

Can Large Language Models Understand You Better? An MBTI Personality Detection Dataset Aligned with Population Traits

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Abstract

The Myers-Briggs Type Indicator (MBTI) is one of the most influential personality theories reflecting individual differences in thinking, feeling, and behaving. MBTI personality detection has garnered considerable research interest and has evolved significantly over the years. However, this task tends to be overly optimistic, as it currently does not align well with the natural distribution of population personality traits. Specifically, (1) the self-reported labels in existing datasets result in incorrect labeling issues, and (2) the hard labels fail to capture the full range of population personality distributions. In this paper, we optimize the task by constructing MBTIBENCH, the first manually annotated high-quality MBTI personality detection dataset with soft labels, under the guidance of psychologists. As for the first challenge, MBTIBENCH effectively solves the incorrect labeling issues, which account for 29.58% of the data. As for the second challenge, we estimate soft labels by deriving the polarity tendency of samples. The obtained soft labels confirm that there are more people with non-extreme personality traits. Experimental results not only highlight the polarized predictions and biases in LLMs as key directions for future research, but also confirm that soft labels can provide more benefits to other psychological tasks than hard labels.¹

1 Introduction

Personality, a key psychological concept, refers to individual differences in thinking, feeling, and behavior (Corr & Matthews, 2009). Among personality models, the Myers-Briggs Type Indicator (MBTI) is one of the most recognized non-clinical frameworks, with broad applications in areas like stance detection (Hosseini et al., 2021). Recently, automatically detecting a person’s MBTI type from their written content (e.g., tweets and blogs) (Plank & Hovy, 2015; Gjurković et al., 2021) has become a growing area of research with both academic significance (Stajner & Yenikent, 2020; Khan et al., 2005) and practical applications (Bagby et al., 2016).

However, MBTI personality detection tends to be overly optimistic, as it currently does not align well with the natural distribution of personality traits within the population. (1) Given the widespread use of MBTI, existing datasets are often derived from social media posts, with labels typically sourced from users’ self-reported MBTI types (Gjurković et al., 2021). Assessments conducted by non-professional psychological institutions, along with

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¹<https://github.com/Personality-NLP/MbtIBench>

inaccurate self-perception, can lead to a **mismatch between the self-reported personality traits and the actual linguistic patterns in the text** (McDonald, 2008; Müller & Moshagen, 2019; Paulhus & Vazire, 2007). For example, a user who self-identifies as an *Extraversion* type might exhibit more *Introversion* traits in their posts (Figure 9 (a)). (2) From a psychological standpoint, **personality is not binary but rather complex, nuanced, and highly individualized** (Wu et al., 2022). Most people don't display extreme personality traits; instead, they tend to fall somewhere in the middle (Tzeng et al., 1989). However, existing datasets use only binary MBTI labels, missing the full spectrum of personality traits in most people (Harvey & Murry, 1994; Wu et al., 2022) (Figure 9 (b)).

In this paper, we make a step toward solving the challenge. We optimize the task by constructing MBTIBENCH, the first MBTI personality detection dataset aligned with population traits. (1) To solve the data quality issues related to self-reported labels, we propose the first data filtering guidelines for MBTI personality detection and apply them on existing datasets to ensure data quality. We manually re-annotate the cleaned datasets under the guidance of psychological experts, aligning each post with correct labels that best describe the personality polarity. (2) To capture the full range of population personality traits, we estimate soft labels for MBTI personality detection by deriving the polarity tendencies of samples. The obtained soft labels confirm the above opinion that there are more people with non-extreme personality traits.

We analyze our MBTIBENCH in detail from multiple perspectives to explore the influence of soft labels compared to hard labels. We further evaluate six large language models (LLMs) and four prompting methods on MBTIBENCH, and highlight the polarized predictions and biases as key directions.

Our contributions are as follows:

- We are the first to challenge the over-optimism in MBTI personality detection from the nature of population personality traits.
- We optimize MBTI personality detection by creating MBTIBENCH, the first soft-labeled MBTI dataset, manually annotated under the guidance of psychologists.
- We highlight the polarized predictions and biases in LLMs as future directions. Our experimental results also confirm that soft labels can provide more benefits to other psychological tasks than hard labels.

2 MBTI Personality Detection

2.1 Existing Datasets Overview

There are three widely used datasets in personality detection based on MBTI, including Twitter (Plank & Hovy, 2015), Kaggle², PANDORA (Gjurković et al., 2021) (Table 1). These three datasets are collected

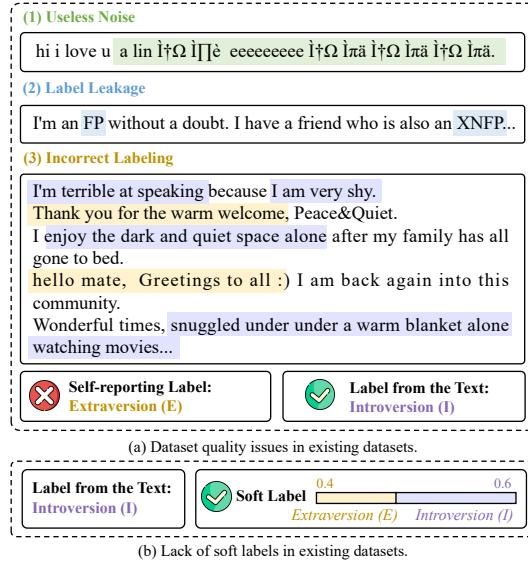


Figure 1: Our MBTIBENCH focuses on the above two limitations in existing MBTI personality detection datasets: data quality issues and the lack of soft labels.

Dataset	Types	Train	Validation	Test
Kaggle	E/I	1194/4011	409/1326	396/1339
	S/N	727/4478	222/1513	248/1487
	T/F	2410/2795	791/944	780/955
	P/J	3096/2109	1063/672	1082/653
PANDORA	E/I	1162/4278	386/1427	377/1437
	S/N	610/4830	208/1605	210/1604
	T/F	3549/1891	1120/693	1182/632
	P/J	3211/2229	1043/770	1056/758
Twitter	E/I	329/571	99/201	111/189
	S/N	206/694	66/234	66/234
	T/F	355/545	139/161	130/170
	P/J	395/505	112/188	111/189

Table 1: Statistics of the Kaggle, PANDORA, and Twitter datasets.

²<https://www.kaggle.com/datasnaek/mbti-type>

from social media posts. Each sample is a set of posts from the corresponding user, and the labels are obtained through users self-reporting their posts. However, as shown in Figure 9, there are issues of label leakage and irrelevant noise that significantly compromise the quality and factual accuracy of the data itself. Moreover, users' lack of clarity in self-reporting often leads to mismatches between self-reported labels and their posts (McDonald, 2008). To address the above issues, we clean and re-annotate existing datasets to construct our MBTIBENCH.

Attitudes	Perceiving Functions	Judging Functions	Lifestyle Preferences
<i>Interact with the world</i>	<i>Gather information</i>	<i>Make decisions</i>	<i>Organize their lives</i>
🌟 Extraversion (E) <i>Energized by interaction Social and talkative</i>	👀 Sensing (S) <i>Practical and realistic Detail-oriented</i>	📝 Thinking (T) <i>Logical and analytical Fact-based</i>	📅 Judgment (J) <i>Organized and structured Planning-oriented</i>
🌙 Introversion (I) <i>Energized by solitude Reflective and thoughtful</i>	🧠 iNtuition (N) <i>Imaginative and innovative Future-focused</i>	❤️ Feeling (F) <i>Compassionate and empathetic Values-driven</i>	🌐 Perception (P) <i>Flexible and spontaneous Adaptable</i>

Figure 2: Definitions of the four dimensions in MBTI personality theory.

2.2 Problem Overivew

MBTI lays out a binary classification based on four distinct functions, and draws the typology of the person according to the combination of those four values (Figure 2):

- Extraversion/Introversion (*E/I*) - preference for how people direct and receive their energy, based on the outer or inner world.
- Sensing/INtuition (*S/N*) - preference for how people take information in, by five senses or by interpretation and meanings.
- Thinking/Feeling (*T/F*) - preference for how people make decisions, by relying on logic or emotions towards people and special circumstances.
- Judgment /Perception (*J/P*) - how people deal with the world, by organizing it or staying open for new information.

The task of MBTI personality detection, which involves automatically inferring a person's MBTI type from their textual content, has attracted significant interest from researchers due to its broad range of potential applications (Khan et al., 2005; Bagby et al., 2016). Given the growing interest in understanding personality through text, MBTI personality detection, that automatically inferring an individual's MBTI type from their written content, has become a prominent area of research, with a broad range of practical applications (Khan et al., 2005; Bagby et al., 2016).

As for hard labels, existing MBTI datasets lay out a binary classification based on four distinct dimensions independently (*E/I, S/N, T/F, J/P*), and draw the typology of the person according to the combination of those four values (e.g. *ESTJ*).

In this paper, we construct a new dataset called MBTIEVAL with soft labels. Soft labels are continual representations of polarity tendency mapped in [0, 1], and we define the four dimensions of soft labels as the degree of *E, S, T*, and *J* polarity, respectively. For example, 40% *Extraverslon* simultaneously represents 60% *Introversion*.

3 Dataset Construction

In this paper, we re-annotate three existing datasets to solve the dataset quality issues. We introduce the construction details below.

3.1 Design Principles

To ensure our annotation quality, we respectively establish data filtering guidelines for useless noise and label leakage issues, and data annotation guidelines for incorrect labeling issues.

3.1.1 Data Filtering Guidelines

We are the first to summarize data filtering guidelines for label leakage and useless noise issues in MBTI personality detection.

We divide the label leakage errors into three categories: (1) Direct Personality Leakage involves direct references to personality types through specific letters ("ENFP") or complete personality type words ("Introverted"). (2) Personality Trait Leakage involves specific MBTI trait descriptors providing enough context to infer certain personality types. For example, *T*_e indicates *extroverted Thinking*. (3) Cross-Theory Trait Leakage involves traits from other personality theories like the Big Five (Furnham, 1996), confirming MBTI personality characteristics.

We divide the useless noise issues into three categories: (1) Information-insufficient Samples indicate samples that are too short (less than 100 words) to contain valuable information for inferring personality types. (2) Garbled Text indicates blocks of text that appears as random, unintelligible characters and symbols. (3) Link and Media References indicates hyperlinks or media file names, which are useless for personality detection.

3.1.2 Data Annotation Guidelines

Personality refers to the combination of characteristics or qualities that form an individual's distinctive character (Mairesse et al., 2007). It encompasses a wide range of traits, behaviors, thoughts, and emotional patterns that evolve from biological and environmental factors (Furnham, 1996; Celli & Lepri, 2018; Chung & Pennebaker, 2011; Line, 1948). A particular personality can determine various outward observable properties or features, including consistent behavioral patterns, communication style, emotional expression and so on.

To address incorrect labeling issues and accurately label personality types, we refer to the methodology outlined in Stajner & Yenikent (2021) to construct our annotation guidelines. Psychology PhD students participate in the formulation of these guidelines. We discuss the personality traits for each dimension based on the dataset, analyzing and adjusting our guidelines through trial annotations. Finally, we annotate the trial samples, which serve as expert guidelines.

3.2 Dataset Preprocessing

We reconstruct the test sets of the three most commonly used personality detection datasets, including Twitter, Kaggle, and PANDORA. Following Stajner & Yenikent (2021), we select

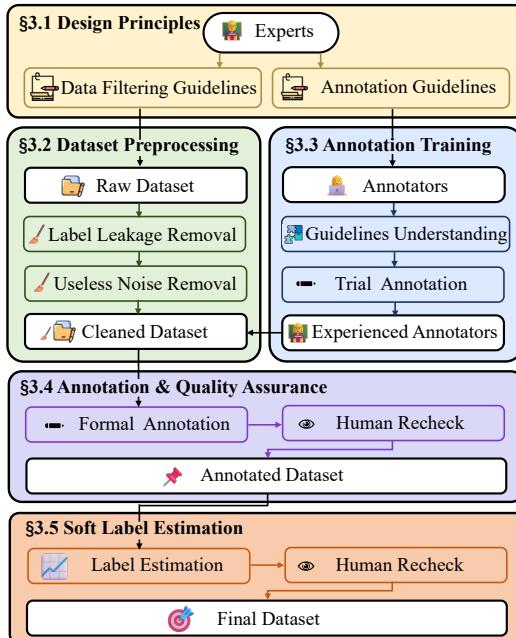


Figure 3: MBTIBENCH construction workflow.

