

Opus

A Prompt Intention Framework for Complex Workflow Generation

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Abstract

This paper introduces the Opus Prompt Intention Framework, designed to improve complex Workflow Generation with instruction-tuned Large Language Models (LLMs). We propose an intermediate Intention Capture layer between user queries and Workflow Generation, implementing the Opus Workflow Intention Framework, which consists of extracting Workflow Signals from user queries, interpreting them into structured Workflow Intention objects, and generating Workflows based on these Intentions. Our results show that this layer enables LLMs to produce logical and meaningful outputs that scale reliably as query complexity increases. On a synthetic benchmark of 1,000 multi-intent query–Workflow(s) pairs, applying the Opus Prompt Intention Framework to Workflow Generation yields consistent improvements in semantic Workflow similarity metrics. In this paper:

1. We introduce the Opus Prompt Intention Framework by applying the concepts of Workflow Signal and Workflow Intention to LLM-driven Workflow Generation.
2. We present a reproducible, customizable LLM-based Intention Capture system to extract Workflow Signals and Workflow Intentions from user queries.
3. We provide empirical evidence that the proposed system significantly improves Workflow Generation quality compared to direct generation from user queries, particularly in cases of Mixed Intention Elicitation.

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1 Introduction

In the modern business environment, well-structured internal processes form the backbone of operational consistency, efficiency, and accountability. Yet, the quality and clarity of process documentation across organizations varies in completeness, accuracy, and granularity, making automation difficult to scale. As businesses face growing demands for agility, cost reduction, and regulatory compliance, many are turning to AI-driven systems to streamline decision-making and operational execution. However, realizing the full potential of automation requires systems that can understand and act on human intent expressed in natural language. This is particularly challenging when user queries are informal, ambiguous, or contain multiple goals. To address this, we adopt the Opus Workflow Intention Framework—a structured representation of Input, Process, and Output—to bridge the gap between human language and machine-executable Workflows. In this paper, we propose the Opus Prompt Intention Framework that leverages LLMs to extract these Intention objects from user queries and evaluate whether incorporating them explicitly into the Workflow Generation process leads to improved quality. We aim to demonstrate that Workflows generated from Intention objects will be more accurate, interpretable, and aligned with user goals than those generated from raw queries alone. Critically, the Opus Prompt Intention Framework enables scalable Workflow Generation with respect to query complexity. As the complexity of user input increases—whether through multi-objective requests, incomplete specifications, or ambiguous phrasing—the proposed framework maintains high accuracy and consistency, while traditional LLM-based approaches degrade in performance. The Opus Prompt Intention Framework not only enables more reliable automation, but also offers a scalable path for organizations to convert informal, fragmented practices into structured, AI-enhanced Workflows that reflect contemporary best practices.

Definitions The Opus Prompt Intention Framework is based on the following concepts introduced in *Opus: A Large Workflow Model for Complex Workflow Generation* by Fagnoni et al. [1] and *Opus: A Workflow Intention Framework for Complex Workflow Generation* by Kingston et al. [2]:

Input: The dataset initiating a **Process**, conforming to validation rules and format specifications. **Input** is multimodal, including structured (e.g. databases, forms) and unstructured (e.g. documents, media) data types such as text, documents, images, audio, and video.

Process: A structured sequence of operational steps transforming **Input** into **Output**. **Process** combines automated and manual steps defining start/end conditions, decision points, parallel paths, roles, success criteria, monitoring, metrics, compliance requirements and error handling.

Output: The result of a **Process** operating on **Input**, meeting predefined quality and business criteria. **Output** can be tangible (e.g. documents) or intangible (e.g. decisions) and include audit trails of their creation. Supported formats include text and documents.

Workflow: A software executable **Process** as a Directed Acyclic Graph (DAG) of **Tasks**. **Workflows** coordinate task execution, manage data flow, and enforce business rules, compliance, and process logic (e.g. conditionals, loops, error handling). **Workflows** support monitoring, logging, audit, state management, concurrency, adaptive modification, and version control.

