SWI: Speaking with Intent in Large Language Models

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Abstract

Intent, typically clearly formulated and planned, functions as a cognitive framework for reasoning and problem-solving. This paper introduces the concept of **Speaking with Intent (SWI)** in large language models (LLMs), where the explicitly generated intent encapsulates the model's underlying intention and provides high-level planning to guide subsequent analysis and communication. By emulating deliberate and purposeful thoughts in the human mind, SWI is hypothesized to enhance the reasoning capabilities and generation quality of LLMs. Extensive experiments on mathematical reasoning benchmarks consistently demonstrate the superiority of Speaking with Intent over Baseline (i.e., generation without explicit intent). Moreover, SWI outperforms answer-trigger prompting methods Chain-of-Thought and Plan-and-Solve and maintains competitive performance with the strong method ARR (Analyzing, Retrieving, and Reasoning). Additionally, the effectiveness and generalizability of SWI are solidified on reasoning-intensive question answering (QA) and text summarization benchmarks, where SWI brings consistent improvement to the Baseline generation. In text summarization, SWI-generated summaries exhibit greater accuracy, conciseness, and factual correctness, with fewer hallucinations. Furthermore, human evaluations verify the coherence, effectiveness, and interpretability of the intent produced by SWI. This proof-of-concept study creates a novel avenue for enhancing LLMs' reasoning abilities with cognitive notions.¹

1 Introduction

Large language models (LLMs) (Zhao et al., 2023; Min et al., 2023; Minaee et al., 2024) have revolutionized Natural Language Processing (NLP) with their excellent generative capabilities (Hurst et al., 2024; Anthropic, 2024; Team et al., 2024). Many recent benchmarks focus on evaluating complex reasoning in mathematics problems (Cobbe et al., 2021; Hendrycks et al., 2021b; Lightman et al., 2024; Vendrow et al., 2025) and multidisciplinary questions (Hendrycks et al., 2021a; Srivastava et al., 2023; Suzgun et al., 2023; Wang et al., 2024e), presenting significant challenges for LLMs. Enhancing LLM reasoning is vital for their ongoing development (Huang & Chang, 2022; Qiao et al., 2023; Patil, 2025).

Recent advancements have introduced various approaches to improve LLM reasoning (Yu et al., 2024; Cheng et al., 2025; Liu et al., 2025a; Xu et al., 2025). Chain-of-Thought (CoT) prompting enhances reasoning (Li et al., 2024b) by providing step-by-step solutions in few-shot exemplars (Wei et al., 2022) or explicitly instructing the model to "think step by step" (Kojima et al., 2022). Beyond CoT variants (Yao et al., 2023a; Wang et al., 2023; Yasunaga et al., 2024), Yin & Carenini (2025) propose Analyzing, Retrieving, and Reasoning (ARR), an answer-trigger prompting method that systematically guides LLMs in question answering and outperforms CoT prompting.

Inspired by ARR (Yin & Carenini, 2025), where intent analysis is identified as its most effective component, we further investigate the powerful potential that intent can unleash in enhancing LLM reasoning. Intent, the goal-oriented intention in our mind (Adams, 1986; Mele, 1989; Mele & Moser, 1994), serves as a guiding framework for problem-solving. As

¹Appendix A Reproducibility Statement. Source code: https://github.com/YuweiYin/SWI



Figure 1: **SWI Overview. (a)** The intent, functioning as meta-thought and planning, guides the analysis with reasoning to answer the question. **(b)** A concrete example generated by our method: Speaking with Intent (SWI) in large language models (LLMs). **(c)** The performance improvement on mathematical reasoning and multiple-choice QA tasks brought by SWI.

illustrated in Figure 1(a), human reasoning (System 2 (Kahneman, 2011)) typically follows a structured thinking loop where intent directs problem analysis and logical reasoning. Hence, we hypothesize that enabling LLMs to explicitly speak with their own intent—rather than merely analyzing the intent of questions—can replicate this meta-cognitive planning process, thereby improving the reasoning ability and generation quality of LLM.

This work introduces Speaking with Intent (SWI), requiring LLMs to articulate their own intent as a planning mechanism during generation. Due to the autoregressive nature of LLMs (Radford et al., 2019) and the attention mechanism (Vaswani et al., 2017), explicitly stated intent provides high-level guidance for subsequent analysis and reasoning. Specifically, we implement SWI using instruction-following LLMs (Ouyang et al., 2022; Rafailov et al., 2023), incorporating system and user prompts for the model (Dubey et al., 2024) to generate intent. As shown in Figure 1(b), each analytical step (in blue) in solving a math problem is guided by a preceding intent statement (in orange), which is a freely generated text instead of a predefined class as in traditional intent modeling (Weld et al., 2022).

To comprehensively evaluate the effectiveness and generalizability of the proposed SWI method, we conduct experiments across three diverse task categories: mathematical reasoning, multiple-choice QA, and text summarization. As shown in Figure 1(c), LLM speaking with intent (SWI) consistently outperforms Baseline, which generates responses without explicit intent. Furthermore, SWI surpasses answer-trigger prompting methods such as Chain-of-Thought (CoT) (Kojima et al., 2022) and Plan-and-Solve (PS) (Wang et al., 2023). Compared with the strong method ARR (Analyzing, Retrieving, and Reasoning) (Yin & Carenini, 2025), SWI maintains competitive performance on mathematical reasoning tasks. For text summarization, SWI produces summaries that are more accurate, concise, and factually reliable, with fewer hallucinations (Ji et al., 2023; Li et al., 2024a) in the output.