Label Leakage Errors		Useless Noise Issues	
Issue Types	Cases	Issue Types	Cases
Direct Personality Leakage	My type is X. Introverted (I) 65.85% Extroverted (E) 34.15% Intuitive (N) 79.41% Sensing (S) 20.59% Feeling (F) 77.14% Thinking(T) 22.86% Judging (J) 69.44% Perceiving (P) 30.56%	Information-insufficient Samples	forward to my meeting with the board of health ...makes me laugh so much
Personality Trait Leakage	For the Se-vibe I get, xSxP. Out of those, I pick X.	Garbled Text	hi i love u a lin l̄Ω l̄Πé eeeeeeee l̄Ω l̄Ω l̄πä l̄Ω l̄Ω u got awkward before de meh bye bye hair l̄Ω l̄á / gh7g5jd3dh " " yayyysss ni / nvapsehrkrk
Cross-Theory Trait Leakage	I feel like this is pretty accurate, was interesting to do. Openness: 53, Conscientiousness: 89 Extraversion: 37 Agreeableness: 94 Neuroticism: 14	Link and Media References	im rdy 2 go room for two ? ? ? ? ? http :/ / t.co / atjd 6ys9zt i can't live in your sleeping bag huh

(a) Cases for label leakage issues.

(b) Cases for useless noise issues.

Figure 4: We are the first to provide dataset quality issues annotation guidelines for MBTI personality detection.

six samples for each type, totaling 286 samples across the three datasets.³ To ensure that the samples provide useful data for personality detection, we filter the dataset. Specifically, we manually remove sentences involving label leakage and useless noise from the samples, using the annotation guidelines from Section 3.1, resulting in a cleaned dataset awaiting annotation.

3.3 Annotation Training

3.3.1 Annotation Guidelines Understanding

We employ three experienced annotators who hold either a Bachelor’s or Master’s degree in English and can use English fluently with extensive annotation experience. We conduct training sessions for them under the guidance of psychology experts, using expert-annotated examples to explain the definition and judgment signals for each MBTI dimension. Annotators read through the entire instance and make independent judgments for each dimension. We refer to the 4-point Likert scale (Likert, 1932) and ask the annotators to assign, for each instance and each MBTI dimension separately, two polar intensity labels. For example, in the *E/I* dimension, they could assign *E-*, *E+*, *I-*, or *I+* labels to reflect the degree of classification signals or their confidence level. In each pilot round, the dataset they annotate consists of 16 instances, which are not used in the final round to ensure the integrity of the final data.

3.3.2 Trial Annotation

We distribute trial annotation samples to the annotators, requiring them to annotate the same samples independently. This is to assess their consistency and understanding of the guidelines, as well as the effectiveness of the guidelines themselves. The trial annotation samples obtained during the pilot rounds show how the proposed guidelines are used in practice and highlight the most challenging aspects of the annotation process (Shi et al., 2023; Chen et al., 2023).

After the trial annotation, we determine the final result for each label by voting and measuring annotation quality using annotation accuracy and Fleiss’ Kappa (Fleiss, 1971). If the accuracy is below 0.8 or the Fleiss’ Kappa does not exceed 0.45, we repeat the “Annotation Training” process, starting

	A1	A2	A3
<i>E/I</i>	OVERALL 87.41%	87.76%	86.36%
	E+ 92.00%	94.34%	100.00%
	E- 86.01% ↓	86.79%	86.90%
	I- 87.63%	84.62% ↓	83.47% ↓
<i>S/N</i>	I+ 90.48%	91.30%	100.00%
	OVERALL 89.86%	85.31%	85.31%
	S+ 87.93% ↓	86.57%	91.67%
	S- 88.12%	85.54%	81.45% ↓
	N- 90.48%	83.52% ↓	84.00%
<i>T/F</i>	N+ 100.00%	86.67%	100.00%
	OVERALL 88.46%	89.86%	88.11%
	T+ 93.33%	90.14%	94.29%
	T- 87.27%	88.73% ↓	90.43%
	F- 89.60%	90.24%	85.25% ↓
<i>J/P</i>	F+ 80.95% ↓	90.32%	85.71%
	OVERALL 88.81%	87.41%	83.57%
	J+ 89.66%	87.04%	95.83%
	J- 85.84% ↓	85.71% ↓	83.17%
	P- 91.20%	88.31%	83.33%
	P+ 89.47%	88.73%	63.64% ↓

Table 2: The annotation accuracy of annotators across the four dimensions.

³There are only four samples for the ESFJ type in the test set of PANDORA.

again from "Annotation Guidelines Understanding" to ensure the effectiveness of the trial annotation.⁴ We conduct three rounds of trial annotation, during which the accuracy and Kappa for the four dimensions steadily increase.

3.4 Annotation and Quality Assurance

3.4.1 Formal Annotation

Once the trial annotation is completed, the annotators become fully acquainted with the annotation guidelines and procedures. The annotators are provided with the cleaned dataset and are expected to annotate independently. We pay them at a rate that is no less than the local average, and they are entitled to take adequate breaks to mitigate the effects of fatigue. Annotators are provided with the cleaned dataset and annotate independently. They are compensated at a rate no less than the local average and are given adequate breaks to reduce fatigue.

3.4.2 Human Recheck

After the formal annotation, we conduct a human recheck of each annotated instance to ensure the annotation quality. If an instance is found to be unreasonably annotated, we summarize the issues and communicate them with the respective annotator. These problematic samples are then mixed with other normal samples and re-annotated by the annotators to prevent direct suggestions or interference. The re-annotated instances account for less than 15% of the total. The final Fleiss' Kappa scores⁵ are not only satisfactory for personality detection (Jiang et al., 2019) but also suitable for soft label estimation, which demonstrates our annotation quality.

Algorithm 1 Soft Label Estimation for the E/I Dimension

- 1: **Input:** Annotated dataset with labels by three annotators.
 - 2: **Initial True Label Calculation**
 - 3: **Co-occurrence Matrix Calculation**
 - 4: **Transition Matrix Formation**
 - 5: **Iterative Calculation**
 - 6: **repeat**
 - 7: Compute the **posterior probability of E** based on the transition matrix T
 - 8: Update the transition matrix T using the posterior probability of E.
 - 9: **until** change in posterior probability of E \leq tolerance.
 - 10: **Tendency Calculation**
 - 11: **Normalization**
 - 12: **Output:** Soft Labels.
-

3.5 Soft Label Generation

3.5.1 Label Estimation

Inspired by the Dawid-Skene model (Dawid & Skene, 1979), we adopt the EM algorithm (Dempster et al., 1977) to derive the polarity tendency of samples. The algorithm effectively fits annotators of varying quality and comprehensively produces realistic rankings for each sample (Passonneau & Carpenter, 2013). We estimate a more objective soft label by processing the hard labels provided by the three annotators, thereby accurately reflecting the comprehensive inclination of the data across various dimensions. In this paper, we use the E/I dimension as an example to introduce the algorithm for estimating soft labels (Algorithm 1).

⁴A Fleiss' Kappa value above 0.4 is satisfactory for subjective tasks (Jiang et al., 2019).

⁵0.4779 for E/I, 0.4686 for S/N, 0.5517 for T/F, 0.4622 for J/P.

1. Initial True Label Calculation: First, we take the annotated data as the initial input and calculate the median of the three annotators' labels as the initial true label.

2. Co-occurrence Matrix Calculation: Next, we compare each annotator's label with the initial true label to obtain a matrix $\mathbf{M} \in \mathcal{R}^{3 \times 4 \times 4}$ where m_{ijk} represents the joint frequency of category j and category k in i-th annotator labels.

3. Transition Matrix Formation: Using Bayes' theorem to merge E+ and E- into E, and store the result in a new matrix T:

$$T_{i0k} = \frac{(N_{i0k} \times P_{E+}) + (N_{i1k} \times P_{E-})}{P_E}.$$

P_{E+} , P_{E-} represent the proportions of labels classified as E+, E-, and P_E is the sum of them.

4. Iterative Calculation: Calculate the initial posterior probability of E from the transition matrix, then update the matrix and recompute until changes are within a predefined tolerance:

$$P(E | r_1, r_2, r_3) = \frac{\prod_{i=1}^3 P_{r_i 0} \times P_E}{\sum_{j=0}^1 \prod_{i=1}^3 P_{r_i j} \times P_E},$$

where r_i represents the label labeled by the i-th annotator.

5. Tendency Calculation: Since the midpoint where posterior probability is 0.5, we accumulate and average values on both sides.

6. Normalization: Finally, we normalize the cumulative frequencies on both sides of the midpoint. Each combination is assigned a final ratio between 0 and 1, reflecting the label's tendency. We define this ratio as the "soft label" of the type *Extraversion*.

3.5.2 Human Recheck

Under the guidance of psychology experts, we review the estimated soft labels to ensure they align with the degree of personality polarity reflected in texts. We find that the use of the EM algorithm in estimating soft labels effectively integrates the annotators' varying accuracy and labeling habits, producing accurate soft labels (Raykar et al., 2010a) (Table 2).

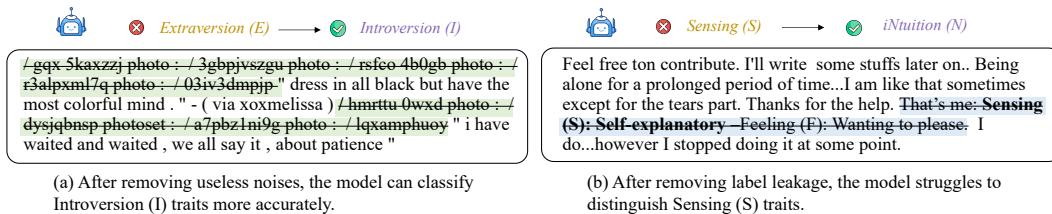


Figure 5: After solving the data quality problem, the performance of the model is affected.

4 Dataset Quality Analysis

We analyze the quality of our datasets from four perspectives to explore the influence of soft labels compared to hard labels (Liu et al., 2020).

4.1 Self-reported Labels Influence Model Performance

We analyze the useless noise issues, self-reported label leakage, and incorrect self-reported labels in Table 3 and Figure 5. The datasets exhibit varying degrees of quality

Dimensions	Kaggle	Twitter	PANDORA
Useless Noise	15.92%	43.13%	2.65%
Label Leakage	31.21%	0.62%	16.56%
Incorrect Labeling	29.17%	29.17%	29.79%

Table 3: Issues solved in three datasets.

issues before refinement that impact model performance. Therefore, filtering the input data to avoid such influence is crucial and we are the first to establish guidelines for manual filtering (Section 3.1).

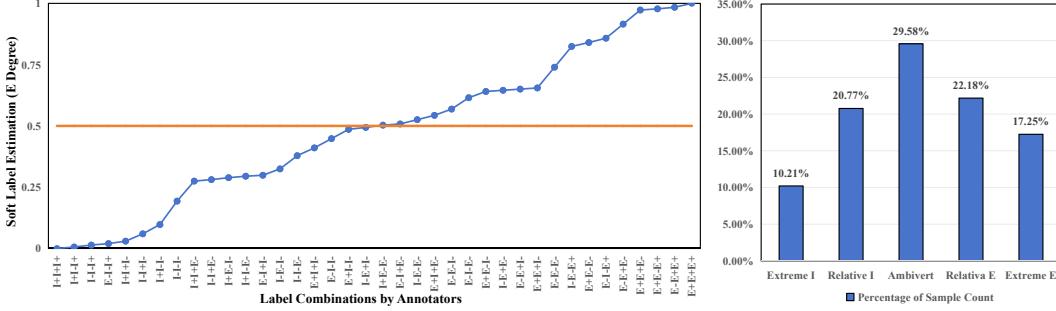


Figure 6: The mapping from hard labels to soft labels of the *E/I* dimension in MBTI BENCH. In (a), we use an EM algorithm to convert annotator label combinations (x-axis) into soft labels ranging from 0 to 1 (y-axis). We then define Extreme I, Relative I, Ambivert, Relative E, and Extreme E based on these soft label values, as shown on the x-axis of (b). The y-axis in (b) shows the sample count for each category.

4.2 Soft Labels Align with Population Traits

We illustrate the estimated soft labels and the corresponding sample count distribution of *E/I*, *S/N*, *T/F*, and *J/P* in Figure 6 and Appendix Figure 10-12. Soft labels exhibit a smooth distribution from 0 to 1, and there are more non-extreme samples than extreme ones. This is consistent with the population distribution and demonstrates that our soft labels align with population traits better compared to hard labels (Harvey & Murry, 1994).

4.3 Label Shifts Across Personality Dimensions

We quantify label changes across four dimensions before and after refinement in the three datasets (Table 4). Across all datasets, a notable shift from *I* to *E* is observed, likely reflecting social media’s interactive nature that promotes extroverted (*E*) behaviors. The *S/J* to *N/P* shift aligns with the fragmented and immediate communication style typical of these platforms. Regarding the *T/F* dimension, Kaggle and PANDORA show more *F* labels reclassified as *T*, possibly due to the rational and in-depth exchanges prevalent on these platforms. In contrast, Twitter shows a greater shift from *T* to *F*, reflecting its focus on emotion-driven content.