Task: An atomic unit of work within a **Workflow**, performing a specific function with defined input/output schemas, objectives, timing constraints, and success criteria. **Tasks** follow a singular responsibility principle, support automation or manual intervention, and maintain contextual awareness of dependencies. **Tasks** are auditable by humans or AI agents against their definition.

Workflow Intention (referred to as **Intention**): The alignment of **Input**, **Process**, and **Output** components defining a **Workflow**'s transformation objective. It specifies how **Input** is processed to achieve desired **Output**, incorporating data formats, quality standards, business rules, and constraints. It is determined by interpreting **Workflow Signals** from direct and indirect sources.

Workflow Signal: A discrete informational cue from **Intention Elicitation** that conveys implicit or explicit information on **Input**, **Process** or **Output** relevant to a **Workflow**.

Complete Intention: A state where sufficient information exists across **Input**, **Process**, and **Output** components for accurate **Workflow** implementation. **Incomplete Intentions**, on the other hand, lack clear specifications or operational requirements, hindering execution.

Intention Elicitation: User-driven communication (e.g. text-based conversations, interface interactions) that contains **Workflow Signals** to further articulate **Workflow Intention(s)**. It captures objectives, constraints, and preferences, distinct **Input/Output** examples.

Mixed Intention Elicitation: A state where the **Intention Elicitation** describes multiple distinct transformation objectives, requiring separation into **Workflow Intentions**, in contrast to **Singular Intention Elicitation**, which expresses a single, well-defined **Workflow Intention**. Separation improves clarity, maintainability, and preserves **Workflow** interfaces.

We consider the problem of Workflow Generation from an Intention Elicitation, where a user provides a query describing the Workflow(s) they intend to generate. Two key principles govern the system design for this problem. First, when a user query does not fully specify a Workflow—formally, when it expresses an Incomplete Intention—the system must be able to reliably identify this condition. Attempting to resolve incomplete specifications directly during Workflow Generation often leads to unreliable or suboptimal results. Instead, the system should proactively flag such incompleteness for user clarification, or attempt to retrieve the missing components from external sources (e.g., knowledge graphs) before proceeding with Workflow Generation. Second, when a user query expresses multiple distinct transformation objectives—a Mixed Intention Elicitation—the system must generate a separate Workflow for each distinct transformation. Generating a single Workflow to satisfy multiple objectives leads to unintended contextual overlaps and reduced accuracy. The system should instead trigger multiple, distinct Workflow Generations, each aligned to a singular objective. These two principles highlight the need for a dedicated preprocessing layer in Workflow Generation. Our results show that the Opus Workflow Intention Framework provides a scalable and reliable foundation for structuring this layer.

2 Background

Workflow, Workflow Intention We adopt the Opus Workflow Framework (Fagnoni et al. [1]) where a Workflow is represented as a Directed Acyclic Graph (DAG) consisting of Input Nodes, Task Nodes, Output Nodes, and Edges that define the Task execution flow from Inputs to Outputs. We generate Workflows at a semantic level: each Node is described using structured semantic features following a predefined schema, typically represented as a JSON object with fields such as name, description, and steps for Task Nodes. The schema is flexible and can be adapted as required, demonstrating the extensibility of the framework. Additionally, we adopt the Opus Workflow Intention Framework (Kingston et al. [2]), which maps business artefacts and Intention Elicitation into Workflow Signals—specifically Input (i), Process (p), and Output (o) elements—and into an Intention Set. In this work, we focus exclusively on Intention Elicitation as user queries, in text format. Since we operate directly at a semantic level using LLMs, each Workflow Signal is represented as a list of strings. This aligns with the Opus Workflow Intention Framework, where Workflow Signals are modeled as vectors and classified against generative families of Input, Process, and Output string elements. In our representation, each string corresponds to a distinct semantic component, enforced through prompt design. The generation of these strings is unconstrained beyond this granularity. Although further classification against generative families is possible, we do not consider this step essential to the core argument of this paper. Intention objects, forming an Intention Set for each Intention Elicitation, are represented as triples (i, p, o) , where each element is a list of strings.

