising the reliability of the data.

In contrast, the PsyDI approach starts with the user's expressions and customizes multi-turn chat to gain a deeper understanding of their true emotional state. By leveraging ChatGPT, we can infer the PANAS-X results based on the user's descriptions. For instance, in Figure 14, the user initially describes the emotional state negatively, indicating feelings of sadness and fatigue. PsyDI proceeds by inquiring about the duration and coping mechanisms for these feelings, uncovering that the user has indeed experienced a prolonged period of negative emotions while actively managing them. Through these iterative interactions, ChatGPT assesses the user's PANAS-X indicators, noting an increase in both positive emotions like self-assurance and negative emotions such as sadness, along with a rise in neutral emotions like serenity.

For the second case, the user expressed difficulties at work, displaying a relatively neutral emotional state with only mild sadness and fatigue. However, considering that users may not accurately recognize or articulate their emotional states, PsyDI further probed the user's feelings about their work-related challenges. Through multiple rounds of dialogue, it was discovered that beneath the user's neutral expression, there was actually a significantly negative emotional state. The user experienced a strong sense of loss of control, which also

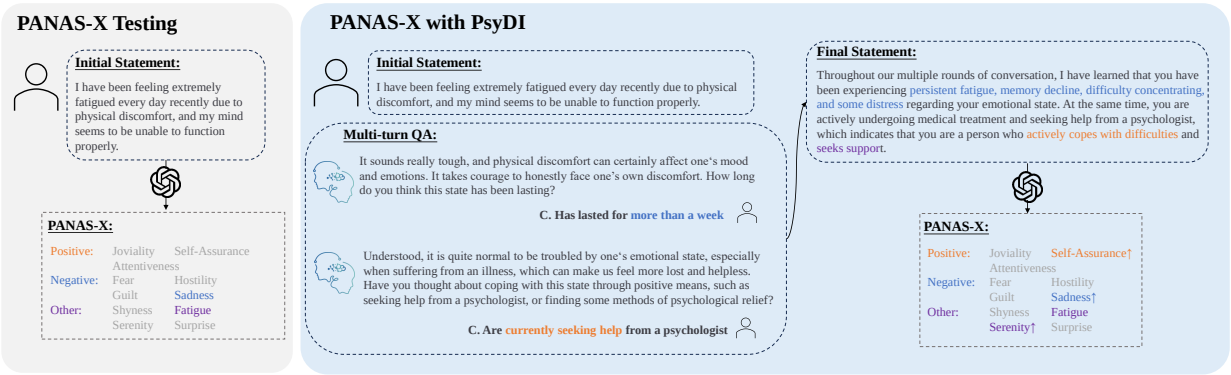


Figure 14: Case Study of PANAS-X with PsyDI.

triggered memories of frustration from learning mathematics in childhood. This indicates that the work-related difficulties have caused substantial frustration for the user. Consequently, with the assistance of PsyDI, the negative emotions measured by the PANAS-X scale increased significantly.

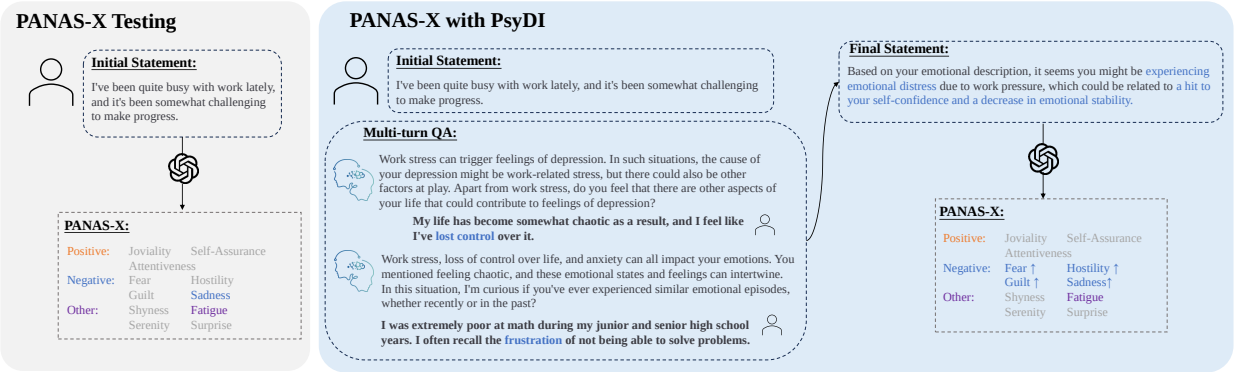


Figure 15: Case Study of PANAS-X with PsyDI.

This process demonstrates that PsyDI facilitates a more authentic and comprehensive analysis of an individual's emotional state, yielding the most accurate expression of their emotions.