Dimensions	Twitter	Kaggle	PANDORA
E / I	55↑ / 41↓ / Δ = 7	56↑ / 40↓ / Δ = 8	49↑ / 45↓ / Δ = 3
S / N	53↑ / 43↓ / Δ = 5	51↑ / 45↓ / Δ = 3	46 / 48 - / Δ = 0
T / F	38↓ / 58↑ / Δ = 10	50↑ / 46↓ / Δ = 2	53↑ / 41↓ / Δ = 5
P / J	53↑ / 43↓ / Δ = 5	51↑ / 45↓ / Δ = 3	46 / 48 - / Δ = 0

Table 4: Statistics of three datasets, showing changes in comparison with baseline.

Annotated Labels	E+E+E+		I-E-I-		I+I-I-	
Soft Labels	1.0	0	0.33	0.67	0.03	0.97
Extraversion			Extraversion	Introversion	Extraversion	Introversion
I hate you D	Magic Micah	BYE :tongue:	Recently, I learned about Zentangle. It's really neat...I like the way you think. ;)		I have bad panic attacks and is hard for me to leave my house. And I hate my neighborhood. Always playing music and mad loud.	
Cases	You must be super intuitive! I'm so impressed by your mind reading skills!		Thanks Sily. I enjoy yours, too. So many times, I've wished to be more extroverted or outgoing or more...I don't know...normal. It's fun...and soothing. I like soothing.		Lol nice that sounds dope and all. But what do I think when I look into the eyes? I don't like talking to people and I can't keep jobs.	
Omg	you're going to teach me how to relationship???	Thank you sensei.	Can't wait to see your next avatar in...5.283 seconds. ;) Thanks Bear87!		I do have social anxiety.	
Yeah you got some silverware, but really are you eatin though??						
Why yes, I did do IB :						

Figure 7: Three cases and their corresponding annotated labels and soft labels.

4.4 Soft Labels Capture Personality Polarity Tendencies

We provide three case as well as their corresponding annotated labels and soft labels in Figure 7. The personality tendencies displayed in user posts are well captured by the annotators and reflected in the annotated labels, while the estimated soft labels also demonstrate a tendency change from extraversion to introversion.

5 Experiment Setup

To evaluate model performance on MBTI BENCH and explore future directions, we conduct experiments across six backbone models and four prompting methods on MBTI BENCH (Liu et al., 2022). In this section, we provide an overview of the experiments.

5.1 Experimental Details

5.1.1 Backbones

We employ several widely used and powerful LLMs as our backbones, including closed-source LLMs: GPT-4 (Achiam et al., 2023) (gpt-4o-mini and gpt-4o), and open-source LLMs: Qwen2 series (Yang et al., 2024) (Qwen2-7B-Instruct and Qwen2-72B-Instruct), Llama3.1 series (Dubey et al., 2024) (Meta-Llama-3.1-8B-Instruct and Meta-Llama-3.1-70B-Instruct). Qwen2 series have a context window of 32K tokens, while Llama 3.1 series and GPT-4o series both have context windows of 128K tokens, which are sufficient to process a large volume of user posts and perform Chain-of-Thought (CoT) (Wei et al., 2022) reasoning. Moreover, we employ the average soft labels of each dimension as the *baseline*, to evaluate model performance.

5.1.2 Prompting Methods

Following the methodologies outlined in Yang et al. (2023), based on each user’s posts P , we apply them to an inference prompt template $t(\cdot)$, where $t(P)$ serves as the actual input to LLMs. We adopt four prompting approaches: (1) Zero-shot involves directly presenting the task description and requiring the model to directly complete the task.⁶ (2) Step-by-step (Kojima et al., 2022) employs the additional phrase *Let’s think step by step* based on zero-shot in the inference prompt.⁷ (3) Few-shot employs two additional examples in the inference prompt based on zero-shot, with each example containing a post and the corresponding complete personality label.⁸ (4) PsyCoT (Yang et al., 2023) requires the model to answer MBTI scale questions and refer to the answers for final personality judgments. We present the detailed content of the prompting methods in Appendix Table 7. We set $temperature = 0$ to eliminate randomness. Each post is truncated to no more than 80 tokens.

5.2 Evaluation

Following Raykar et al. (2010b) and Gjurković et al. (2021), we directly predict soft labels to evaluate the model’s ability to make more detailed estimations of personality traits. Specifically, $t(\cdot)$ instructs the model to assess the degree of each personality trait and generate a score within the range of 1 to 9, for example, $[[7.25]]$.

We employ the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to measure the differences between the predicted soft labels by LLMs and the estimated golden ones. Considering the limited precision of our estimated soft labels, we introduce Segmented MAE (S-MAE) and Segmented RMSE (S-RMSE). Instead of computing the error based solely on the raw predictions, we discretize the continuous 0-1 distribution into ten intervals and evaluate the corresponding RMSE and MAE within these segments. By framing the problem

⁶Standard in Yang et al. (2023).

⁷Zero-shot in Yang et al. (2023).

⁸We manually choose the two examples.

in this way, the error becomes less sensitive to specific small deviations in continuous values and more focused on whether the prediction falls within an appropriate range. Further details are introduced in Appendix E.2.

Backbones	Methods	E/I		S/N		T/F		J/P		Rank
		S-RMSE	S-MAE	S-RMSE	S-MAE	S-RMSE	S-MAE	S-RMSE	S-MAE	
Baseline	-	2.66	2.29	2.70	2.31	2.82	2.43	3.04	2.59	-
gpt-4o-mini	Zero-shot	2.78	2.17	2.77	2.24	2.37	1.99	3.11	2.60	1.00
	Step-by-step	<u>2.82</u>	<u>2.23</u>	3.02	2.42	2.67	2.13	3.52	2.89	2.63
	Few-shot	2.96	2.43	<u>2.84</u>	<u>2.41</u>	<u>2.65</u>	<u>2.15</u>	<u>3.15</u>	2.60	2.38
	PsyCoT	3.02	2.34	4.65	3.90	3.61	2.87	3.96	3.12	3.88
gpt-4o	Zero-shot	2.91	2.28	2.90	2.23	2.62	2.06	3.80	3.15	1.75
	Step-by-step	<u>3.07</u>	<u>2.38</u>	<u>2.96</u>	<u>2.33</u>	<u>2.73</u>	2.19	<u>3.51</u>	<u>2.88</u>	2.38
	Few-shot	2.82	2.13	3.34	2.74	2.76	<u>2.16</u>	3.44	2.81	<u>1.88</u>
	PsyCoT	3.36	2.67	5.02	4.25	3.23	2.49	5.20	4.27	4.00
Qwen2-7B	Zero-shot	<u>3.11</u> \pm 0.00	<u>2.59</u> \pm 0.00	2.68 \pm 0.01	2.29 \pm 0.01	<u>2.90</u> \pm 0.00	<u>2.48</u> \pm 0.00	<u>3.16</u> \pm 0.02	<u>2.65</u> \pm 0.01	1.75
	Step-by-step	<u>3.26</u> \pm 0.08	<u>2.70</u> \pm 0.06	<u>2.69</u> \pm 0.00	<u>2.30</u> \pm 0.00	<u>2.92</u> \pm 0.00	<u>2.50</u> \pm 0.00	<u>3.16</u> \pm 0.00	<u>2.66</u> \pm 0.00	2.88
	Few-shot	<u>3.51</u> \pm 0.01	<u>2.80</u> \pm 0.01	<u>3.29</u> \pm 0.01	<u>2.71</u> \pm 0.01	<u>4.03</u> \pm 0.04	<u>3.23</u> \pm 0.04	<u>3.20</u> \pm 0.02	<u>2.68</u> \pm 0.02	4.00
	PsyCoT	2.68 \pm 0.00	2.30 \pm 0.00	<u>2.70</u> \pm 0.00	<u>2.30</u> \pm 0.01	2.82 \pm 0.00	2.43 \pm 0.00	<u>3.10</u> \pm 0.01	2.62 \pm 0.01	1.38
Qwen2-72B	Zero-shot	<u>2.58</u> \pm 0.00	<u>2.11</u> \pm 0.00	2.70 \pm 0.01	2.28 \pm 0.01	<u>3.00</u> \pm 0.02	<u>2.46</u> \pm 0.02	<u>3.10</u> \pm 0.01	<u>2.61</u> \pm 0.01	1.75
	Step-by-step	2.58 \pm 0.01	2.10 \pm 0.01	<u>2.70</u> \pm 0.01	<u>2.30</u> \pm 0.01	<u>2.92</u> \pm 0.01	2.41 \pm 0.01	<u>3.12</u> \pm 0.02	<u>2.62</u> \pm 0.01	1.75
	Few-shot	<u>2.76</u> \pm 0.02	<u>2.26</u> \pm 0.01	<u>3.09</u> \pm 0.02	<u>2.56</u> \pm 0.02	<u>3.29</u> \pm 0.03	<u>2.70</u> \pm 0.02	3.09 \pm 0.01	2.60 \pm 0.01	2.75
	PsyCoT	<u>2.64</u> \pm 0.01	<u>2.15</u> \pm 0.01	<u>3.99</u> \pm 0.03	<u>3.23</u> \pm 0.03	<u>4.59</u> \pm 0.03	<u>3.75</u> \pm 0.03	<u>4.66</u> \pm 0.04	<u>3.75</u> \pm 0.04	3.75
Llama3.1-8B	Zero-shot	2.77 \pm 0.02	2.39 \pm 0.01	2.83 \pm 0.01	2.37 \pm 0.00	2.86 \pm 0.02	2.44 \pm 0.01	3.10 \pm 0.01	2.64 \pm 0.01	1.00
	Step-by-step	<u>3.76</u> \pm 0.05	<u>3.05</u> \pm 0.03	<u>3.82</u> \pm 0.07	<u>3.07</u> \pm 0.08	<u>3.93</u> \pm 0.12	<u>3.21</u> \pm 0.13	<u>3.73</u> \pm 0.02	<u>2.99</u> \pm 0.03	3.88
	Few-shot	<u>3.67</u> \pm 0.00	<u>3.00</u> \pm 0.01	<u>3.42</u> \pm 0.00	<u>2.77</u> \pm 0.00	<u>3.66</u> \pm 0.00	<u>3.01</u> \pm 0.00	<u>3.44</u> \pm 0.00	<u>2.87</u> \pm 0.00	2.50
	PsyCoT	<u>3.31</u> \pm 0.02	<u>2.80</u> \pm 0.02	<u>3.55</u> \pm 0.00	<u>2.93</u> \pm 0.01	<u>3.54</u> \pm 0.00	<u>2.96</u> \pm 0.00	<u>3.70</u> \pm 0.01	<u>3.12</u> \pm 0.00	2.63
Llama3.1-70B	Zero-shot	2.68 \pm 0.01	2.22 \pm 0.00	3.15 \pm 0.01	<u>2.58</u> \pm 0.01	<u>2.89</u> \pm 0.01	<u>2.41</u> \pm 0.01	3.24 \pm 0.02	2.72 \pm 0.01	1.50
	Step-by-step	<u>2.88</u> \pm 0.01	<u>2.39</u> \pm 0.01	<u>3.20</u> \pm 0.01	<u>2.63</u> \pm 0.01	<u>2.92</u> \pm 0.02	<u>2.38</u> \pm 0.02	<u>3.37</u> \pm 0.02	<u>2.84</u> \pm 0.01	2.75
	Few-shot	<u>2.93</u> \pm 0.02	<u>2.47</u> \pm 0.02	<u>3.17</u> \pm 0.02	<u>2.55</u> \pm 0.02	<u>2.75</u> \pm 0.01	<u>2.24</u> \pm 0.02	<u>3.25</u> \pm 0.02	<u>2.78</u> \pm 0.01	2.00
	PsyCoT	<u>2.94</u> \pm 0.02	<u>2.34</u> \pm 0.01	<u>3.96</u> \pm 0.01	<u>3.17</u> \pm 0.01	<u>3.65</u> \pm 0.03	<u>2.93</u> \pm 0.03	<u>4.00</u> \pm 0.02	<u>3.19</u> \pm 0.03	3.75

Table 5: We conduct experiments using soft labels and use S-RMSE and S-MAE as evaluation metrics, where lower values indicate better performance. The best and second-best results across the four methods for each backbone are **bolded** and underlined.