Additionally, we perform human evaluations to assess the coherence, effectiveness, and interpretability of the intent generated by our SWI method. Evaluators largely agree on the quality of the generated intent, particularly for mathematical reasoning tasks. The evaluation results confirm that Speaking with Intent in LLMs enhances task performance and output explainability. The key contributions of this work are as follows:

- 1. This paper introduces Speaking with Intent (SWI) in LLMs, where the generated intent effectively guides problem analysis and logical reasoning, improving performance across various benchmarks. The source code will be publicly available.
- 2. Extensive experiments across diverse reasoning and generation tasks, including mathematical reasoning, multiple-choice QA, and text summarization, demonstrate that SWI consistently outperforms the Baseline and surpasses established answer-trigger prompting methods such as Chain-of-Thought.
- 3. Human evaluations validate the coherence, effectiveness, and interpretability of the intent generated by SWI. Rather than intent classification, our evaluation practice provides standards for assessing freely generated intent statements.

2 Related Work

LLM Reasoning. Recent LLM research increasingly focuses on enhancing reasoning abilities (Sun et al., 2023; Patil, 2025; Cheng et al., 2025; Liu et al., 2025a). Chain-of-Thought (CoT) prompting facilitates problem-solving by prompting LLMs to generate intermediate reasoning steps (Kojima et al., 2022; Wei et al., 2022; Li et al., 2024b; Yeo et al., 2025). Building on CoT, various reasoning techniques have emerged (Xu et al., 2025). Among them, a recent research ARR (Yin & Carenini, 2025) consistently outperforms CoT on multiple QA tasks, where intent analysis of questions is its most effective component. Inspired by ARR, we enable LLMs to articulate their intent, using it to guide subsequent analysis and reasoning for improved task performance. Results show that Speaking with Intent (SWI) surpasses CoT and ARR on multiple benchmarks. As an intent-driven approach, SWI introduces a novel framework for advancing LLM reasoning and cognitive capabilities.

LLM Planning. Planning plays a critical role in advancing artificial intelligence (Wang et al., 2024c), particularly in developing LLM agents in real and complex environments (Qiao et al., 2024; Mialon et al., 2024; Xu et al., 2024; Drouin et al., 2024; Boisvert et al., 2024; Xie et al., 2024; Mialon et al., 2024; Xu et al., 2024; Drouin et al., 2024; Boisvert et al., 2024; Xie et al., 2024; Juang et al., 2024; Wang et al., 2024; Liu et al., 2025b), recent LLM planning methods enhance reasoning abilities (Huang et al., 2022; Yao et al., 2023b; Hao et al., 2023; Valmeekam et al., 2023; Jiao et al., 2024) by generating problem-solving plans explicitly (Wang et al., 2023; Li & Zhang, 2024; Lyu et al., 2024) or implicitly (Goyal et al., 2024; Wang et al., 2024; Pfau et al., 2024; Chen et al., 2024). In this work, we require LLMs to explicitly speak with their intent in an iterative and dynamic manner, as shown in Figure 1(a), instead of generating all plans first and then solving the task (Wang et al., 2023; Li & Zhang, 2024). The existing iterative planning framework (Lyu et al., 2024) focuses on addressing information retrieval issues in knowledge-intensive long-form generation tasks, while our SWI method generates intents that function as strategic planning to guide problem analysis and logical reasoning.

Intent-related Research. Intent Detection (ID) and New Intent Discovery (NID) (Kumar et al., 2022; Liang et al., 2024; Zhang et al., 2024a; Tang et al., 2024; Zhang et al., 2024c; Qian et al., 2024; Yin et al., 2025), which classify utterances into known or novel intent categories, are longstanding challenges in natural language understanding (Larson et al., 2019; Casanueva et al., 2020; Zhang et al., 2021; Weld et al., 2022). Typically, these tasks are approached as classification problems (Wang et al., 2024b; Yoon et al., 2024; Zhang et al., 2024b; Sakurai & Miyao, 2024), where models assign sentences to predefined intent classes. In contrast, Speaking with Intent (SWI) generates intent as free-form text rather than fixed categories, enhancing flexibility and fluency. SWI naturally integrates intent statements as planning into the reasoning process, providing contextual guidance for subsequent analysis.

3 Speaking with Intent

This section presents the problem-solving workflow of LLMs and introduces Speaking with Intent (SWI), enabling LLMs to explicitly articulate their intent for planning and reasoning.

3.1 Problem-solving Workflow using LLMs

Let $\mathcal{D} = \{\mathcal{X}, \mathcal{Y}\}$ be a dataset, where $\mathcal{X} = \{X_1, X_2, \dots, X_n\}$ is the input information (questions), $\mathcal{Y} = \{y_1, y_2, \dots, y_n\}$ is the corresponding references (correct answers), and *n* is the number of instances in \mathcal{D} . For mathematical reasoning datasets, X_i is the math problem, and y_i is the correct answer (usually an integer number). For multiple-choice QA datasets, X_i contains the question and options, and y_i is the answer label such as (A)/(B)/(C) or Yes/No. For text summarization datasets, X_i is the source article, and y_i is the reference summary.

