PsyPrompt: LLM Prompt Patterns for Goal Contents Pursuit on Social Media

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***Abstract*—Goal contents pursuit serves as an effective indicator to predict individual behaviors and life satisfaction. In current studies, the measures of self-reports are limited by the expenses and subjectivity. Despite the fact that machine learning and deep learning models can effectively utilize user data from social media to objectively classify goal contents pursuit, the workload associated with supervised learning is substantial. By using appropriate prompt patterns, Large Language Models (LLM) can execute diverse tasks in a prompt manner. Thus, we develop six prompt patterns for classifying goal content pursuits of users on social media. The results indicate that some of these prompt patterns successfully classify intrinsic and extrinsic goals. Overall, this research presents an usable prompting paradigm and approach, PsyPrompt, which enhances the methodology of objectively classifying individual goal content pursuits using LLMs.**

Keywords—prompt patterns, Large Language Model, goal contents pursuit, social media, individual psychology

I. INTRODUCTION

Goals play a crucial role in shaping individuals' behaviors, imbuing people's lives with meaning and purpose[1, 2, 3]. Goal contents pursuit reflects the motivational personality, providing a reliable way to predict individuals' psychological dynamics and daily behaviors.[4, 5, 6]. In most current studies, goal contents pursuit is typically measured by self-reports, which are limited by its subjective and expense[7, 8]. Therefore, obtaining individual data and investigating the effects of goal pursuit in conventional studies poses significant challenges. In recent years, some researchers have utilized the rich data consisting of users' digital traces on social media to measure individual behaviors. This approach may provide an objective method to classify individuals' goals content pursuit.

Large Language Models (LLMs) exhibit strong capability in a wide range of natural language tasks[9], and can be applied in various field including computational biology, computer programming, social science and psychology[10]. Given the impressive ability showcased by LLMs in evaluating sentences and generating responses to input prompts, a number of studies have utilized LLMs to perform classification tasks, resulting in notable efficacy[11]. Furthermore, LLMs have the capacity to perform classification tasks without the need for manual annotation, reducing reliance on labeled datasets[12]. In contrast, machine learning and deep learning models typically utilize supervised learning structures to perform classification tasks, thereby limiting the model's ability to generalize across different contexts. Thus, applying LLMs to classification tasks can significantly reduce our workload, all while maintaining the quality of work.

A prompt is a set of instructions provided to an LLM, which programs the LLM by customizing, enhancing, or optimizing its functionality[13]. The prompt can influence subsequent interactions with the LLMs and the output they generates by offering specific rules and guidelines for an LLMs' conversation with a set of initial rules[14]. Prompt engineering is a crucial skill to extend the capabilities of large language models. As LLMs research progresses rapidly, diverse prompt engineering techniques have been developed for enhancing LLMs' performance. Sahoo et al. organized 29 kinds of prompt engineering techniques[15], ranging from zero-shot prompting to the latest advancements. Prompting patterns refer to facilitating of specific tasks, encompassing various prompt engineering techniques. Proposing apt prompt patterns can also release the capabilities of LLMs, which are crucial for task completion.

This study employed the Goal Content Theory view of intrinsic and extrinsic goals to identify goal contents pursuit among users on social media platforms[16]. Although goal contents pursuit has been measured through self-reporting and the establishment of machine learning and deep learning models, no prior research has developed prompt patterns utilizing LLMs for this task. To address this gap, we conduct the goal contents pursuit classification across six prompt patterns. The launch of ChatGPT on November 30, 2022, brought LLM to the limelight of a wider audience. ChatGPT enabled users to steer conversations to complete diverse tasks, including question answering, information seeking, and text summarization[12]. ChatGPT has surpassed 100 million users, and the open-source GPT-3.5-turbo model has been widely utilized. Considering the model's functionalities and user base, we chose to utilize GPT-3.5-turbo for our work.

Our contributions are summarized as follows:

- Providing an approach to establish prompt patterns for classification tasks of individual psychology.
- Presenting a paradigm proficient in categorizing the pursuit of goal content as well as classification task.

II. PROMPT PATTERNS

A. The elicitations of prompt patterns

Based on content and format of the prompting, our prompt patterns are delineated into the following points.