Large Language Models (LLMs) Recent advancements in LLMs have significantly improved text generation, multimodal reasoning, and processing efficiency. Built on Transformer architectures [3], LLMs leverage attention mechanisms for scalable parallel computation. Beyond pattern recognition and text generation, modern reasoning-oriented models integrate Reinforcement Learning [4–7], Mixture of Experts (MoE) [8–10], and long-context handling [11–14] to improve logical consistency and decision-making. Leading these developments are OpenAI’s GPT-4o [15], o1 [16], o3-mini [17], and GPT-4.5 [18]; Anthropic’s Claude Opus [19], Sonnet 3.5 [20] and 3.7 [21]; and DeepSeek’s R1 [4]. Persistent hallucinations, high computational costs, and training data bottlenecks necessitate robust pipelines and frameworks to improve alignment and enhance reliability in real-world applications. Building on these advancements, LLMs provide a strong foundation for extracting Workflow Signals and generating Workflows from user queries, including complex, multi-intent scenarios. Although current models may struggle with processing multiple Intentions simultaneously, their capacity to parse nuanced language, reason over context, and infer latent structure positions them as well-suited for aligning Workflow Signals—even when such Signals are implicit. This capability enables the construction of modular and interpretable Intention objects that guide Workflow Generation. Whether through direct query-to-Workflow Generation or via structured Intentions, LLMs offer the flexibility and language grounding required to bridge natural language with executable systems.

Workflow Quality The core argument of this paper is that Workflow Generation is significantly improved when guided by explicit Workflow Intentions. To substantiate this claim, we evaluate generated Workflows using two categories of metrics: (1) semantic and structural metrics, which assess Workflow similarity, and (2) LLM-based metrics, where LLMs are prompted to evaluate Workflow quality under predefined criteria. For semantic and structural metrics, we adopt metrics used in the Opus Workflow Framework [1]. These include BLEU (Bilingual Evaluation Understudy, Papineni et al. [22]), a precision-based metric widely used in machine translation; ROUGE (Recall-Oriented Understudy for Gisting Evaluation, Lin et al. [23]) and its variants—ROUGE-N (N-gram overlap), ROUGE-L (Longest common subsequence), and ROUGE-S (Skip-bigram co-occurrence)—commonly applied in summarization evaluation; METEOR (Metric for Evaluation of Translation with Explicit ORdering, Banerjee et al. [24]), which extends BLEU by incorporating stemming, synonym matching, and a higher recall weighting; and BERTScore (Zhang et al. [25]), which leverages contextual embeddings from pre-trained language models (specifically BERT) to measure textual similarity. For LLM-based evaluation, we adopt the LLM-as-a-Judge framework, where LLMs are used to evaluate model outputs. Jiawei et al. [26] provide a comprehensive overview of this approach, addressing challenges related to bias, robustness, and alignment with human judgments. When properly configured, LLM-based evaluation provides a powerful tool for qualitative assessment of complex Workflows. However, the inherent imprecision of LLM judgments—stemming from variability in model outputs and susceptibility to bias—requires mitigation strategies such as prompt calibration and repeated sampling. Employing multiple models as evaluators can help temper these limitations by diversifying judgment perspectives.

3 System Overview

We implement a reproducible Intention Capture system using LLMs, designed to be model-agnostic and demonstrated that even a basic Intention Capture improves Workflow Generation unequivocally. The system consists of two LLMs, as illustrated in Figure 1: the first extracts Input, Process, and Output Signals from an Intention Elicitation ; the second generates the Intention Set, where each Intention object comprises aligned Input, Process, and Output Signals. In this context, a Signal is a list of granular string elements within its category (Input, Process, or Output), mirroring the classification of encoded artifacts into predefined elements of families as defined in the Opus Workflow Intention Framework [2]. We evaluate the accuracy of the generated Signals and Intention Set using loss functions analogous to those employed in the Opus Workflow Intention Framework.