In this work, we employ instruction-following LLMs (aka Chat LLMs) M for experiments and apply the chat template with the system prompt P_s and user prompt P_u . The system prompt specifies the general behavior of the model (assistant), and the user prompt poses

questions to the model. Therefore, the generated output \hat{y}_i is obtained by

$$\hat{y}_i = \mathcal{M}(P_s, P_u, X_i; \Theta, \zeta), \tag{1}$$

where P_s is the system prompt, P_u is the user prompt, and X_i is the task input. These string objects are concatenated using line breaks ("\n") as the delimiter. With parameters Θ and hyper-parameters ζ , the LLM \mathcal{M} generates new tokens one by one until reaching the generation limit or generating the "end-of-text" special token provided by the tokenizer.

3.2 Baseline vs. Speaking with Intent

In this work, we require LLMs to speak with intent (SWI) by presenting detailed instructions in the system prompts P_s and restating the SWI requirement in the user prompt P_u . Figure 2 presents the system prompt and user prompt of Baseline generation (P_s^{base} and P_u^{base}) and our SWI method (P_s^{swi} and P_u^{swi}).

Baseline - System Prompt Ps ^{base}	SWI - System Prompt P _s ^{swi}
You are a helpful assistant.	You are a helpful assistant.
You are good at mathematical	You are good at mathematical reasoning. Your final answer must start
reasoning. Your final answer must	with "Final Answer:"
start with "Final Answer:"	During generation, follow all the requirements below:
Baseline-User Prompt Pubase Answer the following question.	 Always explicitly state your own intent before speaking each sentence. Each intent statement should explain the sentence followed up. Your intent must start with the "<intent>" tag and end with the</intent>
SWI-UserPrompt P _u swi Speak with intent and answer the following question.	"" tag. 4. At last, clearly and concisely give your final answer starting with "Final Answer:"

Figure 2: LLM Prompts. The system and user prompts of Baseline and our SWI method.

3.3 Result Evaluation

Lastly, we extract the final answer (after "Final Answer:" in \hat{y}_i), denoted as \tilde{y}_i , and compute the overall performance of \mathcal{M} on the dataset \mathcal{D} by

$$s = \frac{1}{n} \sum_{i=1}^{n} \mathcal{S}(y_i, \tilde{y}_i), \tag{2}$$

where the score function $S(\cdot, \cdot)$ returns a value in the range of [0, 1]. Different tasks adopt different score functions to evaluate the model performance.

For mathematical reasoning tasks, we first extract numbers in \tilde{y}_i and apply text normalization to both \tilde{y}_i and the reference y_i , and then conduct exact match to check if the generated answer \tilde{y}_i is correct.

For multiple-choice QA tasks, we adopt the Option Selection metric introduced by Yin & Carenini (2025), which evaluates the LLM perplexity of different option concatenations and selects the one with lowest perplexity as the model's choice.

To evaluate the quality of summaries, we apply the standard ROUGE (Lin, 2004) as the automatic evaluation metric S and complement it with a more sophisticated fact-checking analysis as described in Section 5.2.

4 Main Experiments on Mathematical Reasoning

This section presents the main experiments to verify the effectiveness of SWI on mathematical reasoning. To ensure reproducibility, we fixed all random seeds, set the generation temperature to zero, and conducted all experiments twice, yielding reproducible results.²

4.1 Models

In all experiments, we employ LLaMA3-8B-Instruct (Dubey et al., 2024) as the model \mathcal{M} for generation and evaluation. It is an open-weights, instruction-following, and Transformer-based (Vaswani et al., 2017) LLM with 8 billion model parameters. We use the model checkpoint and tokenizer provided by Hugging Face Transformers (Wolf et al., 2020).

²Please refer to Appendix A for the reproducibility statement and Appendix B for dataset details.

4.2 Datasets

The proposed SWI method aims to enhance LLM reasoning, so we conduct extensive experiments on various mathematical reasoning benchmarks, ranging from grade-school to competition-level problems. In the math reasoning task, the model is asked to solve the given math problem and present the final answer. We consider grade-school math problems including GSM8K (Cobbe et al., 2021), GSM8K-Platinum (Vendrow et al., 2025), and MATH500 (Lightman et al., 2024), as well as three competition-level math benchmarks: AMC23, AIME24, and AIME25, which have 40, 30, and 30 math problems, respectively. Despite the smaller scale, these math problems are much more challenging than those in GSM8K and MATH500. The dataset statistics are presented in Table 1.

Task	Dataset	Split	Size	# Tok.
Mathematical Reasoning	GSM8K (Cobbe et al., 2021) GSM8K-P (Vendrow et al., 2025) MATH500 (Lightman et al., 2024)	Test Test Test	1,319 1,209 500	124 124 134

Table 1: **Mathematical Reasoning Datasets**. "# Tok." is the average number of tokens in the Baseline prompt of each instance, tokenized by the LLaMA (Dubey et al., 2024) tokenizer. The system prompt of SWI (Figure 2) bring about 80 extra tokens for each instance.

4.3 Experimental Comparison

The main comparison is LLM generation with intent (**SWI**) or without intent (**Baseline**), and the effectiveness of SWI is verified if the former outperforms the latter. For mathematical reasoning and multiple-choice QA tasks, we also compare SWI with answer-trigger prompting methods **CoT** (Kojima et al., 2022) and **ARR** (Yin & Carenini, 2025), as well as previous LLM planning method Plan-and-Solve (**PS**) prompting (Wang et al., 2023).