6 Results and Analysis

6.1 Model Evaluation

In this paper, we conduct experiments on MBTI BENCH across four inference prompt methods and six backbones introduced in Section 5.1. The main results of our experiments are shown in Table 5 and Figure 8. We address the following research questions (RQs):

RQ 1: Can LLMs consistently outperform simple baselines in soft label prediction? We provide a baseline model introduced in Sec. 5.1.1, which computes the mean soft label for each MBTI dimension across the entire dataset, and evaluate several LLMs using different prompting methods. Surprisingly, in certain cases, even the best prompting methods for these LLMs fail to outperform the baseline model. For instance, the baseline model achieves an S-RMSE of 3.722 and an S-MAE of 3.017 for the *S/N* dimension. However, the few-shot prompting method using the Llama3.1-70B backbone only achieved an S-RMSE of 3.754 and an S-MAE of 3.073, which is worse than the baseline. These results suggest that for certain models, the model may struggle to capture the underlying personality distribution as effectively as a simple baseline that leverages the dataset’s overall distribution.

RQ 2: How do different methods perform on MBTI BENCH? The Zero-shot method demonstrates superior overall performance across all six backbones. As shown in Table 5, it achieves the lowest average S-MAE. This means that the Zero-shot method performs well on the majority of samples, with relatively small errors and the lowest average error. Zero-shot achieves the lowest average RMSE on most backbones, and achieves comparable RMSE

with the best method on gpt-4o and Llama3.1-8B. Considering that S-RMSE is more sensitive to larger errors (i.e., cases with extreme deviations in predictions), this indicates that the zero-shot model performs well overall, but may have significant deviations in the extreme values of certain backbones. In contrast, other methods may amplify the inherent biases of the models. For example, the PsyCoT method tends to predict 0 in certain dimensions, while few-shot methods are more influenced by the provided examples.

RQ 3: How do different backbone models exhibit biases in soft label prediction? Different backbone models exhibit varying biases in their soft label predictions (Figure 8 and Appendix Figure 18- 20).⁹ GPT-4o shows less bias compared to Llama 3.1, while Qwen2 more frequently assigns a score of 5. We hypothesize that these discrepancies stem from differences in their training corpora, leading to varied score distributions.

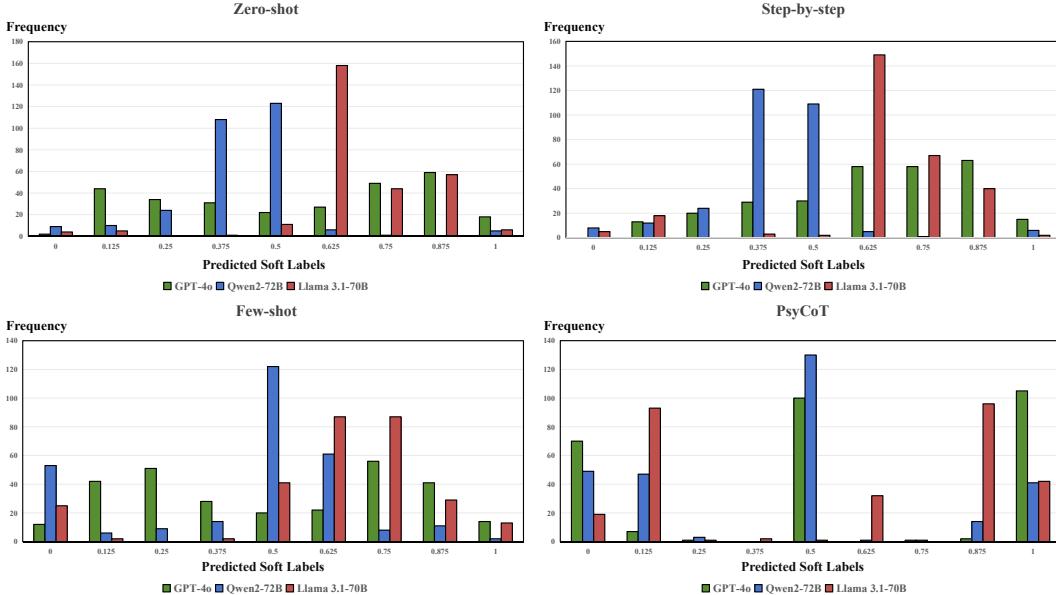


Figure 8: The score distribution of LLMs on MBTI BENCH for the T/F dimension.

6.2 Discussion

6.2.1 Can Soft Labels Better Align with Population Traits?

To validate the effectiveness of soft labels, we follow Ji et al. (2023) and incorporate personality traits into the stress identification task. This task is both challenging and representative, with substantial real-world significance. We use the Dreaddit stress detection dataset (Turcan & McKeown, 2019), where the LLM is provided with a *post* from one poster and tasked with determining whether the poster is likely to suffer from very severe stress or not (*w/o MBTI*). We predict the user’s MBTI personality types using both hard-label (*w/ Hard*) and soft-label (*w/ Soft*) approaches with LLM, based on the *post*. These personality types are then used as auxiliary inputs for stress identification.

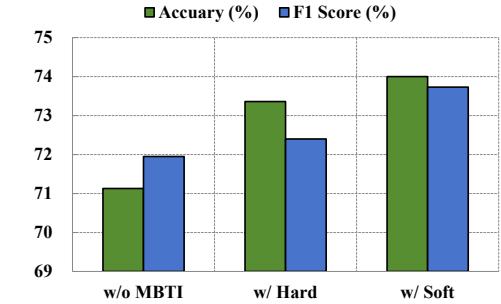


Figure 9: We integrate personality traits into stress detection, demonstrating that the use of soft labels (*w/ Soft*) enhances performance on personality-related tasks .

⁹We show the results of each first round on three backbones.

To evaluate the robustness of our results, we repeat the stress identification experiments 10 times and perform a t-test to assess the statistical significance of the outcomes. The results are shown in Figure 9.

We analyze the experimental results conclude that: (1) The inferior performance of *w/o MBTI* (Acc: 72.13, F1: 71.95) indicates that MBTI personality traits contribute to stress identification. (2) *w/ Soft* (Acc: 74.00, F1: 73.73) outperforms *w/ Hard* (Acc: 73.36, F1: 72.40), indicating that soft labels more accurately align with population personality traits than hard labels.

6.2.2 What Is the Difference in Behavior Between Hard Labels and Soft Labels?

We evaluate the performance on MBTIBENCH using the mapped hard labels and analyze the distribution of both hard and soft labels (Appendix Table 10). For the hard label evaluation, personality detection is treated as a classification task. The model is required to independently classify the user’s personality on each dimension, producing outputs such as *CHOICE: A* or *CHOICE: B*. We present the detailed content of the prompting methods in Appendix Table 8 for hard labels. We find that when applying multi-step reasoning methods, the model tends to produce more extreme classification results, as shown in Appendix Figure 13-16. This leads to inferior performance of Zero-shot in the hard label metrics compared to the other three methods, while in the soft label evaluation, Zero-shot demonstrates stronger performance.

7 Related Works

The Big Five and MBTI are two widely used personality frameworks in the fields of computational linguistics and natural language processing (Yang et al., 2021). In this paper, we focus on MBTI, one of the most widely used non-clinical psychometric assessments because it translates well into the behavioral context (Stajner & Yenikent, 2021) and is widely adopted in diverse real-world applications (Kuipers et al., 2009; Garden & Sloan, 2011; Gountas & Gountas, 2000). MBTI distinguishes itself in applied psychological settings by offering an approach that simplifies interpersonal and organizational dynamics, making it particularly valuable for enhancing team functionality and personal development initiatives (Myers et al., 1980).

The quality issues of datasets will affect the accurate evaluation of LLM performance and the iteration of methods in personality detection tasks (Liu et al., 2023). There have been some early explorations of dataset quality in previous work (Stajner & Yenikent, 2021), but they only annotated one commonly used Twitter dataset. These studies do not consider the impact of data noise and do not annotate complete samples. Additionally, these works do not validate their conclusions through model experiments. These limitations indicate that there is still room for improvement in the discussion of dataset quality. Some studies assess the ability of LLMs to determine the personality of humans or the LLMs themselves (Ji et al., 2023; Caron & Srivastava, 2023; Rao et al., 2023).

8 Conclusion

MBTI is one of the most popular personality theories and has garnered considerable research interest over the years. In this paper, we point out the over-optimism in MBTI personality detection from the nature of population personality traits. Specifically, (1) the self-reported labels in existing datasets result in data quality issues and (2) the hard labels fail to capture the full range of population personality distributions. We construct MBTIBENCH, the first high-quality manually annotated MBTI personality detection dataset with soft labels, under the guidance of psychologists. We filter and annotate the data, and estimate soft labels by deriving the polarity tendency of samples. Experiment results highlight the polarized predictions and bias as future directions.

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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.
- Shlomo Engelson Argamon, Sushant Dhawle, Moshe Koppel, and James W. Pennebaker. Lexical predictors of personality type. 2005.
- R Michael Bagby, Tara M Gralnick, Nadia Al-Dajani, and Amanda A Uliaszek. The role of the five-factor model in personality assessment and treatment planning. *Clinical Psychology: Science and Practice*, 23(4):365, 2016.
- Graham Caron and Shashank Srivastava. Manipulating the perceived personality traits of language models. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 2370–2386, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.156. URL <https://aclanthology.org/2023.findings-emnlp.156>.
- Fabio Celli and B. Lepri. Is big five better than mbti? a personality computing challenge using twitter data. In *Italian Conference on Computational Linguistics*, 2018.
- Bao Chen, Yuanjie Wang, Zeming Liu, and Yuhang Guo. Automatic evaluate dialogue appropriateness by using dialogue act. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 7361–7372, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.492. URL <https://aclanthology.org/2023.findings-emnlp.492>.
- Cindy Chung and James Pennebaker. The psychological functions of function words. In *Social communication*, pp. 343–359. Psychology Press, 2011.
- Philip J Corr and Gerald Ed Matthews. *The Cambridge handbook of personality psychology*. Cambridge University Press, 2009.
- A. Philip Dawid and Allan Skene. Maximum likelihood estimation of observer error-rates using the em algorithm. *Journal of The Royal Statistical Society Series C-applied Statistics*, 28: 20–28, 1979.
- Arthur P. Dempster, Nan M. Laird, and Donald B. Rubin. Maximum likelihood from incomplete data via the em - algorithm plus discussions on the paper. 1977.
- Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.
- Joseph L. Fleiss. Measuring nominal scale agreement among many raters. *Psychological Bulletin*, 76:378–382, 1971.

- Adrian Furnham. The big five versus the big four: the relationship between the myers-briggs type indicator (mbti) and neo-pi five factor model of personality. *Personality and Individual Differences*, 21:303–307, 1996.
- Annamaria Garden and Sloan. Relationships between mbti profiles , motivation profiles , and career paths. 2011.
- Alastair J. Gill and Jon Oberlander. Taking care of the linguistic features of extraversion. *Proceedings of the Twenty-Fourth Annual Conference of the Cognitive Science Society*, 2019.
- Matej Gjurković, Mladen Karan, Iva Vukojević, Mihaela Bošnjak, and Jan Snajder. PAN-DORA talks: Personality and demographics on Reddit. In *Proceedings of the Ninth International Workshop on Natural Language Processing for Social Media*, pp. 138–152, June 2021. doi: 10.18653/v1/2021.socialnlp-1.12. URL <https://aclanthology.org/2021.socialnlp-1.12>.
- John Gountas and Sandra Gountas. A new psychographic segmentation method using jungian mbti variables in the tourism industry. *Tourism Analysis*, 5:151–156, 2000.
- Robert James Harvey and William D. Murry. Scoring the myers-briggs type indicator: Empirical comparison of preference score versus latent-trait methods. *Journal of Personality Assessment*, 62:116–129, 1994.
- Marjan Hosseini, Eduard Constantin Dragut, Dainis Boumber, and Arjun Mukherjee. On the usefulness of personality traits in opinion-oriented tasks. In *Recent Advances in Natural Language Processing*, 2021.
- Yuzhe Ji, Wen Wu, Hong Zheng, Yiqiang Hu, Xi Chen, and Liang He. Is chatgpt a good personality recognizer? a preliminary study. *ArXiv*, abs/2307.03952, 2023.
- Hang Jiang, Xianzhe Zhang, and Jinho D. Choi. Automatic text-based personality recognition on monologues and multiparty dialogues using attentive networks and contextual embeddings. *ArXiv*, abs/1911.09304, 2019.
- Amir A Khan, Kristen C Jacobson, Charles O Gardner, Carol A Prescott, and Kenneth S Kendler. Personality and comorbidity of common psychiatric disorders. *The British Journal of Psychiatry*, 186(3):190–196, 2005.
- Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. In *ICML 2022 Workshop on Knowledge Retrieval and Language Models*, 2022.
- Michal Kosinski, David Stillwell, and Thore Graepel. Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, 110:5802 – 5805, 2013.
- Ben S Kuipers, Malcolm J Higgs, Natalia V Tolkacheva, and Marco C de Witte. The influence of myers-briggs type indicator profiles on team development processes: An empirical study in the manufacturing industry. *Small Group Research*, 40(4):436–464, 2009.
- Rensis Likert. A technique for the measurement of attitude scales. 1932.
- William F. Line. Description and measurement of personality. *American Journal of Psychiatry*, 104:591–592, 1948.
- Zeming Liu, Haifeng Wang, Zheng-Yu Niu, Hua Wu, Wanxiang Che, and Ting Liu. Towards conversational recommendation over multi-type dialogs. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault (eds.), *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 1036–1049, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.98. URL <https://aclanthology.org/2020.acl-main.98>.