1) Motivation elicitations: The motivation refers to the problem we aim to address and the rationale for the problem. Our study endeavors to evaluate the degrees of intrinsic and extrinsic goal contents pursuit of these social media users by using LLMs. In this section, we will explain the definitions of intrinsic and extrinsic goals. According to Goal Content Theory, extrinsic goals are associated with personal status, sappearance, image, and economy[16], while intrinsic goals focus on personal growth, health, communal relationships, and emotional intimacy[2, 17]. After task definition, we can proceed smoothly with the subsequent prompts.

2) Classification elicitation: The classification is based on the features of subject, such as the demographic characteristics and the behavioral features. In this part, our study focuses on the educational level of users, indicated by the prompt: “The group primarily consists of undergraduate and graduate students”. Additionally, we provided the score range and mean values for intrinsic and extrinsic goal pursuit among the participants, along with the distribution of their scores categorized as high, medium, and low.

3) Context elicitations: The context involves the background of the issue. The data for our study are sourced from the digital footprints of users on the social media platform Weibo. Previous studies have demonstrated the impact of goal pursuit on users' engagement within online communities. Indeed, users' behavioral features on social media platforms serve as the viewfinder to reflect their goal contents oriented[7,18]. Thus, we contemplate integrating the behavioral features of Weibo users into the prompts, such as the content posted, posting frequency, mentions, retweets, the followers, and the followed account.

*4) Analytical methods’ elicitation:*The prompt in this section aims to provide an analytical perspective, methods, or approaches to our problems. The analytical perspective of our study builds upon the previous study[19], which analyzes users across five dimensions of personal data, behavioral patterns, content, emotion, and social interaction. Specifically, personal data refer to the users’ information on Weibo, including age, gender, occupation and educational background. Behavioral patterns involve three types of user behavior : posting frequency, mentions, and retweets. Content includes text, images, and videos posted by users on Weibo, which helps understand users' interests, hobbies, emotions, and expressions. Emotion represents users' emotional states, including positivity, negativity, and anxiety, through the analysis of their posted content. Social interaction focuses on metrics such as follower count, followed accounts, engagement with followers, comments, and replies. Furthermore, we predefine the standards for “low”, “medium”, and “high” degrees of pursuit for intrinsic and extrinsic goals and demographic characteristics. These standards are defined according to the five dimensions we mentioned above.

5) Dialogue elicitations: This section is focused on the prompt with different dialogue structure. In this study, we utilize LLMs for task-oriented dialogues. Our dialogue is classified into two categories: one-step dialogue and multi-step dialogue. One-step dialogue typically refers to a single-turn dialogue or continuous prompts conducted for addressing a specific task. In our study, the prompt patterns for one-step dialogue encompass Task-Only and Continuous Dialogue. Multi-step dialogue involves multiple prompts for the task,which are not necessarily continuous. The prompt patterns of this type including Multi-Step Dialogue, Multi-Step Dialogue with Scoring, Multi-Step Dialogue with Standards-Based Classification, and Extended Multi-Step Dialogue with Separate Classification.

B. Six prompt patterns

In this section, we employed six prompting patterns to investigate the use of Large Language Models (LLMs) in the task of classifying goal contents pursuit. These patterns generally follow a hierarchical structure, enabling each subsequent pattern to incorporate additional information from the preceding one. The detailed description of the six prompting patterns is as follows. Table I presents an overview of the elicitation and structure associated with each prompt pattern, while an example illustrating dialogues within pattern 3) are shown in Fig. 1.

1) Task-Only: Based on the demographic characteristics of the samples and the users' Weibo information (including personal data, posted content, and time of posting), we classify the user's degree of pursuit for intrinsic and extrinsic goals as "low", "neutral", or "high", excluding any specific analytical methods.

2) Continuous Dialogue: In the first dialogue, we analyze the user across five dimensions (content, emotion, social interaction, personal data, and behavioral patterns) using their Weibo data. In the subsequent dialogue, we combine the content from the previous dialogue with demographic characteristics to classify the user's levels of intrinsic and extrinsic goal pursuit.

3) Multi-Step Dialogue: First, we objectively describe the user's posted content on Weibo. Second, we analyze the user across five dimensions using their Weibo data. Third, we combine the outputs from the first two dialogues with demographic characteristics to classify the user's level of intrinsic and extrinsic goal pursuit.

4) Multi-Step Dialogue with Scoring: Following the first and second steps in the Multi-Step Dialogue Prompt, we provide a score for the user's intrinsic and extrinsic goals based on the combined outputs and demographic characteristics in the third conversation. Note that we apply k-means clustering to the scoring results to obtain classifications subsequently.