CoT aims to elicit LLM reasoning using the answer-trigger prompt Φ_i^{CoT} as "Let's think step by step", while ARR, with a more systematic design, utilizes an enhanced Φ_i^{ARR} as "Let's analyze the intent of the question, find relevant information, and answer the question with step-by-step reasoning." Finally, PS applies the following prompt Φ_i^{PS} to construct plans before problem-solving: "Let's first understand the problem and devise a plan to solve the problem. Then, let's carry out the plan and solve the problem step by step." With answer-trigger prompts Φ_i , the generation process (Eq. 1) is given by

$$\hat{y}_i = \mathcal{M}(P_s, P_u, X_i, \Phi_i; \Theta, \zeta), \tag{3}$$

where P_s is the system prompt, P_u is the user prompt, and X_i is the task input. Θ and ζ are the parameters and hyper-parameters of the LLM \mathcal{M} , respectively.

4.4 Experimental Results

SWI vs. Baseline. As shown in Table 2, SWI improves Baseline (generation without intent) performance by an average of +3.34 points, showing its effectiveness in enhancing LLM's problem analysis and mathematical reasoning abilities.

Method	GSM8K	GSM8K-P	MATH500	Competition	Avg.
Baseline	78.47	81.14	36.80	10.56	51.74
SWI (ours)	81.20	84.20	41.60	13.33	55.08

Table 2: Mathematical Reasoning Results. The exact matching scores (%) of LLaMA-3-8B-Instruct on multiple mathematical reasoning datasets with or without Speaking with Intent.

SWI vs. Answer-Trigger Prompting Methods. Table 3 presents the results of our SWI method and three answer-trigger prompting methods: CoT, PS, and ARR. We observe that

SWI significantly outperforms PS, suggesting that the dynamic generation of intents in SWI provides more effective analytical guidance than the static construction of multiple plans at the outset, as in PS. Furthermore, compared to the reasoning-eliciting methods CoT and ARR, SWI demonstrates superior performance over CoT and achieves competitive results with ARR. Notably, SWI surpasses ARR in solving competition-level mathematics problems, which are more challenging and thus indicate the potential of SWI.

Method	GSM8K	GSM8K-P	MATH500	Competition	Avg.
CoT (Kojima et al., 2022)	79.30	82.22	42.60	7.78	52.98
PS (Wang et al., 2023)	73.54	76.43	39.20	8.61	49.45
ARR (Yin & Carenini, 2025)	81.96	85.36	44.40	<u>10.28</u>	55.50
SWI (ours)	81.20	84.20	41.60	13.33	<u>55.08</u>

Table 3: **Mathematical Reasoning Results.** The exact matching scores (%) of LLaMA-3-8B-Instruct on multiple mathematical reasoning datasets using our SWI method or answer-trigger prompting methods. The underlined values indicate the second-best scores.

5 Generalizability of Speaking with Intent

The main experiments have verified the effectiveness of Speaking with Intent, this section further studies the generalizability of the proposed SWI method on different categories of tasks: multiple-choice QA and text summarization.

5.1 Multiple-choice Question Answering

Many challenging benchmarks are designed as multiple-choice QA tasks, where the model is asked to select the most appropriate one from the given options to answer the question.

5.1.1 QA Datasets

Our SWI method is evaluated on various QA datasets involving reading comprehension (Liu et al., 2020), commonsense reasoning (Talmor et al., 2019; Sap et al., 2019), world knowledge (Mihaylov et al., 2018), and reasoning-intensive multitask understanding tasks with multiple subtasks covering diverse topics (Clark et al., 2018; Suzgun et al., 2023; Hendrycks et al., 2021a; Wang et al., 2024e). The dataset statistics are presented in Table 4.

Туре	Dataset	Split	Size	# Tok.
Reading	LogiQA (Liu et al., 2020)	Test	651	185
Commonsense	CSQA (Talmor et al., 2019) SIQA (Sap et al., 2019)	Valid Valid	1,221 1,954	127 117
World Knowledge	OBQA (Mihaylov et al., 2018) ARC (Clark et al., 2018)	Test Test	500 3,548	127 144
Multitask Understanding	BBH (Suzgun et al., 2023) MMLU (Hendrycks et al., 2021a) MMLU-Pro (Wang et al., 2024e)	Test Test Test	5,511 13,842 12,032	203 193 270

Table 4: **Multiple-choice QA Datasets.** "# Tok." is the average number of tokens in the Baseline prompt of each instance, tokenized by the LLaMA (Dubey et al., 2024) tokenizer.

5.1.2 QA Results

Table 5 shows that our SWI method consistently improves the Baseline (generation without intent) by a large margin, i.e., +10.08 points on average. The results demonstrate the efficacy of Speaking with Intent in reasoning-intensive question answering.

Method	Reading	Commo	nsense	World Knowledge		Multitask Understanding			Avg.	
memou	LogiQA	CSQA	SIQA	OBQA	ARC	BBH	MMLU	MMLU-Pro	11.8.	
Baseline	20.74	66.91	29.58	70.60	76.44	56.65	52.40	39.27	51.57	
SWI (ours)	33.03	72.73	46.37	81.60	87.82	64.29	62.19	45.16	61.65	

Table 5: **Multiple-choice QA Results.** The accuracy scores (%) of LLaMA3-8B-Instruct on various multiple-choice QA datasets with or without Speaking with Intent.