- Zeming Liu, Jun Xu, Zeyang Lei, Haifeng Wang, Zheng-Yu Niu, and Hua Wu. Where to go for the holidays: Towards mixed-type dialogs for clarification of user goals. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (eds.), *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1024–1034, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.73. URL <https://aclanthology.org/2022.acl-long.73>.
- Zeming Liu, Ping Nie, Jie Cai, Haifeng Wang, Zheng-Yu Niu, Peng Zhang, Mrinmaya Sachan, and Kaiping Peng. XDailyDialog: A multilingual parallel dialogue corpus. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 12240–12253, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.684. URL <https://aclanthology.org/2023.acl-long.684>.
- François Mairesse, Marilyn A. Walker, Matthias R. Mehl, and Roger K. Moore. Using linguistic cues for the automatic recognition of personality in conversation and text. *J. Artif. Intell. Res.*, 30:457–500, 2007.
- Jennifer McDonald. Measuring personality constructs: The advantages and disadvantages of self-reports, informant reports and behavioural assessments. 2008.
- Sascha Müller and Morten Moshagen. Controlling for response bias in self-ratings of personality: A comparison of impression management scales and the overclaiming technique. *Journal of Personality Assessment*, 101:229 – 236, 2019.
- Isabel Briggs Myers et al. Gifts differing: Understanding personality type. 1980.
- R. Passonneau and Bob Carpenter. The benefits of a model of annotation. *Transactions of the Association for Computational Linguistics*, 2:573–573, 2013.
- Delroy L. Paulhus and Simine Vazire. The self-report method. 2007.
- James W. Pennebaker and Laura A. King. Linguistic styles: language use as an individual difference. *Journal of personality and social psychology*, 77 6:1296–312, 1999.
- Barbara Plank and Dirk Hovy. Personality traits on twitter—or—how to get 1,500 personality tests in a week. In *WASSA@EMNLP*, 2015.
- Haocong Rao, Cyril Leung, and Chunyan Miao. Can chatgpt assess human personalities? a general evaluation framework. In *Conference on Empirical Methods in Natural Language Processing*, 2023. URL <https://api.semanticscholar.org/CorpusID:257279816>.
- Vikas C Raykar, Shipeng Yu, Linda H Zhao, Gerardo Hermosillo Valadez, Charles Florin, Luca Bogoni, and Linda Moy. Learning from crowds. *Journal of machine learning research*, 11(4), 2010a.
- Vikas Chandrakant Raykar, Shipeng Yu, Linda H. Zhao, Gerardo Hermosillo, Charles Florin, Luca Bogoni, and Linda Moy. Learning from crowds. *J. Mach. Learn. Res.*, 11:1297–1322, 2010b.
- Klaus R. Scherer. Vocal communication of emotion: A review of research paradigms. *Speech Commun.*, 40:227–256, 2003.
- Xiaoming Shi, Zeming Liu, Chuan Wang, Haitao Leng, Kui Xue, Xiaofan Zhang, and Shaoting Zhang. MidMed: Towards mixed-type dialogues for medical consultation. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 8145–8157, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.453. URL <https://aclanthology.org/2023.acl-long.453>.
- Sanja Stajner and Seren Yenikent. A survey of automatic personality detection from texts. In Donia Scott, Nuria Bel, and Chengqing Zong (eds.), *Proceedings of the 28th International Conference on Computational Linguistics*, pp. 6284–6295, Barcelona, Spain (Online), December 2020. International Committee on Computational Linguistics. doi: 10.18653/v1/2020.coling-main.553.

- Sanja Stajner and Seren Yenikent. Why is mbti personality detection from texts a difficult task? In *Conference of the European Chapter of the Association for Computational Linguistics*, 2021.
- Elsbeth Turcan and Kathy McKeown. Dreaddit: A Reddit dataset for stress analysis in social media. In Eben Holderness, Antonio Jimeno Yepes, Alberto Lavelli, Anne-Lyse Minard, James Pustejovsky, and Fabio Rinaldi (eds.), *Proceedings of the Tenth International Workshop on Health Text Mining and Information Analysis (LOUHI 2019)*, pp. 97–107, Hong Kong, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-6213. URL <https://aclanthology.org/D19-6213>.
- Oliver C. S. Tzeng, Roger Ware, and Jeaw mei Chen. Measurement and utility of continuous unipolar ratings for the myers-briggs type indicator. *Journal of Personality Assessment*, 53: 727–738, 1989.
- Ben Verhoeven, Walter Daelemans, and Barbara Plank. Twisty: A multilingual twitter stylometry corpus for gender and personality profiling. In *International Conference on Language Resources and Evaluation*, 2016.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, brian ichter, Fei Xia, Ed H. Chi, Quoc V Le, and Denny Zhou. Chain of thought prompting elicits reasoning in large language models. In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho (eds.), *Advances in Neural Information Processing Systems*, 2022.
- Cort J. Willmott and Kenji Matsuura. Advantages of the mean absolute error (mae) over the root mean square error (rmse) in assessing average model performance. *Climate Research*, 30:79–82, 2005.
- Wen Wu, C. Zhang, Xixin Wu, and Philip C. Woodland. Estimating the uncertainty in emotion class labels with utterance-specific dirichlet priors. *IEEE Transactions on Affective Computing*, 14:2810–2822, 2022.
- Kosuke Yamada, Ryohei Sasano, and Koichi Takeda. Incorporating textual information on user behavior for personality prediction. In *Annual Meeting of the Association for Computational Linguistics*, 2019.
- An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, et al. Qwen2 technical report. *arXiv preprint arXiv:2407.10671*, 2024.
- Feifan Yang, Tao Yang, Xiaojun Quan, and Qinliang Su. Learning to answer psychological questionnaire for personality detection. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pp. 1131–1142, 2021.
- Tao Yang, Tianyuan Shi, Fanqi Wan, Xiaojun Quan, Qifan Wang, Bingzhe Wu, and Jiaxiang Wu. Psycot: Psychological questionnaire as powerful chain-of-thought for personality detection. *ArXiv*, abs/2310.20256, 2023.

A Ethical Statement

A.1 Data Access and Privacy

Our research utilizes data from three sources: PANDORA, Twitter, and Kaggle. We obtain special access and adaptation permission for the PANDORA dataset, ensuring compliance with data usage policies. The Twitter and Kaggle datasets are publicly available and freely accessible for academic research. All data used is sourced from these existing datasets, and we do not interact directly with or collect data from social media users. This ensures that the privacy of individuals is strictly maintained, as we have not accessed or manipulated their social media accounts. Once the paper is accepted, we will make our code and dataset publicly available.

A.2 Annotator Recruitment

Our three annotators hold undergraduate or master's degrees in English and are fluent in the language, with extensive experience in annotation. Under the guidance of a psychological expert, we provide them with meticulous training, as described in Section 3.3, enabling them to master the definitions and annotation criteria of MBTI proficiently. The annotators involved in our study are fairly compensated at rates not lower than the local average wage. They are provided with sufficient time to complete their tasks, ensuring that they can work without experiencing undue fatigue. All annotators give informed consent before participating in the study.

A.3 Annotation Guidelines and Expert Involvement

Our annotation guidelines are developed under the guidance of psychology experts. Both the pre-annotation and formal annotation recheck processes are conducted with their guidance, ensuring the accuracy and reliability of the annotations.

A.4 Scope of Analysis

Our analysis focus solely on the textual content of the datasets, specifically examining features related to the MBTI (Myers-Briggs Type Indicator). We do not make any inferences or judgments about the individuals behind the data, such as their habits, gender, opinions, or preferences. Our study strictly concentrates on the text itself and the MBTI-related features it contains, ensuring that no personal attributes or identities are considered in our analysis.

B FAQs

B.1 The relatively small sample size may limit dataset generalizability?

(1) Future Scalability: We fully agree that expanding the dataset through semi-automated methods could further enhance its generalizability. In future work, we plan to use LLMs fine-tuned on MBTIBench to label additional data with soft labels, followed by human quality checks. (2) Current Dataset Scope: In this initial work, our goal is to present MBTIBENCH as a high-quality, population-aligned dataset that supports MBTI soft-label evaluation. Given the costs of expert-led annotation, we consider the current dataset size to be sufficient for effective model evaluation and to maintain high reliability ?? . We are committed to open-sourcing MBTIBench to facilitate broader use and encourage semi-automated expansion by the community.

B.2 Potential biases introduced by annotators?

We recognize the potential impact of annotator bias on consistency. (1) Annotator Training: We conduct multiple rounds of trial annotations for professional annotators, using both Fleiss' Kappa and accuracy metrics to ensure consistency and reliability in their annotations.

(2) Soft Label Generation: We employ an EM algorithm that accounts for annotator variability and adjusts weights to produce soft labels for each sample (Sec. 3.5). For example, as shown in Appendix Table 2, annotator A3 has a lower accuracy on P+ labels (63.64%). The EM algorithm assigns less weight to A3’s P+ labels, resulting in a more balanced and realistic distribution, as shown in Appendix Figure 12(a). We will provide a more detailed explanation in future revisions.

C Data Annotation Guidelines

Personality refers to the combination of characteristics or qualities that form an individual’s distinctive character (Mairesse et al., 2007). It encompasses a wide range of traits, behaviors, thoughts, and emotional patterns that evolve from biological and environmental factors (Furnham, 1996; Celli & Lepri, 2018; Chung & Pennebaker, 2011; Line, 1948). A particular personality can determine various outward observable properties or features, including consistent behavioral patterns, communication style, emotional expression and so on.

To address incorrect labeling issues and accurately label personality types, we refer to the methodology outlined in Stajner & Yenikent (2021) to construct our annotation guidelines. Psychology PhD students participate in the formulation of these guidelines. We discuss the personality traits for each dimension based on the dataset, analyzing and adjusting our guidelines through trial annotations. Finally, we annotate the trial samples, which serve as expert guidelines. The detailed annotation guidelines are in Table 6.

D Dataset Quality Analysis

D.1 Soft Labels Align with Population Traits

We illustrate the estimated soft labels and the corresponding sample count distribution of E/I in Figure 6 and S/N, T/F, and J/P in Appendix Figure 10-12. Soft labels exhibit a smooth distribution from 0 to 1, and there are more non-extreme samples than extreme ones. This is consistent with the population distribution and demonstrates that our soft labels align with population traits better compared to hard labels (Harvey & Murry, 1994).

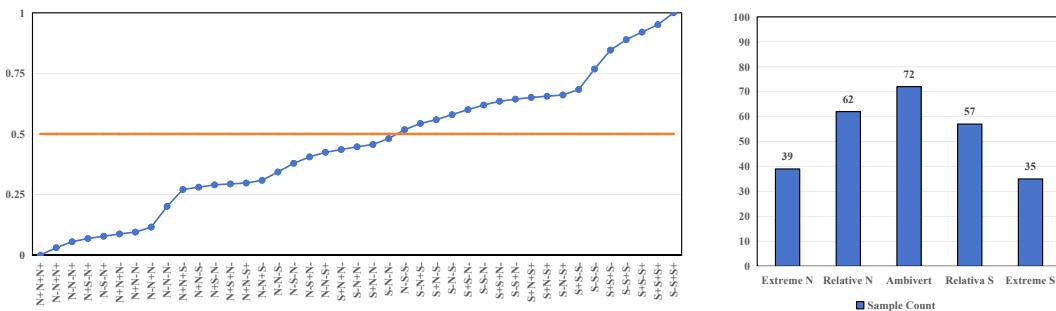


Figure 10: Distribution and Polarity distribution of soft labels for the S/N dimension in MBTIBENCH.