5) Multi-Step Dialogue with Standards-Based Classification: Following the Multi-Step Dialogue Prompt, but in the third conversation, we use predefined standards for "low", "medium", and "high" levels of intrinsic and extrinsic goals, along with the combined outputs and demographic characteristics, to classify the user's goal pursuit levels.

TABLE I. AN OVERVIEW OF THE ELICITATIONS AND STRUCTURE ASSOCIATED WITH EACH PROMPT PATTERNS

Prompt patterns	Elicitations and structure
Task-Only	• Provide demographic characteristics of the samples and the user's Weibo information (personal data, content posted, and time of posting). • Classify the user's degrees of pursuit for intrinsic and extrinsic goals into "low", "neutral", or "high" • Exclude any specific analytical methods.
Continuous Dialogue	In the first dialogue • Provide the user's Weibo information. • Analyze the user across five dimensions (content, emotion, social interaction, personal data, and behavioral patterns). In the subsequent dialogue • Provide demographic characteristics. • Classify the user's intrinsic and extrinsic goal pursuit degrees.
Multi-Step Dialogue	In the first dialogue • Provide the user's posted content on Weibo. • Objectively state the content of the user's Weibo posts and count the number of posts related to various fields. In the second dialogue • Provide the user's Weibo information. • Analyze the user across five dimensions. In the third dialogue • Provide the outputs from the first two dialogues and demographic characteristics. • Classify the user's intrinsic and extrinsic goal pursuit degrees.
Multi-Step Dialogue with Scoring	In the first two dialogues • As same as Multi-Step Dialogue In the third dialogue • Provide the outputs from the first two dialogues and demographic characteristics. • Score the user's intrinsic and extrinsic goal pursuit degrees. (Subsequently, apply k-means clustering to the scoring results to obtain classifications.)
Multi-Step Dialogue with Standards-Based Classification	In the first two dialogues • As same as Multi-Step Dialogue In the third dialogue • Provide the outputs from the first two dialogues, predefined standards for "low", "neutral", or "high" degrees of pursuit for intrinsic and extrinsic goals and demographic characteristics. • Classify the user's intrinsic and extrinsic goal pursuit degrees.
Extended Multi-Step Dialogue with Separate Classification	In the first two dialogues • As same as Multi-Step Dialogue In the third dialogue • Provide the outputs from the first two dialogues, predefined standards for "low", "neutral", or "high" levels of pursuit for intrinsic goals and demographic characteristics. • Classify the user's intrinsic goal pursuit degree. In the fourth dialogue • Provide the outputs from the first two dialogues, predefined standards for "low", "neutral", or "high" levels of pursuit for extrinsic goals and demographic characteristics. • Classify the user's extrinsic goal pursuit degree.