5.2 Text Summarization

The results on math and QA benchmarks have solidified the efficacy of SWI on reasoningintense tasks. Beyond reasoning tasks, we hypothesize that Speaking with Intent benefits natural language generation tasks like summarization by more explicitly analyzing the source document point by point and better planning the generation of the final summary.

5.2.1 Summarization Datasets

To verify the hypothesis, we test the effect of SWI on various text summarization datasets. CNN/DailyMail (CDM) (Hermann et al., 2015; See et al., 2017), Extreme summarization (XSum) (Narayan et al., 2018), and XL-Sum (Hasan et al., 2021) contain diverse articlesummary pairs from news articles. SAMSum (Gliwa et al., 2019) and DialogSum (Chen et al., 2021) are dialogue summarization datasets. WikiLingua (Ladhak et al., 2020) extracts article and summary pairs from wikiHow. The dataset statistics are presented in Table 6.

Туре	Dataset	Split	Size	# Tok.
News Article	CDM (Hermann et al., 2015)	Test	11,490	920
	XSum (Narayan et al., 2018)	Test	11,334	542
	XL-Sum (Hasan et al., 2021)	Test	11,535	613
Dialogue	SAMSum (Gliwa et al., 2019)	Test	819	209
	DialogSum (Chen et al., 2021)	Test	1,500	263
Wiki Article	WikiLingua (Ladhak et al., 2020)	Test	3,000	525

Table 6: **Text Summarization Datasets.** "# Tok." is the average number of tokens in the Baseline prompt of each instance, tokenized by the LLaMA (Dubey et al., 2024) tokenizer.

5.2.2 Summarization Results

Automatic Evaluation of Summaries. We evaluate the quality of summaries using the ROUGE score (Lin, 2004), which counts the overlaps of the generated summaries and reference summaries. Specifically, we average the ROUGE-1 (unigrams), ROUGE-2 (bigrams), ROUGE-L (longest common subsequences), and ROUGE-LSum (sentence-level ROUGE-L) scores as the final ROUGE score. As shown in Table 7, our SWI method consistently surpasses the Baseline on ROUGE scores, confirming its effectiveness in enhancing the quality of text summaries.

Method	ľ	News Art	icle	Dia	logue	Wiki Article	Avg.	
	CDM	XSum	XL-Sum	SAMSum	DialogSum	WikiLingua	11.6.	
Baseline	23.38	11.90	11.29	24.14	16.92	15.01	17.11	
SWI (ours)	24.00	13.82	13.50	24.37	20.64	17.86	19.03	

Table 7: **Text Summarization Results.** The ROUGE scores (%) of the LLaMA3-8B-Instruct model on various text summarization datasets with or without Speaking with Intent (SWI).

5.2.3 Fact Checking of Summaries

LLMs frequently generate hallucinated content (Ji et al., 2023; Li et al., 2024a), which can not be detected by lexical metrics like ROUGE. To assess this issue, we adopt a more semantically sophisticated fact-checking metric proposed by Hwang et al. (2025), which quantifies factual consistency by calibrating the extent of fabricated statements (low precision) and omitted factual information (low recall). Specifically, we use GPT-4o-mini (Hurst et al., 2024) to decompose both generated and reference summaries into atomic fact sets and measure their coverage to quantify factual consistency.

We evaluate 100 samples from each summarization dataset using this fact-checking metric, with results presented in Table 8. Speaking with Intent (SWI) generates more concise and accurate summaries, improving precision, whereas baseline summaries tend to be more lengthy and verbose, resulting in higher recall scores. Overall, SWI consistently outperforms the Baseline generation in terms of F1 score.

Dataset	Method	Precision	Recall	F1	Dataset	Method	Precision	Recall	F1
CDM	Baseline SWI	26.06 <u>34.22</u>	<u>76.28</u> 55.89	36.37 37.79	SAMSum	Baseline SWI	39.95 <u>47.82</u>	<u>75.92</u> 69.88	46.90 50.88
XSum	Baseline SWI	11.06 <u>14.77</u>	$\frac{48.38}{37.30}$	15.15 16.29	DialogSum	Baseline SWI	23.99 <u>34.92</u>	$\frac{57.08}{45.19}$	29.55 31.20
XL-Sum	Baseline SWI	8.96 <u>12.96</u>	$\frac{61.88}{46.72}$	13.79 16.51	WikiLingua	Baseline SWI	23.33 <u>32.40</u>	<u>65.55</u> 54.98	30.63 35.78

Table 8: **Summarization evaluation results.** We compare the atomic facts drawn from the generated and reference summaries, and compute recall, precision, and F1 scores (%).

5.2.4 Case Study

To provide more insights into the benefits of Speaking with Intent, we conduct a case study on the CDM summarization dataset (Hermann et al., 2015; See et al., 2017). Figure 3 showcases the SWI outputs, where the generated intent is well formulated and articulated, guiding a point-by-point summarization process that leads to a final summary that is accurate, concise, and abstractive, while effectively capturing the key information of the source article. This probably leads to the high Precision and F1 scores of SWI in Table 8, suggesting the validity of Speaking with Intent in text generation tasks.