E Experimental Setup

E.1 Prompting Methods

Following the methodologies outlined in Yang et al. (2023), based on each user’s posts P , we apply them to an inference prompt template $t(\cdot)$, where $t(P)$ serves as the actual input to LLMs. We adopt four prompting approaches including Zero-shot, Step-by-step (Kojima

Dimension	Classification	Linguistic signals	Criteria for Judgment	Examples	Published Articles
Attitudes	Extraversion (E)	Social interaction Immediate Response More assertive, positive, enthusiastic	Text predominantly features interaction with others or references to social activities; Use of intensifiers and exclamation marks; We references.	"hello mate, Greetings to all!" "I'm so impressed by your mind reading skills!" "You s are so predictable:tongue:"	Pennebaker & King (1999) Stajner & Yenikent (2021)
	Introversion (I)	Individual activities Introspection Less assertive	Text predominantly features individual reflection and personal interests; Hedging; References.	"in the dark All my' ideals fall apart When they come..." "I do have social anxiety." "I super anxious all the time and tense."	
Perceiving Functions	Sensing (S)	Concrete details Past/present experiences (reality); Less assertive	Text rich in specific sensory details and real-life examples; Clear, concise, simplified and straightforward	"I did a quick google search." "I posted some guesses in the anime/ manga thread." "She called the cops on me and they arrested my whole family for some reason."	Mairesse et al. (2007) Gill & Oberlander (2019)
	iNtuition (N)	Abstract concepts Future possibilities	Text rich in abstract ideas and future-oriented thoughts; Artistic, longer, complex writing style.	"Ibelieve strongly in hard work when it is for a good cause, practicality when it." "if money wasn't an issue I'd study forensic psychology and anthropology." "Knowing others is intelligence; knowing yourself is true wisdom."	
Judging Functions	Thinking (T)	Objective Logical decision-making	Text displays logical reasoning and analysis; Mention of opinions, ideas, comparisons; Direct.	"Poverty is often a result of under education."	
	Feeling (F)	Subjective Emotionally-driven choices	Text displays expressions of personal values and emotions; Mention of people, values, feelings; Tactful, indirect.	"I think that this is absolutely true. Except for 3 things: 1. In my opinion: There should be one more section in the love-map: Reaction to change." "I think the problem is also in the way that we utilize conveniences-Not in the conveniences..."	Scherer (2003) Argamon et al. (2005) Kosinski et al. (2013)
Lifestyle Preferences	Judging (J)	Planning Organized	Text shows a preference for planning and organization; Past simple tense or present perfect tense; Adherence to conventional grammatical standards in a formal writing format.	"When I'm working out ideas in my head I'll use my whiteboard and gesture to myself while thinking." "Right now I am trying to get to 15 posts on this forum." "Now that I know I'm going to be a mom, I'm debating whether or not we should vaccinate our child."	Plank & Hovy (2015) Verhoeven et al. (2016) Yamada et al. (2019)
	Perceiving (P)	Flexibility Organized	Text shows openness to new experiences and adaptability; Present simple tense; Casual writing with occasional lapses in grammar.	"For as long as I can remember. As a kid I was in gymnastics, ballet, soccer, piano lessons, you name it. never stuck with any of them." "WHAAAAT! That's so insane! Oh my gosh my mind has just been blown." "I think!!! will have tea... ;gentleman:"	

Table 6: To address incorrect labeling issues and accurately label personality types, we refer to the methodology outlined in Stajner & Yenikent (2021) to construct our annotation guidelines. Psychology PhD students participate in the formulation of these guidelines.

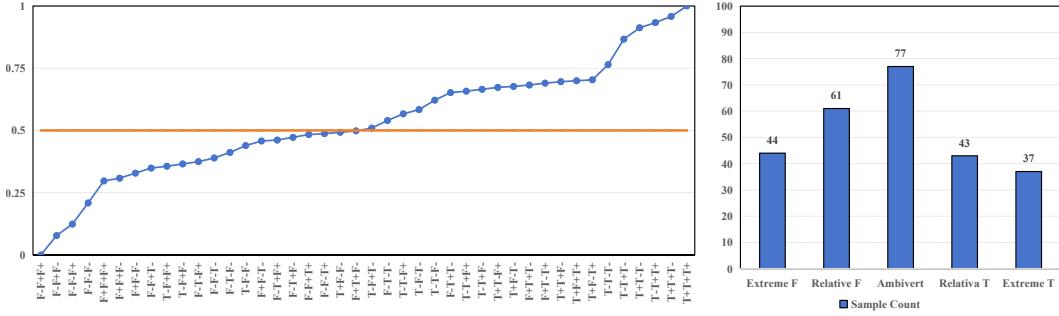


Figure 11: Distribution and Polarity distribution of soft labels for the *T/F* dimension in MBTI BENCH.

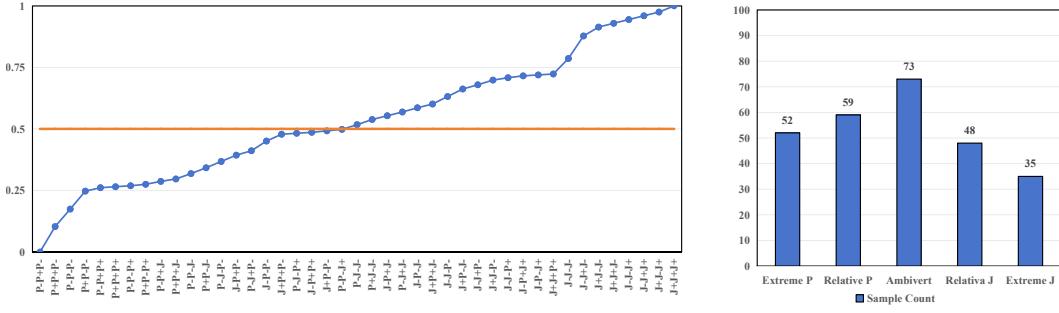


Figure 12: Distribution and Polarity distribution of soft labels for the *J/P* dimension in MBTI BENCH

et al., 2022), Few-shot, and PsyCoT (Yang et al., 2023). We present the detailed content of the prompting methods of soft labels in Appendix Table 7.

E.2 Metrics

We use accuracy (Acc) and macro F1 score as evaluation metrics for hard labels. For soft labels, we treat human-annotated labels and model outputs as two continuous distributions. We employ the following metrics to measure the differences between them:¹⁰

E.2.1 Segmented Root Mean Square Error

We adopt a similar approach to Raykar et al., using the Root Mean Square Error (RMSE) to measure the average distance between the predicted and actual values of the model. Since we map the continuous 0-1 distribution into 10 discrete intervals, the S-RMSE calculation is performed using the indices of these intervals.

$$\text{S-RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\text{bin}(y_i) - \text{bin}(\hat{y}_i))^2} \quad (1)$$

Here, y_i represents the actual values, \hat{y}_i denotes the predicted values, $\text{bin}(\cdot)$ maps the continuous distribution into discrete intervals, and n is the total number of samples. Due to the squaring operation, S-RMSE is particularly sensitive to large errors.

¹⁰We also analyze the consistency between MAE and RMSE as soft label metrics, as illustrated in Figure 17. RMSE and MAE exhibit a strong linear correlation.

Method	Template
Zero-shot	<p>System: Given the following text from a user’s social media posts, determine the first dimension (Extraversion or Introversion) of Myers-Briggs Type Indicator (MBTI) personality type best fits the user. You need to rate the statement with a score 0-10, where 0=more E and 10=more I, output your final score by strictly following this format: “[[score]]” and do not give reason.</p> <p>User: <ALL POSTS ></p> <p>Assistant: [[score]]</p>
Step-by-step	<p>System: Given the following text from a user’s social media posts, determine the first dimension (Extraversion or Introversion) of Myers-Briggs Type Indicator (MBTI) personality type best fits the user. You need to rate the statement with a score 0-10, where 0=more E and 10=more I, output your final score by strictly following this format: “[[score]]”. Let’s think step by step.</p> <p>User: <ALL POSTS ></p> <p>Assistant: <Thinking step-by-step ></p> <p>User: According to above, what is the score of EI dimension. Output your final score by strictly following this format: “[[score]]” and do not give reason.</p> <p>Assistant: CHOICE: [[score]]</p>
Few-shot	<p>System: Given the following text from a user’s social media posts, determine the first dimension (Extraversion or Introversion) of Myers-Briggs Type Indicator (MBTI) personality type best fits the user. You need to rate the statement with a score 0-10, where 0=more E and 10=more I, output your final score by strictly following this format: “[[score]]” and do not give reason.</p> <p>User: Consider the first example: <First example ></p> <p>The score is [[score]]</p> <p>Consider the second example: <Second example ></p> <p>The score is [[score]]</p> <p>Consider the third example: <ALL POSTS ></p> <p>The score is</p> <p>Assistant: [[score]]</p>
PsyCoT	<p>System: You are an AI assistant who specializes in text analysis and I am User. We will complete a text analysis task together through a multi-turn dialogue. The task is as follows: we have a set of posts written by an author, and at each turn I will give you a Question about the author. According to the author’s posts, you need to choose the possible options ONLY. DO NOT give your reason, just wait for the next user input. After opting all the choices, I will ask you the EI dimension (Extraversion or Introversion) score of the author. You need to rate the statement with a score 0-10, where 0=more E and 10=more I.</p> <p>AUTHOR’S POSTS: <ALL POSTS ></p> <p>User: Q: The author is usually: A: “A good mixer with gropus of people”, B: “Quiet and reserved”, or C: “Not sure whether A or B”. Provide a choice ID in the format: “CHOICE: <A/B/C >” only, and do not give the explanation. do not generate User input.</p> <p>Assistant: CHOICE: <A or B ></p> <p>... (<Questionnaires >)</p> <p>User: According to above, what is the score of EI dimension. Output your final score by strictly following this format: “[[score]]” and do not give reason.</p> <p>Assistant: [[score]]</p>

Table 7: Inference prompt templates for soft labels.

E.2.2 Segmented Mean Absolute Error

We adopt a method similar to Willmott & Matsuura (2005), using the Mean Absolute Error (MAE) to measure the average difference between the predicted and actual values. Similar to S-RMSE, we adopt S-MAE on discrete intervals.

$$\text{S-MAE} = \frac{1}{n} \sum_{i=1}^n |bin(y_i) - bin(\hat{y}_i)| \quad (2)$$

where y_i represents the actual value, \hat{y}_i represents the predicted value, $bin(\cdot)$ maps the continuous distribution into discrete intervals, and n is the total number of samples. Compared to the Segmented Root Mean Square Error (S-RMSE), S-MAE is less sensitive to outliers as it calculates the error using absolute differences. This makes S-MAE provide a more straightforward interpretation of average model error, making it suitable for scenarios

Method	Template
Zero-shot	System: Given the following text from a user’s social media posts, determine the first dimension of Myers-Briggs Type Indicator (MBTI) personality type best fits the user. Predicting whether the author is A: “Introversion” or B: “Extraversion”. Provide a choice in the format: ‘CHOICE: <A/B>’ and do not give reason User: <ALL POSTS> Assistant: CHOICE: <A or B>
Step-by-step	System: Given the following text from a user’s social media posts, determine the first dimension of Myers-Briggs Type Indicator (MBTI) personality type best fits the user. Predicting whether the author is A: “Introversion” or B: “Extraversion”. Let’s think step by step. Finally a choice in the format: ‘CHOICE: <A/B>’ and do not give reason User: <ALL POSTS> Assistant: <Thinking step-by-step> User: According to above, the author is more likely to be: A: “Introversion” or B: “Extraversion”. Provide a choice in the format: “CHOICE: <A/B>” and do not give the explanation. Assistant: CHOICE: <A or B>
Few-shot	System: Given the following text from a user’s social media posts, determine the first dimension of Myers-Briggs Type Indicator (MBTI) personality type best fits the user. Predicting whether the author is A: “Introversion” or B: “Extraversion”. Provide a choice in the format: ‘CHOICE: <A/B>’ and do not give reason User: Consider the first example: <First example> The choice is CHOICE: <A or B> Consider the second example: <Second example> The choice is CHOICE: <A or B> Consider the third example: <ALL POSTS> The choice is Assistant: CHOICE: <A or B>
PsyCoT	System: You are an AI assistant who specializes in text analysis and I am User. We will complete a text analysis task together through a multi-turn dialogue. The task is as follows: we have a set of posts written by an author, and at each turn I will give you a Question about the author. According to the author’s posts, you need to choose the possible options ONLY. DO NOT give your reason, just wait for the next user input. After opting all the choices, I will ask you if the author is A: “Introversion” or B: “Extraversion”, and then you need to give your choice. AUTHOR’S POSTS: <ALL POSTS> User: Q: The author is usually: A: “A good mixer with groups of people”, B: “Quiet and reserved”, or C: “Not sure whether A or B”. Provide a choice ID in the format: “CHOICE: <A/B/C>” only, and do not give the explanation. do not generate User input. Assistant: CHOICE: <A or B> ... (<Questionnaires>) User: According to above, the author is more likely to be: A: “Introversion” or B: “Extraversion”. Provide a choice in the format: “CHOICE: <A/B>” and do not give the explanation. Assistant: CHOICE: <A or B>

Table 8: Inference prompt templates for hard labels.

where the goal is to understand the typical magnitude of prediction errors without being influenced by extreme values.