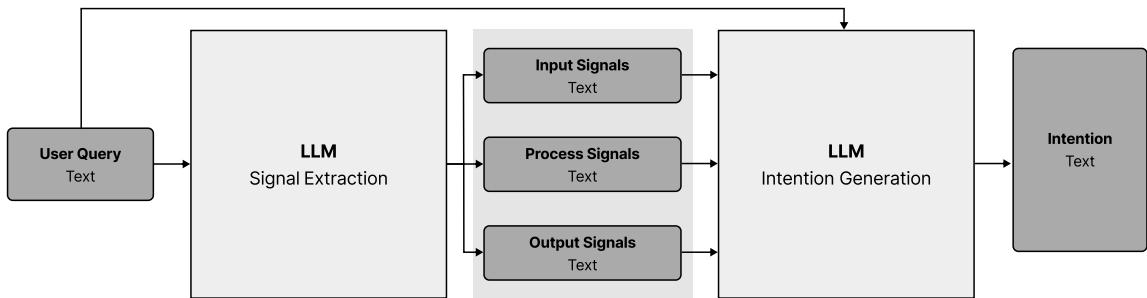


Figure 1: LLM-based Intention Capture

4 Data and Methodology

Starting with 1,000 registered services spanning 100 industries, we construct a Process Pool P_g consisting of semantic Process string elements. For each Process element, we generate corresponding Input and Output elements, forming a Complete Intention object $\gamma = (i, p, o)$, where each component is a list containing at least one item. This construction yields the Input Pool I_g and the Output Pool O_g . We then define the Intention Pool Γ_p , where each Intention is composed of three lists, each populated with elements from I_g , P_g and O_g .

For each Intention $\gamma = (i, p, o)$, we generate a corresponding Intention Elicitation (as a user query) \mathcal{U} - a string crafted from i, p , and o , ensuring these components are explicitly stated and incorporated. To increase linguistic entropy and make the mapping non-injective, we introduce controlled variations in phrasing that preserve semantic content. This simulates user query diversity—akin to adding noise to a signal without loosing information. From \mathcal{U} , we generate a Workflow W , represented as a string (structure detailed in Appendix A.1, Figure 6). To simulate multi-intent scenarios, we sample a variable number $n_k \in [1, 10]$ of Intention Objects from Γ_p to form an Intention Set, comprising the Reference Intention Sets:

$$\Gamma^* = \{\Gamma^{*,k}\}_k \quad \text{where} \quad \Gamma^{*,k} = \{(i, p, o)_j^k\}_{j=1}^{n_k} \quad (1)$$

Each $\Gamma^{*,k}$ is used to construct:

1. A set of Singular Intention Elicitation (user query) $\{\mathcal{U}_j^k\}_{j=1}^{n_k}$, where each query corresponds to an Intention object in $\Gamma^{*,k}$.
2. A combined Mixed Intention Elicitation \mathcal{U}_m^k , synthesized by aggregating all individual user queries corresponding to the Intention objects within $\Gamma^{*,k}$.
3. A Reference Workflow Set $\mathcal{W}^{*,k} = \{W_j^k\}_{j=1}^{n_k}$, where each Workflow is generated from a Singular Intention Elicitation.

The Sample Set is defined as:

$$\mathcal{S} = \left\{ \left(\Gamma^{*,k}, \{\mathcal{U}_j^k\}_{j=1}^{n_k}, \{W_j^k\}_{j=1}^{n_k}, \mathcal{U}_m^k \right) \right\}_k, \quad \forall k, n_k \in [1, 10] \quad (2)$$

Each sample k consists of:

1. A Mixed Intention Level $n_k \in [1, 10]$, defined as the number of Intention objects used to generate the Mixed Intention Elicitation.
2. A Reference Intention Set $\Gamma^{*,k} = \{(i, p, o)_j^k\}_{j=1}^{n_k}$ composed of Complete Intention objects.
3. Singular Intention Elicitations (user queries) $\{\mathcal{U}_j^k\}_{j=1}^{n_k}$, each corresponding to an Intention in $\Gamma^{*,k}$.
4. A Reference Workflow Set $\mathcal{W}^{*,k} = \{W_j^k\}_{j=1}^{n_k}$, where each Workflow is generated from its corresponding Singular Intention Elicitation.

5. A Mixed Intention Elicitation \mathcal{U}_m^k synthesized as a user query from all the Singular Intention Elicitations in the sample.

We generate 100 samples per Mixed Intention Level, leading to 1000 samples.