Source Article	SWI Output (Intent + Analysis + Final Summary)
Shhh! Don't make a sound. This dog is lost in deep	<intent> I will summarize the article about a dog</intent>
concentration. Kristina Patrick from Alaska filmed her	named Pakak performing a skillful trick. The intent
German Shepherd Pakak performing a very skillful trick.	is to provide a concise overview of the article's
Video footage shows the pup lying on her back with a	main points.
tennis ball neatly clutched between her front paws.	Kristina Patrick from Alaska has a German Shepherd
Keeping her eyes fixed on the toy, she then proceeds to	named Pakak that is known for its impressive skills.
lift it into the air being careful not to drop it.	<intent> I will describe the specific trick that</intent>
After freezing still for several seconds, Pakak lowers	Pakak performed to showcase its abilities. The
the ball slowly down. She then places it in between her	intent is to provide a clear understanding of the
teeth, back to where it started. Pakak's owner says she	trick.
loves playing with balls. Other videos reveal the pup	The dog was seen lying on its back with a tennis
also has a passion for swimming and being by the sea.	ball between its front paws, lifting it into the air
Pet's got talent: Kristina Patrick from Alaska filmed	without dropping it, and then placing it back
her German Shepherd, Pakak, performing a skillful	between its teeth.
trick . Easy does it: Video footage shows the pup lying	<pre><intent> I will mention the dog's other interests to</intent></pre>
on her back with a tennis ball neatly clutched between	
her front paws - she then proceeds to lift it into the	
air being careful not to drop it.	diverse talents.
	Pakak also enjoys swimming and spending time by the
Reference Summary	sea, according to its owner.
	body about aing to ito owner.
Kristina Patrick from Alaska filmed her German	Final Summary:
Shepherd Pakak performing a very skillful trick.	Kristina Patrick's German Shepherd, Pakak, is a
Footage shows the pup taking the ball from her mouth	· · · · · · · · · · · · · · · · · · ·
with her paws and holding it up high in the air to	talented dog that can perform a skillful trick
admire it. She then carefully lowers it back down to	involving a tennis ball, and it also enjoys swimming
the starting point.	and spending time by the sea.

Figure 3: Case Study. Task input and SWI output on text summarization task.

6 Intent Quality Evaluation

Although we have shown that Speaking with Intent boosts performance across a broad range of tasks, verifying the quality of generated intents is also significant. Thus, we hire human evaluators to assess the quality of generated intent across three criteria: coherence, effectiveness, and interpretability. Coherence measures how well the intent guides analysis and reasoning, effectiveness evaluates its contribution to problem-solving, and interpretability assesses its role in enhancing user understanding of the generated content.³ For each instance, human evaluators are provided with evaluation instructions, task input (e.g., the math problem, question with options, or source article), SWI-generated output, and assessment check boxes. They are then asked to evaluate the following aspects:

- Coherence: In general, does the analysis align coherently with the intent statements?
- **Effectiveness**: Overall, do the intent statements help with the planning and reasoning for solving the problem?
- **Interpretability**: Do you think providing the intent can help you better understand the reasoning process than not providing it?

Evaluation scores range from 1 (Bad), 2 (Fair), to 3 (Good). Agreement ratios are calculated as follows: 1 if all three evaluators agree, 0.5 if two agree, and 0 if all scores differ. As shown in Table 9, human evaluation scores for all aspects across datasets exceed 2, indicating that the generated intent is generally well-regarded. Notably, math reasoning tasks achieve scores near 3 with agreement ratios approaching 100%, demonstrating that SWI-generated intent is particularly coherent, effective, and interpretable in mathematical problem-solving.

The relatively low scores observed in QA tasks may be attributed to the lack of multi-step guidance: the number of generated intents in QA tasks is often 1 or 2, while that in math and summarization is usually at least three. This finding indicates the advantages of multi-round iterative intents, although SWI can boost task performance even with few intents generated.

Task	Dataset	Coherence Score Agree		Effectiveness Score Agree		Interpretability Score Agree	
Math Reasoning	GSM8K	2.90	85%	2.97	95%	2.97	95%
	MATH500	2.87	80%	2.87	80%	2.83	80%
Multiple-choice QA	BBH	2.37	55%	2.37	50%	2.33	45%
	MMLU	2.67	75%	2.53	55%	2.37	45%
Summarization	CDM	2.83	80%	2.77	70%	2.83	75%
	XSum	2.70	70%	2.60	65%	2.57	65%

Table 9: Intent Quality Evaluation by Humans. The score ranges from 1 (Bad) to 3 (Good).

7 Conclusion

In this work, we introduce Speaking with Intent (SWI) in LLMs, where the generated intent (as high-level planning) guides subsequent analysis, improving the reasoning and generation abilities. Extensive experiments across mathematical reasoning, multiple-choice QA, and text summarization benchmarks consistently show the benefits of SWI over the Baseline method that generates without explicit intent. In addition, SWI outperforms answer-trigger prompting methods like Chain-of-Thought on mathematical reasoning benchmarks. In text summarization, SWI produces summaries that are more accurate, concise, and factually reliable, with fewer hallucinations. Furthermore, human evaluations solidify the coherence, effectiveness, and interpretability of LLM-generated intent. This study opens a new avenue for enhancing LLM reasoning abilities and beyond.

Impact Statement. As intent is a fundamental aspect of natural language processing, empowering, eliciting, and enhancing the intent understanding and generation abilities can potentially drive AI systems (including multimodal models) to the next level. Moreover, Speaking with Intent can also be applied to various domains beyond NLP, such as healthcare, law, and finance. These applications are cost-sensitive, so explicitly showing the intent of AI models will help with the transparency and interpretability of critical decision-making.

³Please refer to Appendix C for more details on human evaluation.