E.3 Experimental Details for Hard Label Prediction

We directly match the model outputs to the options *CHOICE: A* and *CHOICE: B*. Take *E/I* as an example, considering that some models have limited instruction-following capabilities, we also accept outputs like *CHOICE: <A>*, *CHOICE: a*, *CHOICE: E*, and *CHOICE: Introversion*. Although these outputs do not strictly match the correct answer, they reveal the model’s preference for a particular personality option. We attribute this to a deficiency in the model’s ability to follow instructions rather than a flaw in its personality detection capabilities. Therefore, we accept these outputs as well. If the model’s output does not match any of the specified rules, such as *CHOICE: C* or *CHOICE: Cannot give answers*, we

categorize it as an invalid category. We present the detailed content of the prompting methods of hard labels in Appendix Table 8.

F Results and Analysis

F.1 Soft Label Evaluation with MAE and RMSE

In this section, we introduce the model evaluation results with MAE and RMSE. The results are in Appendix Table 9. Zero-shot is the best method on most backbones (5 out of 6). Considering the limited precision of our estimated soft labels, the errors tend to be sensitive to specific small deviations in continuous values when applying MAE and RMSE. To address this issue, we introduce Segmented MAE (S-MAE) and Segmented RMSE (S-RMSE). Instead of computing the error based solely on the raw predictions, we discretize the continuous 0-1 distribution into nine intervals and evaluate the corresponding RMSE and MAE within these segments. Therefore, the results with S-MAE and S-RMSE in Sec. 6.1 focus more on whether the prediction falls within an appropriate range.

Backbones	Methods	E/I		S/N		T/F		J/P		Rank
		RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	
gpt-4o-mini	Zero-shot	0.320	0.240	0.310	0.250	0.270	0.220	0.340	0.280	1.000
	Step-by-step	<u>0.330</u>	<u>0.250</u>	0.350	0.280	0.320	0.250	0.400	0.320	2.750
	Few-shot	<u>0.330</u>	<u>0.270</u>	0.320	<u>0.270</u>	<u>0.290</u>	<u>0.240</u>	0.340	0.280	1.875
	PsyCoT	0.350	0.270	0.510	0.420	0.400	0.330	0.460	0.360	3.875
gpt-4o	Zero-shot	0.330	0.260	0.330	0.260	0.300	0.240	0.420	0.350	1.750
	Step-by-step	0.350	0.270	<u>0.340</u>	<u>0.270</u>	<u>0.310</u>	0.250	0.390	<u>0.320</u>	2.250
	Few-shot	0.320	0.240	0.380	0.310	<u>0.310</u>	0.240	0.390	0.310	1.625
	PsyCoT	0.360	0.290	0.520	0.440	0.350	0.270	0.530	0.430	4.000
Qwen2-7B	Zero-shot	<u>0.350</u>	<u>0.290</u>	0.300	0.260	<u>0.320</u>	0.270	0.340	0.290	1.625
	Step-by-step	0.370	0.300	0.300	0.260	<u>0.320</u>	0.280	0.340	0.290	2.125
	Few-shot	0.380	0.310	0.360	0.300	0.450	0.360	0.340	0.290	3.500
	PsyCoT	0.290	0.260	0.300	0.260	0.310	0.270	0.330	0.280	1.000
Qwen2-72B	Zero-shot	0.280	<u>0.240</u>	0.300	0.260	<u>0.330</u>	0.270	0.330	0.280	1.375
	Step-by-step	0.280	0.230	0.300	0.260	0.320	0.260	0.330	0.280	1.000
	Few-shot	0.310	0.250	0.350	0.290	0.370	0.310	0.330	0.280	2.750
	PsyCoT	0.290	<u>0.240</u>	0.460	0.370	0.510	0.420	0.530	0.440	3.625
Llama3.1-8B	Zero-shot	0.310	0.270	0.320	0.270	0.310	0.270	0.330	0.290	1.000
	Step-by-step	0.430	0.360	0.440	0.360	0.450	0.370	0.410	0.330	3.750
	Few-shot	0.410	0.340	0.390	<u>0.310</u>	<u>0.410</u>	<u>0.340</u>	<u>0.380</u>	<u>0.320</u>	2.250
	PsyCoT	<u>0.380</u>	<u>0.320</u>	0.420	0.350	0.420	0.350	0.410	0.350	2.875
Llama3.1-70B	Zero-shot	0.300	0.250	0.360	0.300	<u>0.340</u>	<u>0.280</u>	0.360	0.300	1.250
	Step-by-step	0.330	<u>0.270</u>	0.370	0.300	<u>0.340</u>	<u>0.280</u>	0.370	0.310	2.125
	Few-shot	<u>0.330</u>	<u>0.270</u>	<u>0.370</u>	0.300	0.320	0.260	0.360	0.300	1.375
	PsyCoT	0.340	<u>0.270</u>	0.430	0.350	0.410	0.330	0.430	0.350	3.750

Table 9: We conduct experiments using soft labels and use RMSE and MAE as evaluation metrics, where lower values indicate better performance. The best and second-best results across the four methods for each backbone are **bolded** and underlined.

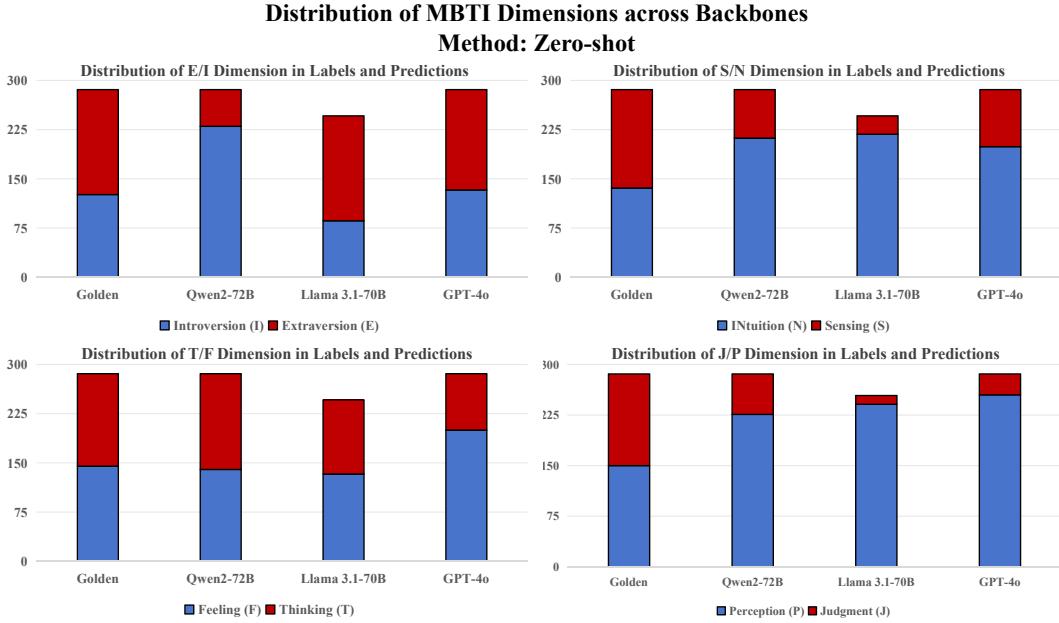
F.2 Hard Label Evaluation

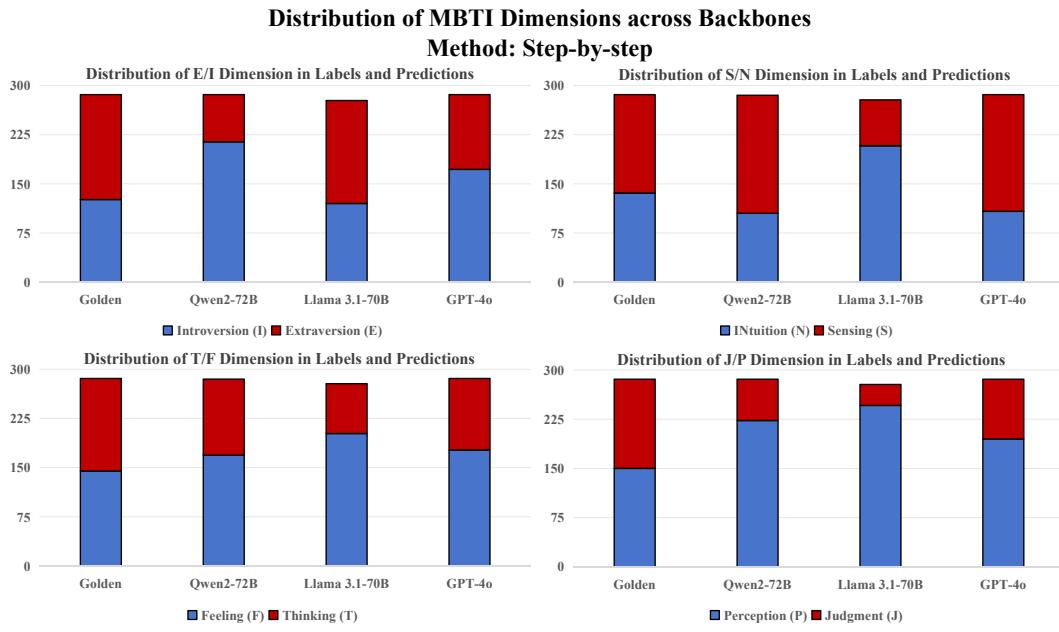
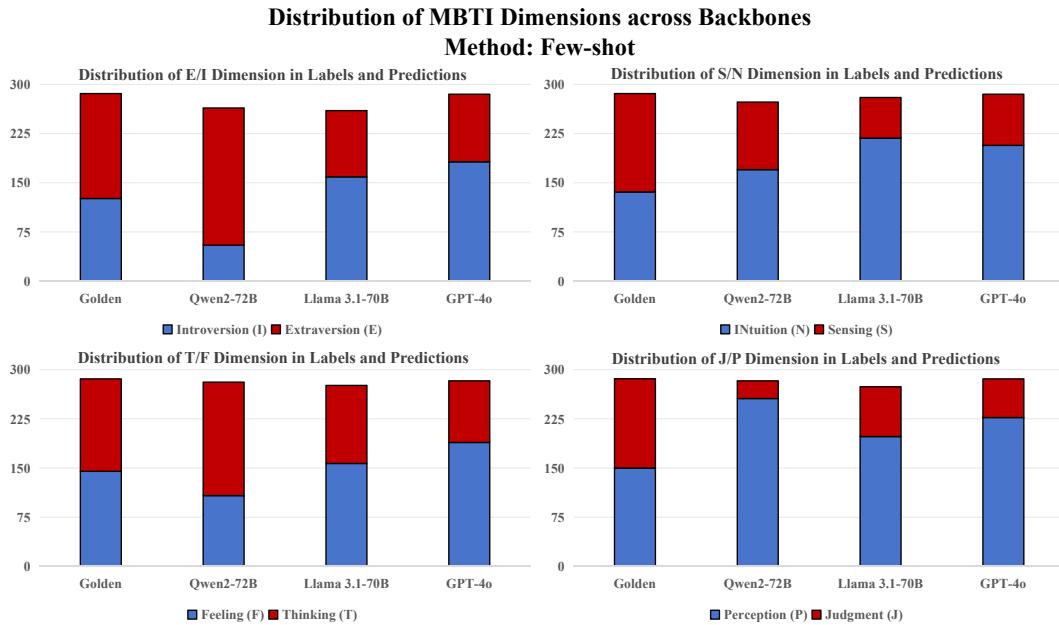
We provide the results of six LLMs with hard labels in Table 10.

We observe a significant discrepancy between Acc and F1 scores on the JP dimension across several backbones. We consider this is due to the inherent characteristics of the JP personality dimension, which introduces bias in the model’s predictions. As shown in Figure 13-16, all three backbones tend to favor the P-type personality.