Evaluation Procedure (per sample k)

For each sample k , we perform the following steps:

1. Signal Extraction: Extract Decoded Signals from the Mixed Intention Elicitation:

$$\hat{s}^k = f_{\text{signal}}(\mathcal{U}_m^k) = (\hat{i}, \hat{p}, \hat{o})^k$$

2. Intention Generation: Compute the loss between Decoded Signals and the Reference aggregated Signals:

$$\mathcal{L}_{\text{signal}}(\hat{s}^k, s^{*,k}) ; s^{*,k} = (\cup_{l=1}^{n_k} i_l^k, \cup_{l=1}^{n_k} p_l^k, \cup_{l=1}^{n_k} o_l^k)$$

3. Intention Generation: Generate the Decoded Intention Set using the Mixed Intention Elicitation and Decoded Signals:

$$\hat{\Gamma}^k = f_{\text{Intention}}(\mathcal{U}_m^k, \hat{s}^k) = \{\hat{\gamma}_j^k\}_j$$

4. Intention Loss: Evaluate the Intention Set prediction against the Reference Intention Set:

$$\mathcal{L}_{\text{Intention}}(\hat{\Gamma}^k, \Gamma^{*,k})$$

5. Workflow Generation: Generate the Decoded Workflow Sets under two conditions:

- $\hat{\mathcal{W}}_\Gamma^k = \{\hat{W}_{\Gamma,j}^k\}_{j=1}^{|\hat{\Gamma}^k|} = f_{\text{wfg},\Gamma}(\hat{\Gamma}^k)$ with Intention guidance, and
- $\hat{\mathcal{W}}^k = \{\hat{W}_j^k\}_{j=1}^{\hat{n}_k} = f_{\text{wfg}}(\mathcal{U}_m^k)$ without Intention guidance.

6. Workflow Evaluation: Compare both Decoded Workflow Sets to the Reference Workflow Set using the Workflow Generation loss: $\mathcal{W}^{*,k}$: $\mathcal{L}_{\text{wfg}}(\hat{\mathcal{W}}^k, \mathcal{W}^{*,k}), \mathcal{L}_{\text{wfg}}(\hat{\mathcal{W}}_\Gamma^k, \mathcal{W}^{*,k})$.

The purpose of this paper is to evaluate the effectiveness of the Opus Prompt Intention Framework in improving Workflow Generation from Intention Elicitation. We compare Workflows generated under two conditions: (1) a baseline process where an LLM generates Workflows directly from a Mixed Intention Elicitation, and (2) an Intention-aware process where the same Elicitation is processed through the Intention Capture system prior to Workflow Generation.

Reference Workflows are constructed independently from Singular Intention Elicitations, each describing a Complete Intention, before being combined into the Mixed Intention Elicitation. The Intention Capture system seeks to reconstruct these seed Intentions from the Mixed Elicitation, enabling Workflow Generation to be aligned to the original distinct user intents. By holding the LLM constant across all conditions—Reference Workflow Generation, Workflow Generation without Intention separation, and Intention-aware Generation—we isolate the impact of Intention-awareness. This ensures that observed improvements stem from the framework itself, not from differences in the underlying model. The upper bound of achievable Workflow quality is defined by the Reference Workflows generated from Singular Intention Elicitations, bounding the maximum potential improvements achievable through Intention separation. The key evaluation metric is the system’s ability to accurately reconstruct the original Intentions and generate Workflows that satisfy a one-Intention-per-Workflow principle. Unlike our previous work [1], which evaluated the ability of LLMs to perform Workflow Generation based solely on their intrinsic knowledge and showed that it alone was insufficient for producing high-quality outputs, this paper disentangles the impact of Intention separation from the LLM’s intrinsic knowledge on Workflow Generation. By modularizing Intention Capture as a distinct step, we explicitly quantify the impact of structural guidance on Workflow quality.

4.1 Signal Extraction

For Signal Extraction f_{signal} , we prompt an LLM to generate distinct Input, Process and Output elements from a user query, producing three lists: i , p , and o . Let $\hat{s} = (\hat{i}, \hat{p}, \hat{o})$ represent the Decoded Workflow Signal, and $s^* = (i^*, p^*, o^*)$ the corresponding Reference Workflow Signal.