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A Reproducibility Statement

A.1 LLM Generation

For all experiments in § 4 and § 5, we employ LLaMA3-8B-Instruct (Dubey et al., 2024), an open-weights, instruction-following, and Transformer-based (Vaswani et al., 2017) LLM with 8 billion model parameters, and use the model checkpoint and tokenizer⁴ provided by Hugging Face Transformers (Wolf et al., 2020). Only in the fact-checking evaluation for summaries (§ 5.2.3), we adopt the proprietary model GPT-40-mini (Hurst et al., 2024) to decompose the generated summary and reference summary into two sets of atomic facts.

For each running session, the experiments are conducted on a single NVIDIA V100 GPU with 32GB memory. To avoid out-of-memory issues, all the models are loaded in a half-precision (float16) mode, and the generation batch size is 1. The input sequence is not truncated since we do not want to lose the context information, but we set the maximum number of newly generated tokens as 4096 during generation.

To guarantee reproducibility, we fixed the seeds as 42 for all random modules, set the LLM generation temperature as 0 for deterministic generation without sampling, and ran all experiments twice, obtaining reproducible generation results and evaluation scores. The source code is available on GitHub: https://github.com/YuweiYin/SWI

A.2 Experimental Cost

In the generation stage, the total computational cost is approximately 1,500 GPU hours on NVIDIA V100 clusters (about 58 days). In the evaluation stage, only the option selection process for multiple-choice QA tasks requires GPU usage (Yin & Carenini, 2025), and the overall running time is roughly 100 hours on V100 clusters. In the fact-checking experiments (§ 5.2.3), the expense for GPT-40-mini API calls is below US\$10.

⁴https://huggingface.co/meta-llama/Llama-3.1-8B-Instruct

B Tasks and Datasets

To comprehensively study the effectiveness and generalizability of the proposed SWI method, we consider three different categories of tasks in our experiments: mathematical reasoning, multiple-choice QA, and text summarization. Table 10 presents the dataset sources. Please note that the URLs may be subject to change by the dataset providers.

Task	Dataset	URL
	GSM8K (Cobbe et al., 2021)	Link
	GSM8K-P (Vendrow et al., 2025)	Link
Mathematical	MATH500 (Lightman et al., 2024)	Link
Reasoning	AMC23 (American Mathematics Competitions)	Link
_	AIME24 (American Invitational Math Examination)	Link
	AIME25 (American Invitational Math Examination)	Link
	LogiQA (Liu et al., 2020)	Link
	CSQA (Talmor et al., 2019)	Link
	SIQA (Sap et al., 2019)	Link
Multiple-choice QA	OBQA (Mihaylov et al., 2018)	Link
Multiple-choice QA	ARC (Clark et al., 2018)	Link
	BBH (Suzgun et al., 2023)	Link
	MMLU (Hendrycks et al., 2021a)	Link
	MMLU-Pro (Wang et al., 2024e)	Link
	CDM (Hermann et al., 2015)	Link
	XSum (Narayan et al., 2018)	Link
Text	XL-Sum (Hasan et al., 2021)	Link
Summarization	SAMSum (Gliwa et al., 2019)	Link
	DialogSum (Chen et al., 2021)	Link
	WikiLingua (Ladhak et al., 2020)	Link

Table 10: Dataset sources.

B.1 Mathematical Reasoning

In the mathematical reasoning task, the model is asked to solve the given math problem and present the final answer. We consider the following math datasets.

GSM8K. Grade School Math 8K (GSM8K) (Cobbe et al., 2021) is a dataset of 8.5K highquality linguistically diverse grade school math word problems. The dataset was created to support the task of question answering on basic mathematical problems that require multi-step reasoning.

GSM8K-P. GSM8K-Platinum (Vendrow et al., 2025) is a revised version of the full test set of GSM8K (Cobbe et al., 2021). It revises the labels of mislabeled examples and removes any question that is determined to be poorly written (mostly due to ambiguity in the problem statement), providing a more accurate assessment of mathematical reasoning capabilities.

MATH500. MATH500 (Lightman et al., 2024) consists of 500 questions from the MATH test set (Hendrycks et al., 2021b). The distribution of difficulty levels and subjects in MATH500 is representative of the MATH test set as a whole.

Competition. We consider three competition-level math benchmarks: **AMC23**, **AIME24**, and **AIME25**, drawn from American Mathematics Competitions and American Invitational Mathematics Examination. AMC23, AIME24, and AIME25 have 40, 30, and 30 math problems, respectively. Despite the smaller scale, these math problems are much more challenging than those in GSM8K and MATH500.

B.2 Multiple-choice QA

Since many challenging benchmarks are designed as multiple-choice question-answering tasks, our SWI method is also evaluated on various reasoning-intense QA datasets, where the model is asked to select the most appropriate one from the given options to answer the question.

LogiQA. LogiQA Liu et al. (2020) is a reading comprehension dataset that requires the model to have logical reasoning for question-answering.

CSQA. CommonsenseQA (CSQA) (Talmor et al., 2019) examines the model on commonsense question-answering problems constructed using information from ConceptNet Speer et al. (2017).

SIQA. SocialIQA (SIQA) (Sap et al., 2019) is a large-scale QA benchmark for commonsense reasoning about social situations, which probes emotional and social intelligence in everyday situations.

OBQA. OpenBookQA (OBQA) (Mihaylov et al., 2018) asks the model to answer the question based on the given elementary-level science facts and broad commonsense knowledge.