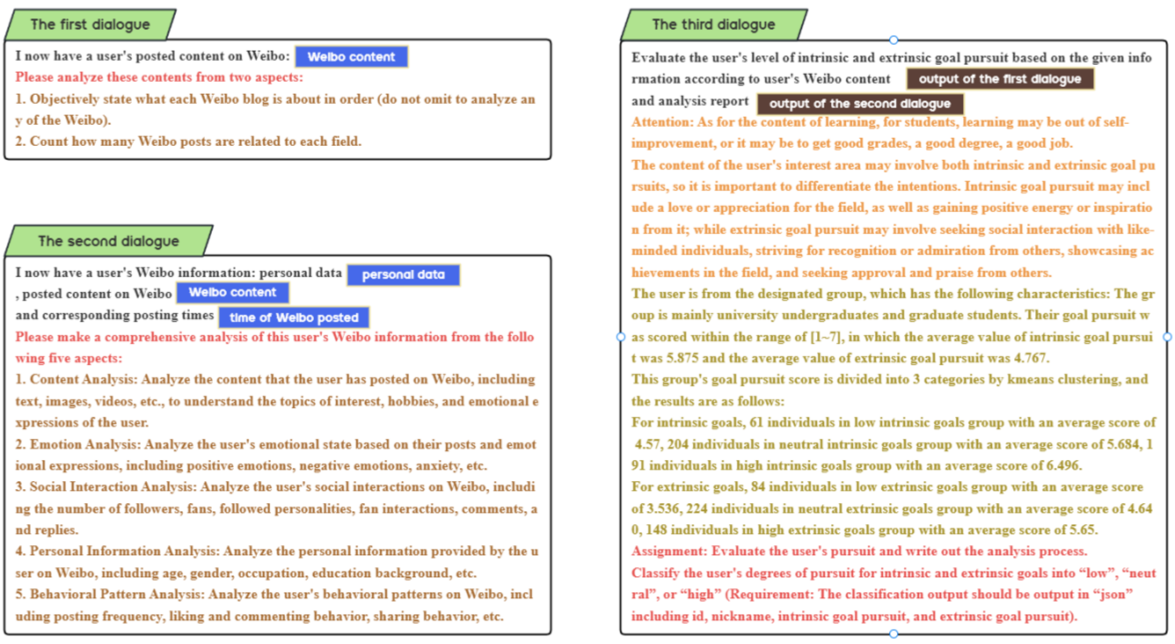


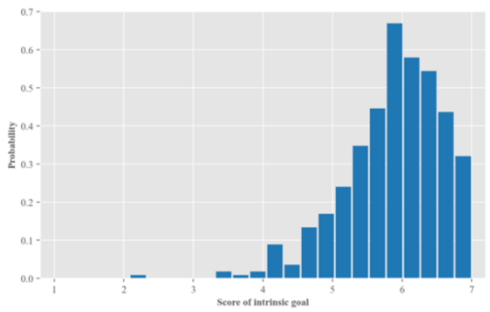
Fig. 1. An Example of Multi-Step Dialogue for Goal Contents Pursuit

6) Extended Multi-Step Dialogue with Separate Classification : Following the Multi-Step Dialogue Prompt for the first two dialogues, we evaluate the level of internal and external goal pursuit, respectively. In the third dialogue, we classify the user's intrinsic goal pursuit level using the results from the first two dialogues, demographic characteristics, and evaluation standards. In the fourth dialogue, we classify the user's extrinsic goal pursuit level using the same approach.

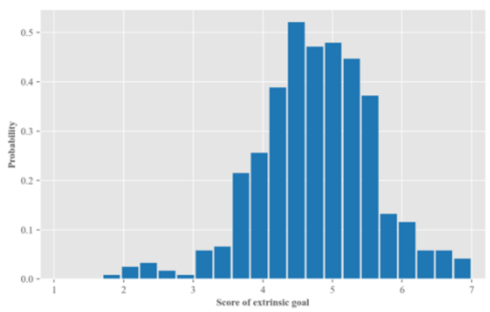
III. DATA SETS AND EVALUATION METRICS

The data utilized in this study are sourced from Predicting Intrinsic and Extrinsic Goal Contents Pursuit on Social Media[19], comprising a total of 456 samples, which include Weibo data and degrees of intrinsic and extrinsic goal contents pursuit. All of these Weibo users are students from Universities in China, including 127 males and 329 females. The goal contents pursuit was measured by Aspiration Index with the Chinese version. Participants were presented with 35 items that they rated on 7-point scales representing the importance of goal contents. The distribution of scores is illustrated in Fig. 2. For intrinsic goals, it exhibits a long-tail distribution, while for extrinsic goals it follows a Gaussian distribution.This implies that, regarding intrinsic goals, the majority of individuals have high scores and few have low scores.

K-means clustering algorithm exhibits flexibility and adaptability in relation to psychological scores[20]. Thus, previous study utilized K-means method to classify the intrinsic and extrinsic goals of samples[19]. According to the distribution of goals' scores and the K-means method, the samples can be divided into three intrinsic goals groups (IG3) of high intrinsic goals, neutral intrinsic goals, and low intrinsic goals; three extrinsic groups (EG3) of high extrinsic goals, neutral extrinsic goals, and low extrinsic goals.



(a) Intrinsic goal



(b) Extrinsic goal

Fig. 2. The distribution of self-reports scores of participants

TABLE II. DEMOGRAPHIC CHARACTERISTICS (N = 456)

Measure	Item	No.	Frequency (%)
Gender	Male	127	27.9
	Female	329	72.1
Age	<20	61	13.4
	20–30	389	85.3
	>30	6	1.3
Intrinsic goals	High intrinsic goals group	204	44.7
	Neutral intrinsic goals group	191	41.9
	Low intrinsic goals group	61	13.4
Extrinsic goals	High extrinsic goals group	224	49.1
	Neutral extrinsic goals group	148	32.5
	Low extrinsic goals group	84	18.4

[a.] The groups of intrinsic and extrinsic was categorized by K-means algorithm.