Input Loss Definition Let $\hat{i} = \{x_1, \dots, x_{|\hat{i}|}\}$ and $i^* = \{y_1, \dots, y_{|i^*|}\}$ be the Decoded and Reference Input element lists. Each string $x_j \in \hat{i}$ and $y_k \in i^*$ is embedded using the all-MiniLM-L6-v2 model from the Sentence Transformers library [27]:

$$v(x_j) \in \mathbb{R}^d, v(y_k) \in \mathbb{R}^d, d \in \mathbb{N}$$

Embeddings are l_2 -normalized:

$$u(x_j) = \frac{v(x_j)}{\|v(x_j)\|}, u(y_k) = \frac{v(y_k)}{\|v(y_k)\|}$$

We define the similarity between two normalized vectors a and b as:

$$\text{Sim}(a, b) = \sqrt{\frac{1 + \langle a, b \rangle}{2}} \quad (3)$$

This function is maximal when $a = b$ and null when $a = -b$. While not a metric (as it doesn’t satisfy the triangle inequality), it provides a bounded, normalized measure of alignment between semantic embeddings. Alternative choices could include the standard cosine similarity, but this mapping makes aggregation and loss interpretation more straightforward.

The Input Loss \mathcal{L}_I is defined as:

$$\mathcal{L}_I^2 = \begin{cases} 1 - \frac{1}{|i^*|} \max_{\sigma \in \mathcal{F}_{|\hat{i}|, |i^*|}} \left\| \left(\text{Sim}(\mathbf{u}(x_1), \mathbf{u}(y_{\sigma(1)})), \dots, \text{Sim}(\mathbf{u}(x_{|\hat{i}|}), \mathbf{u}(y_{\sigma(|\hat{i}|)})) \right) \right\|^2 & \text{if } |i^*| \geq |\hat{i}| \\ 1 - \frac{1}{|\hat{i}|} \max_{\sigma \in \mathcal{F}_{|i^*|, |\hat{i}|}} \left\| \left(\text{Sim}(\mathbf{u}(x_{\sigma(1)}), \mathbf{u}(y_1)), \dots, \text{Sim}(\mathbf{u}(x_{\sigma(|i^*|)}), \mathbf{u}(y_{|i^*|})) \right) \right\|^2 & \text{if } |i^*| \leq |\hat{i}| \end{cases}$$

where $\mathcal{F}_{n,m}$ denotes the set of all functions mapping $\llbracket 1, n \rrbracket$ to $\llbracket 1, m \rrbracket$.

The Input Loss simplifies to:

$$\mathcal{L}_I^2 = \begin{cases} 1 - \frac{1}{|i^*|} \max_{\sigma \in \mathcal{F}_{|\hat{i}|, |i^*|}} \sum_{j=1}^{|\hat{i}|} \frac{1 + \langle \mathbf{u}(x_j), \mathbf{u}(y_{\sigma(j)}) \rangle}{2} & \text{if } |i^*| \geq |\hat{i}| \\ 1 - \frac{1}{|\hat{i}|} \max_{\sigma \in \mathcal{F}_{|i^*|, |\hat{i}|}} \sum_{k=1}^{|i^*|} \frac{1 + \langle \mathbf{u}(x_{\sigma(k)}), \mathbf{u}(y_k) \rangle}{2} & \text{if } |i^*| < |\hat{i}| \end{cases}, \quad \mathcal{L}_I^2 \in [0, 1] \quad (4)$$

This metric is designed to maximize the sum of squared similarities, encouraging each decoded embedding to align closely with its best possible counterpart. It inherently penalizes both under-sized and over-sized predictions equivalently, as the total similarity is normalized by the size of the Reference or Decoded Set, leading to lower scores when elements are missing or redundant. The formulation allows multiple Decoded elements to align with the same Reference element, which prevents unnecessary penalties for granular representation differences (e.g., a prediction of [ID Card, Passport] compared to a Reference [ID Card & Passport]).