ARC. AI2 Reasoning Challenge (ARC) (Clark et al., 2018) contains grade-school science questions. It is divided into a Challenge and an Easy set, where the former contains only questions answered incorrectly by both a retrieval-based algorithm and a word co-occurrence algorithm.

BBH. BIG-Bench Hard (BBH) (Suzgun et al., 2023) is a suite of challenging tasks filtered from BIG-Bench (Srivastava et al., 2023). Solving these problems often requires multi-step reasoning. In this work, 4 (out of 27) subtasks in BBH (word_sorting, object_counting, dyck_languages, and multistep_arithmetic_two) are discarded as they are not multiple-choice QA tasks.

MMLU. MMLU (Hendrycks et al., 2021a) comprehensively measures the multitask language understanding abilities on 57 subtasks including elementary mathematics, history, computer science, and more.

MMLU-Pro. MMLU-Pro (Wang et al., 2024e) extends the mostly knowledge-driven MMLU benchmark by integrating more challenging, reasoning-focused questions and expanding the choice set from four to ten options.

B.3 Text Summarization

Beyond math reasoning and multiple-choice QA, we hypothesize that Speaking with Intent benefits natural language generation tasks like summarization, where the generated intent can guide the model in summarizing the source article point by point. Hence, we test the effect of SWI on the following text summarization datasets (English only).

CNN/DailyMail. CNN/DailyMail (CDM) (Hermann et al., 2015; See et al., 2017) contains over 300K unique news articles written by journalists at CNN and the Daily Mail.

XSum. Extreme summarization (XSum) (Narayan et al., 2018) is a real-world, large-scale dataset consisting of online articles from the British Broadcasting Corporation (BBC).

XL-Sum. XL-Sum (Hasan et al., 2021) is a comprehensive and diverse dataset comprising 1.35 million professionally annotated article-summary pairs from BBC News. The dataset covers 45 languages and we only use the English subset.

SAMSum. SAMSum (Gliwa et al., 2019) contains about 16K messenger-like conversations with summaries. Linguists were asked to create conversations similar to those they write on a daily basis, reflecting the proportion of topics of their real-life messenger conversations.

DialogSum. DialogSum (Chen et al., 2021) is a large-scale dialogue summarization dataset, consisting of 13,460 dialogues with corresponding manually labeled summaries and topics.

WikiLingua. WikiLingua (Ladhak et al., 2020) is a large-scale, multilingual dataset for evaluating cross-lingual abstractive summarization systems. It extracts article and summary pairs in 18 languages from wikiHow, and we only use the English subset.

C Human Evaluation Details

Participant Requirements. We hire human evaluators from the cloud-sourcing platform CloudResearch⁵ to conduct human evaluation on the quality of the generated intent: coherence, effectiveness, and interpretability. To ensure the annotation quality, we apply several requirements to select qualified human evaluators, as shown in Table 11.

Туре	Requirements
Native Language	English
Country of Residence	Australia, Canada, Ireland, New Zealand, UK, US
Education	Undergraduate student, Graduate student
Reputation	Approved Projects Count: \geq 1,000 Approval Rating: \geq 90%

Table 11: The requirements for human evaluators.

Evaluation Tasks. For each task category, we select two datasets: GSM8K (Cobbe et al., 2021) and MATH500 (Lightman et al., 2024) for mathematical reasoning, BBH (Suzgun et al., 2023) and MMLU (Hendrycks et al., 2021a) for multiple-choice QA, and CDM (Hermann et al., 2015; See et al., 2017) and XSum (Narayan et al., 2018) for text summarization. We randomly sample 12 instances per dataset and divide them into two batches of six. Each batch includes a dummy instance with deliberately reversed intents to ensure evaluators are actively engaged rather than randomly selecting responses. Evaluator submissions are accepted or rejected based on completion time and performance on the dummy instance.

For each instance, human evaluators are provided with evaluation instructions, task input (e.g., the math problem, question with options, or source article), SWI-generated output, and assessment check boxes. They are then asked to evaluate the following aspects:

- **Coherence**: In general, does the analysis align coherently with the intent statements?
- **Effectiveness**: Overall, do the intent statements help with the planning and reasoning for solving the problem?
- **Interpretability**: Do you think providing the intent can help you better understand the reasoning process than not providing it?

Each batch is assessed by three different human evaluators, with each person uniquely assigned to only one batch. Evaluation scores range from 1 (Bad), 2 (Fair), to 3 (Good). Agreement ratios are calculated as follows: 1 if all three evaluators agree, 0.5 if two agree, and 0 if all scores differ.

Human Evaluation Quality. As mentioned above, we decided to accept or reject the evaluator's submission based on the task completion time and the results on the dummy instance that is deliberately modified to have a lower coherence. As a result, about 60% of the evaluators still rated the dummy instance as good coherence, meaning they failed the dummy test and potentially did not fully focus on the evaluation process, which poses a general caveat to the quality of cloud-sourcing annotations. Overall, we rejected about 10% of submissions that both failed the dummy test and took an unreasonably short time to complete the annotation. After rejecting them, we hired other evaluators until the intent quality evaluation was finished.

Human Evaluation Cost. The pay rate for each human evaluator is US\$10 per hour, completing a batch of 6 instances takes an evaluator 10-15 minutes on average, and the total cost of the intent quality evaluation is about US\$120.

⁵https://www.cloudresearch.com/