As shown in Table II, among the participants, a distribution regarding intrinsic goals showed 61 individuals with low intrinsic goals, 204 with neutral intrinsic goals, and 191 with high intrinsic goals. As for extrinsic goals, there were 84 individuals with low extrinsic goals, 224 with neutral extrinsic goals, and 148 with high extrinsic goals. The study's procedures and materials received approval from the University's Institutional Review Board (IRB), and informed consent was obtained from each participant.

Aforementioned models were used to build category classification for intrinsic and extrinsic goal pursuit. We adapted Accuracy(*ACC)*, Precision, Recall and macor F1 score(*F1*) to estimate our models. We obtained true positive(*TP*), true negative(*TN*), false positive(*FP*) and false negative(*FN*) for the category i = low, neutral, high.

Calculations for ACC for intrinsic goals and extrinsic goals are below:

$$ACC=\frac{\sum_{i=low,neutral,high} TP_i+TN_i}{\sum_{i=low,neutral,high} TP_i+TN_i+FP_i+FN_i}$$

Calculations for the precision and recall for each category i are below:

$$Precision_i=\frac{TP_i}{TP_i+FP_i}$$

$$Recall_i=\frac{TP_i}{TP_i+FN_i}$$

Calculations for F1 for intrinsic goals and extrinsic goals are below:

$$F1=\frac{1}{3}\sum_{i=low,neutral,high}\frac{2(Precision_i\cdot Recall_i)}{Precision_i+Recall_i}$$

IV. RESULTS AND DISCUSSION

In this section, we present the performance results obtained from various prompt patterns. Table III details the performance of the six prompt patterns in predicting participants' intrinsic and extrinsic goals within three categories: low, neutral, and high. Fig. 3. presents the accuracy (%) and the F1 score (%) for six prompt patterns.

TABLE III. THE PERFORMANCE FOR THE PROMPT PATTERNS

Predict target	**Prompt Patterns**	**ACC**	**F1**	**Low**		**Neutral**		**High**	
				Precision	**Recall**	**Precision**	**Recall**	**Precision**	**Recall**
Intrinsic goals	Neural network in the previous work[19]	0.406	0.414	/	/	/	/	/	/
	Task-Only	0.456	0.341	0.125	0.033	0.478	0.627	0.453	0.408
	Continuous Dialogue	0.439	0.323	0.077	0.016	0.491	0.397	0.424	**0.618**
	Multi-Step Dialogue	0.450	0.331	**0.250**	0.016	0.481	0.446	0.430	0.592
	Multi-Step Dialogue with Scoring	0.393	0.332	0.150	**0.148**	0.438	0.515	0.417	0.340
	Multi-Step Dialogue with Standards-Based Classification	0.458	0.322	0.125	0.016	0.460	0.735	0.475	0.304
	Extended Multi-Step Dialogue with Separate Classification	**0.513**	**0.386**	0.222	0.066	**0.509**	**0.799**	**0.568**	0.351
Extrinsic goals	Neural network in the previous work[19]	0.436	0.432	/	/	/	/	/	/
	Task-Only	0.461	0.346	**0.414**	0.143	0.490	0.772	0.338	0.169
	Continuous Dialogue	0.474	0.337	0.182	0.071	0.514	0.795	0.416	0.216
	Multi-Step Dialogue	0.434	0.333	0.264	**0.345**	0.498	0.710	0.370	0.068
	Multi-Step Dialogue with Scoring	0.441	0.281	0.100	0.036	0.501	**0.799**	0.275	0.128
	Multi-Step Dialogue with Standards-Based Classification	0.447	0.335	0.253	0.440	0.542	0.723	0.455	0.034
	Extended Multi-Step Dialogue with Separate Classification	**0.524**	**0.441**	0.356	0.190	**0.567**	0.732	**0.484**	**0.399**