Backbones	Methods	E/I		S/N		T/F		J/P		Overall	
		Acc	F1								
gpt-4o-mini	Zero-shot	64.69	<u>64.02</u>	54.90	<u>53.29</u>	60.49	54.33	<u>58.39</u>	<u>55.82</u>	59.62	56.87
	Step-by-step	<u>66.43</u>	63.88	<u>59.44</u>	<u>59.42</u>	<u>72.38</u>	<u>71.68</u>	<u>59.09</u>	54.92	64.34	62.48
	Few-shot	61.19	61.08	53.50	34.79	66.78	65.86	58.04	51.36	59.88	53.27
	PsyCoT	<u>66.08</u>	65.96	52.45	45.20	74.13	73.71	57.69	56.62	<u>62.59</u>	60.37
gpt-4o	Zero-shot	<u>66.08</u>	<u>66.06</u>	61.19	60.02	70.28	68.96	57.69	48.83	<u>63.81</u>	60.97
	Step-by-step	67.83	66.98	<u>65.03</u>	64.26	72.73	72.29	61.19	59.46	66.70	65.75
	Few-shot	61.19	40.69	55.94	36.10	<u>72.03</u>	47.68	<u>59.79</u>	<u>55.26</u>	62.24	44.93
	PsyCoT	62.24	42.40	48.95	29.28	69.58	<u>69.00</u>	53.85	40.36	58.66	45.26
Qwen2-7B	Zero-shot	59.79	59.48	<u>51.05</u>	45.93	52.80	44.78	52.45	34.40	54.02	46.15
	Step-by-step	<u>61.89</u>	<u>61.81</u>	49.65	45.14	52.80	41.65	<u>52.80</u>	36.47	<u>54.29</u>	46.27
	Few-shot	46.85	41.84	<u>51.05</u>	<u>49.10</u>	<u>55.94</u>	<u>50.61</u>	53.15	52.76	51.75	48.58
	PsyCoT	63.29	63.00	<u>55.24</u>	55.10	68.88	68.77	47.55	<u>46.03</u>	58.74	58.23
Qwen2-72B	Zero-shot	<u>63.64</u>	<u>58.10</u>	53.15	50.84	69.58	69.58	56.64	51.88	<u>60.75</u>	57.60
	Step-by-step	66.43	62.92	63.64	41.92	68.53	45.57	56.99	<u>52.61</u>	63.90	50.76
	Few-shot	55.59	35.11	<u>55.94</u>	37.92	65.73	43.96	56.64	31.50	58.48	37.12
	PsyCoT	44.76	32.82	50.00	30.24	41.61	35.36	59.79	59.18	49.04	39.40
Llama3.1-8B	Zero-shot	51.40	51.02	53.85	35.78	52.80	30.40	52.45	35.06	52.63	38.07
	Step-by-step	60.14	59.86	61.54	61.52	65.73	65.45	56.29	50.87	60.93	59.43
	Few-shot	<u>54.90</u>	54.36	54.20	<u>53.72</u>	61.19	60.53	<u>55.24</u>	46.06	<u>56.38</u>	<u>53.67</u>
	PsyCoT	46.15	37.20	51.40	42.78	57.34	48.59	53.15	36.01	52.01	41.15
Llama3.1-70B	Zero-shot	<u>52.80</u>	37.59	46.50	28.59	63.64	<u>45.57</u>	52.10	28.45	53.76	35.05
	Step-by-step	55.24	<u>37.41</u>	52.80	33.96	<u>67.83</u>	44.64	<u>54.90</u>	31.23	57.69	36.81
	Few-shot	51.05	35.57	<u>48.25</u>	<u>30.03</u>	68.53	46.37	60.84	39.85	<u>57.17</u>	37.96
	PsyCoT	50.00	36.55	33.92	22.54	57.34	42.62	34.97	28.74	44.06	32.61

Table 10: We first perform classification experiments on our dataset using hard labels.

Figure 13: Model prediction bias on *Zero-shot*.

Figure 14: Model prediction bias on *Step-by-step*.Figure 15: Model prediction bias on *Few-shot*.

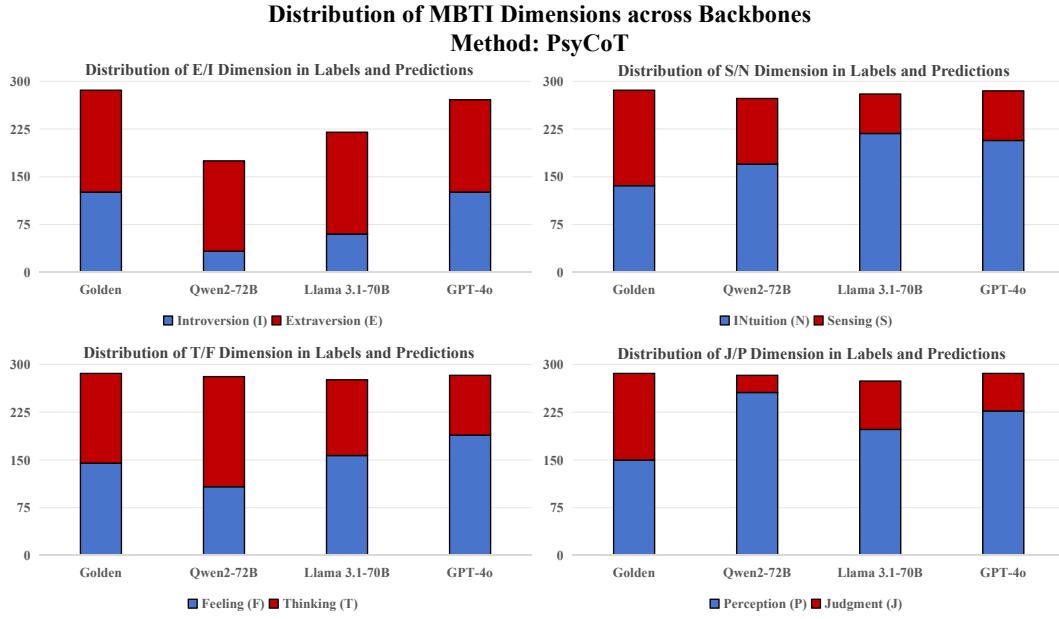
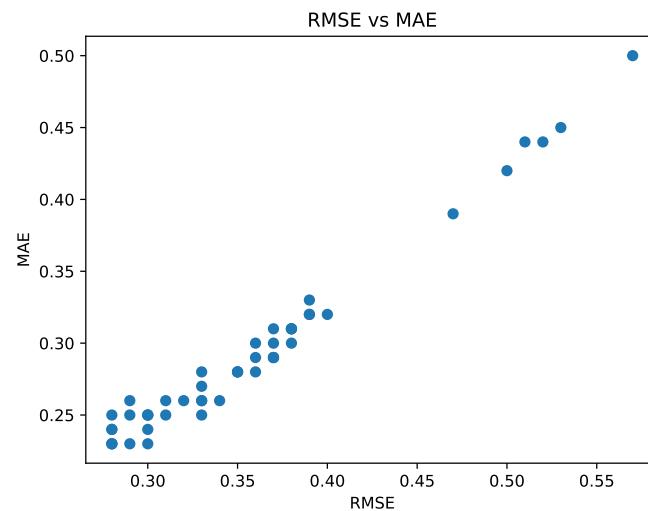
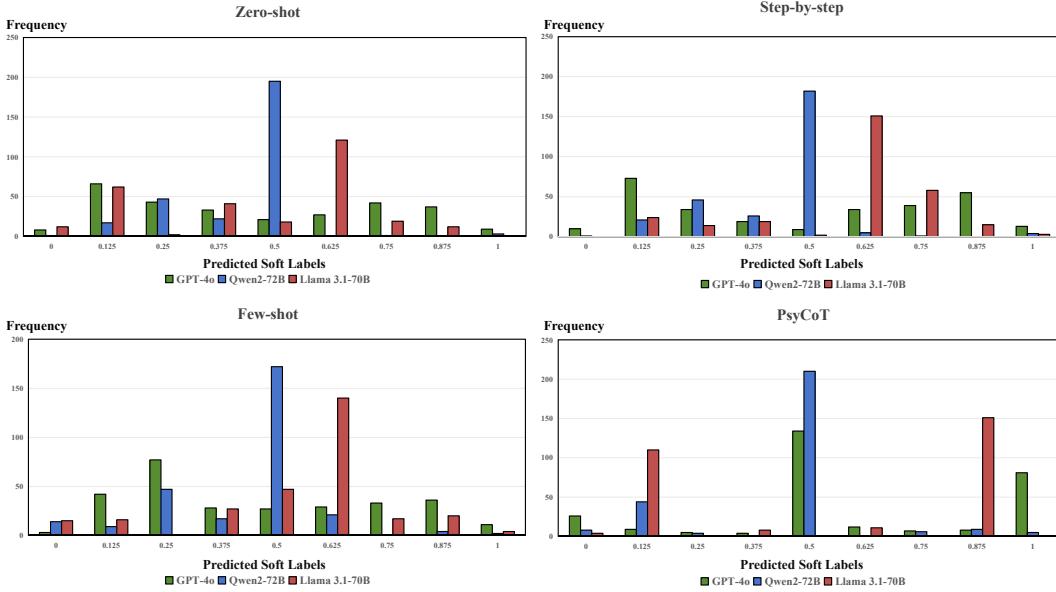
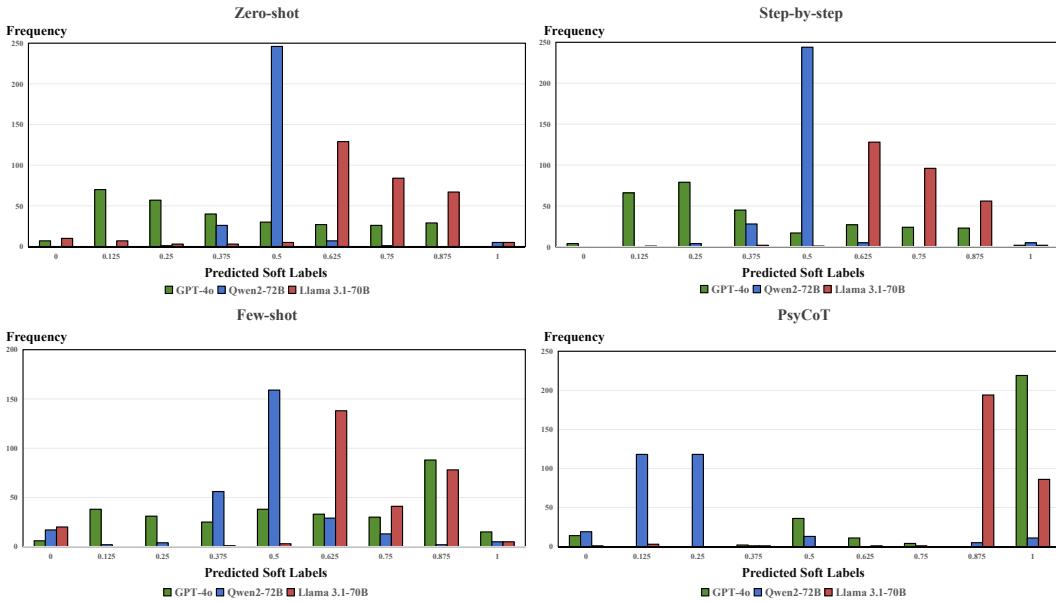
Figure 16: Model prediction bias on *PsyCoT*.

Figure 17: Consistency between RMSE and MAE.

Figure 18: The score distribution of LLMs on MBTI BENCH for the *E/I* dimension.Figure 19: The score distribution of LLMs on MBTI BENCH for the *S/N* dimension.

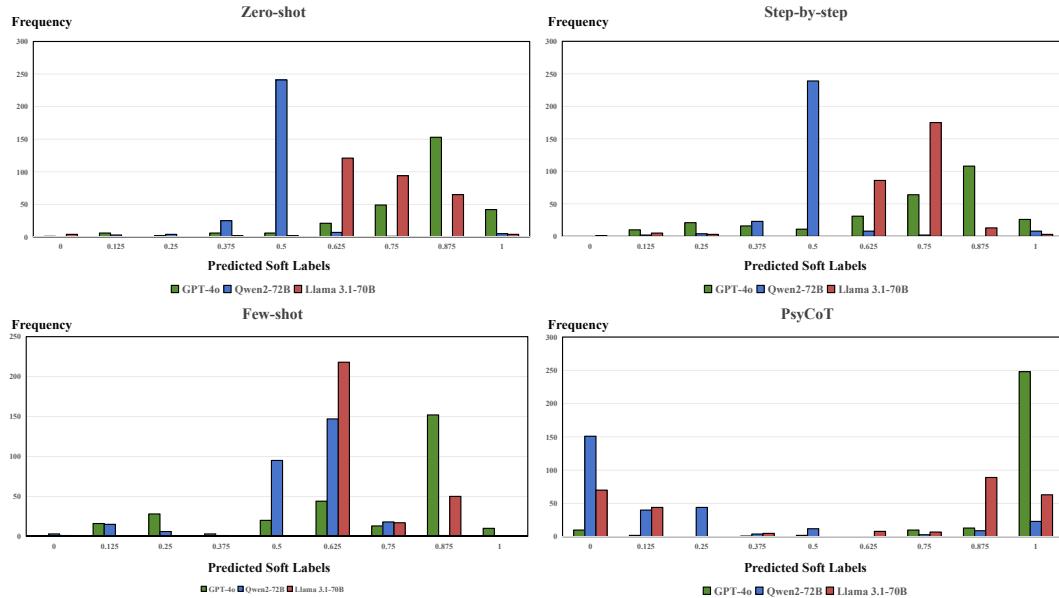


Figure 20: The score distribution of LLMs on MBTIBENCH for the *J/P* dimension.