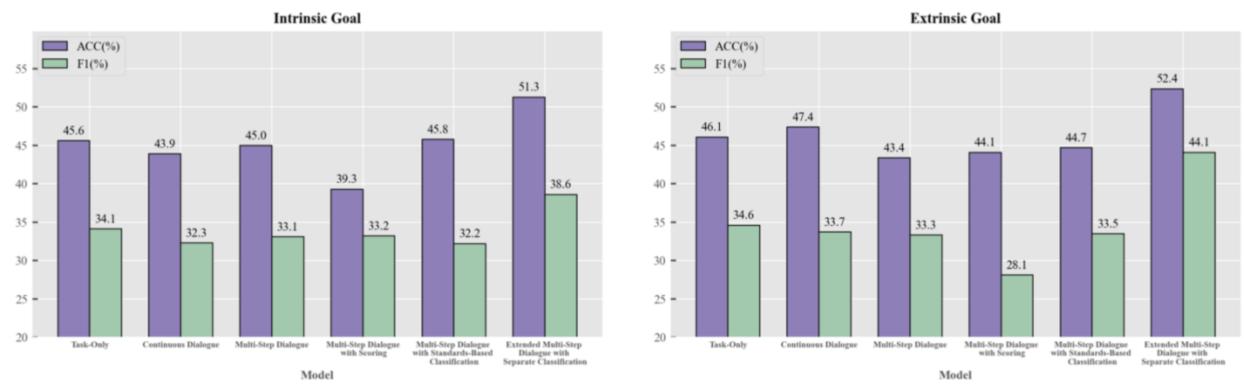


Fig. 3. The accuracy (%) and the F1 score (%) for six prompt patterns

A. *Task-Only*

Task-Only prompting demonstrates moderate performance among all six prompt patterns. As illustrated in Table III, this prompting outperforms the baseline solutions, achieving an accuracy of 45.6% and an F1 score of 34.1% for the intrinsic goals, and an accuracy of 46.1% and an F1 score of 34.6% for the extrinsic goals. The classification results indicate a bias towards the "neutral" category for both intrinsic and extrinsic goals, resulting in suboptimal performance in predicting the "low" and "high" categories. In addition, compared to the classification performance of the previous study utilizing machine learning models, the accuracy of this prompt surpasses that of the NN model by 5% for the intrinsic goals and by 2.5% for the extrinsic goals. Moreover, it is slightly better than the KNN model by 2.2% for the extrinsic goals. Nonetheless, it remains inferior to the other three models across all ACC and F1 metrics.

B. Continuous Dialogue

Continuous Dialogue prompting performs well for the extrinsic goals, with an second-highest accuracy of 47.4% and an F1 score of 33.7%. Furthermore, compared to the machine learning models utilized in previous study, the accuracy of the prompt is only lower than that of the LR model. Regarding the results for the intrinsic goals, we observe that they are not as favorable as those of Task-Only prompting, tending to be excessively classified into the "high" category.

C. Multi-Step Dialogue

Multi-Step Dialogue prompting demonstrates average performance in predicting both intrinsic and extrinsic goals, with accuracy and F1 score of 45% and 33.1% for intrinsic goals, and 43.4% and 33.3% for extrinsic goals. Specifically, the results indicate a tendency to underestimate the degree of intrinsic and extrinsic goal content pursuit. The classification of intrinsic goal pursuit shows a pronounced bias towards the "high" category, while extrinsic goal pursuit demonstrates a notable inclination towards the "low" and "neutral" categories. Furthermore, compared to the performance of the machine learning models utilized in previous study, the accuracy of this prompt is only slightly higher than that of the NN model, yet lower than the accuracy of other models.

D. Multi-Step Dialogue with Scoring

This prompting has the lowest accuracy in predicting intrinsic goals among the six prompt patterns, achieving an accuracy of 39.3%. Additionally, there is an issue of Extrinsic goals classification overly favoring the "neutral" category. In predicting intrinsic goals, the accuracy of this prompting is lower than that of all machine learning models, while in predicting extrinsic goals, it is slightly higher than that of the NN and KNN models.

E. Multi-Step Dialogue with Standards-Based Classification

The results of this prompt pattern for predicting intrinsic goals rank relatively high among all six patterns. In addition, there is a certain underestimation in the degree of extrinsic goal content pursuit, reflected in the classification of Extrinsic goals leaning towards the "low" and "neutral" categories to some extent. Furthermore, compared to the accuracy of the machine learning models, the accuracy of this prompting surpasses that of the NN model by 5.2% for the intrinsic goals.

F. Extended Multi-Step Dialogue with Separate Classification

The prompting demonstrated the best performance among the six prompt patterns in predicting intrinsic and extrinsic goals, achieving the highest accuracy of 51.3% and 52.4%, and the highest F1 score of 38.6% and 44.1% respectively. Also, we can observe that it significantly outperforms the baseline. Specifically, despite the classification of the intrinsic goals leaning towards the "neutral" category excessively, the predictive distribution of intrinsic and extrinsic goals is closest to reality. Additionally, the accuracy of this prompt pattern in predicting both intrinsic and extrinsic goals is significantly superior to that of all machine learning models， indicating its potential for more precise classification of both types of goals.

Through an overview of the data in Table II, the following key points can be summarized：

- In comparing the outcomes of Multi-Step Dialogue with Scoring and Multi-Step Dialogue, it is evident that GPT performs poorly in numerical scoring tasks while excels in demonstrating proficiency in classification tasks.
- Comparing Continuous Dialogue and Multi-Step Dialogue reveals significant differences in outcomes despite nearly identical prompt content, indicating limited influence of preceding dialogues on current ones.
- Comparing Multi-Step Dialogue with Standards-Based Classification to Extended Multi-Step Dialogue with Separate Classification, significant differences in outcomes are observed despite identical prompt content. This observation suggests that simultaneous execution of multiple tasks results in mutual influence among them.

V. CONCLUSION

A. Theoretical Contributions

This study introduces a systematic approach to establishing prompt patterns for classification tasks, particularly focusing on the classification of goal content pursuit. By leveraging the versatility of LLMs, researchers can effectively design prompt patterns tailored to specific classification tasks, contributing to the methodological development in utilizing LLMs for objective classification. Then, the integration of Goal Content Theory with prompt engineering techniques represents a novel approach in the domain of psychological research. By incorporating theoretical frameworks such as intrinsic and extrinsic goals into prompt design, this study bridges the gap between theoretical constructs and computational methodologies, enhancing the interpretability and applicability of LLM-based classification models in psychology. Furthermore, this study demonstrates the potential of LLMs, in psychological research contexts. By showcasing the efficacy of LLMs in classifying goal content pursuits without the need for manual annotation, it expands the scope of AI in analyzing complex psychological phenomena, thereby contributing to the advancement of computational psychology.

B. Practical Contributions

The development of six prompt patterns for classifying goal content pursuit provides a practical framework for researchers and practitioners in psychology and social sciences. These prompt patterns offer a user-friendly and adaptable approach to objectively classify goal pursuit behaviors, facilitating empirical research and data-driven insights into individual motivations and behaviors. By leveraging LLMs for classification tasks, this study effectively reduces the workload associated with traditional supervised learning approaches. The ability of LLMs to perform classification tasks in a prompt manner minimizes the need for manual annotation and labeled datasets, streamlining the process of analyzing large-scale social media data and promoting efficiency in research endeavors. Additionally, the utilization of GPT-3.5-turbo, a widely accessible LLM model, underscores the practicality and accessibility of LLM-based methodologies in psychological research. With the widespread availability of ChatGPT and similar models, researchers can readily apply LLMs to diverse classification tasks, democratizing access to advanced natural language processing capabilities and fostering innovation in psychological research methodologies.

C. Limitations and Research in future

While our research introduces six innovative prompt patterns for classifying goal content pursuits on social media using Large Language Models (LLMs), several limitations must be acknowledged. Firstly, the performance of the developed prompts is only around 50%, indicating that while some success was achieved in classifying intrinsic and extrinsic goals, there is significant room for improvement. Secondly, our study primarily focused on prompts patterns for classifying with a single LLM, which restricts the generalizability of our findings. The performance and effectiveness of the prompt patterns would be evaluated across other available LLMs, such as GPT-4o and other contemporary models.

Future research could focus on four aspects:

- Refining and optimizing the prompt patterns proposed in this study for classifying goal content pursuit and other domains of psychological research. By conducting empirical evaluations and fine-tuning the prompt design, researchers can enhance the accuracy and effectiveness of LLM-based classification models, thereby advancing the state-of-the-art in psychological outcome analysis.

- Exploring hybrid approaches that incorporating multimodal data sources, including text, images, and videos from social media platforms, that could enrich the classification process of psychological outcome and enhance the accuracy and interpretability of LLM-based classification models.

- Prioritizing ethical guidelines and data protection protocols to ensure the responsible and transparent use of user-generated content in goal content analysis. Additionally, exploring methods for anonymizing and de-identifying sensitive user information can mitigate potential risks and safeguard the privacy rights of social media users.

- Further exploration of different individual psychological traits and constantly updated large language models is necessary. Our study solely focused on examining users' pursuit of Goal Content on social media. Future research endeavors could further test with a broader range of LLMs and involve developing more powerful application to enhance the PsyPrompt framework.

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