Loss for Process and Output Without loss of generality, we extend the Input Loss to Process and Output, defining their respective Losses as:

$$\mathcal{L}_P^2 = \begin{cases} 1 - \frac{1}{|p^*|} \max_{\sigma \in \mathcal{F}_{|\hat{p}|, |p^*|}} \sum_{j=1}^{|\hat{p}|} \frac{1 + \langle \mathbf{u}(x_j), \mathbf{u}(y_{\sigma(j)}) \rangle}{2} & \text{if } |p^*| \geq |\hat{p}| \\ 1 - \frac{1}{|\hat{p}|} \max_{\sigma \in \mathcal{F}_{|p^*|, |\hat{p}|}} \sum_{k=1}^{|p^*|} \frac{1 + \langle \mathbf{u}(x_{\sigma(k)}), \mathbf{u}(y_k) \rangle}{2} & \text{if } |p^*| \leq |\hat{p}| \end{cases}, \quad \mathcal{L}_P^2 \in [0, 1] \quad (5)$$

$$\mathcal{L}_O^2 = \begin{cases} 1 - \frac{1}{|o^*|} \max_{\sigma \in \mathcal{F}_{|\hat{o}|, |o^*|}} \sum_{j=1}^{|\hat{o}|} \frac{1 + \langle \mathbf{u}(x_j), \mathbf{u}(y_{\sigma(j)}) \rangle}{2} & \text{if } |o^*| \geq |\hat{o}| \\ 1 - \frac{1}{|\hat{o}|} \max_{\sigma \in \mathcal{F}_{|o^*|, |\hat{o}|}} \sum_{k=1}^{|o^*|} \frac{1 + \langle \mathbf{u}(x_{\sigma(k)}), \mathbf{u}(y_k) \rangle}{2} & \text{if } |o^*| \leq |\hat{o}| \end{cases}, \quad \mathcal{L}_O^2 \in [0, 1] \quad (6)$$

Signal Loss To compute the combined Signal Loss for the Decoded semantic Workflow Signal triple $\hat{s} = (\hat{i}, \hat{p}, \hat{o})$, we aggregate the element-wise Losses as follows:

$$\mathcal{L}_{\text{signal}}^2(\hat{s}, s^*) = \mu_I \mathcal{L}_I^2 + \mu_P \mathcal{L}_P^2 + \mu_O \mathcal{L}_O^2, \quad \mathcal{L}_{\text{signal}}^2 \in [0, 1] \quad (7)$$

where $\mu_I + \mu_P + \mu_O = 1$ and $\mu_I, \mu_P, \mu_O \in [0, 1]$

The weighting coefficients μ_I , μ_P , and μ_O control the relative contribution of the Input \mathcal{L}_I^2 , Process \mathcal{L}_P^2 , and Output \mathcal{L}_O^2 Losses in the total Loss function.

4.2 Intention Generation

For Intention Generation $f_{\text{Intention}}$, we prompt an LLM to generate an Intention Set, composed of Workflow Intention objects. The prompt is conditioned on both the Intention Elicitation and the extracted Workflow Signals. Each Intention object γ consists of three lists: i_γ (Input), p_γ (Process) and o_γ (Output). Let $\hat{\Gamma} = \{\hat{\gamma}_j\}_j$ denotes the Decoded (LLM-generated) Intention Set, $\Gamma^* = \{\gamma_j^*\}_j$ being the Reference Intention Set. We extend the Signal Loss to define the Intention Loss, which measures the alignment between the Decoded and Reference Intention Sets. The Intention Loss is defined as:

$$\mathcal{L}_{\text{Intention}}^2 = \begin{cases} 1 - \frac{1}{|\Gamma^*|} \max_{\sigma \in \mathcal{I}_{|\hat{\Gamma}|, |\Gamma^*|}} \sum_{j=1}^{|\hat{\Gamma}|} 1 - \mathcal{L}_{\text{signal}}^2(\hat{\gamma}_j, \gamma_{\sigma(j)}^*) & \text{if } |\Gamma^*| \geq |\hat{\Gamma}| \\ 1 - \frac{1}{|\Gamma|} \max_{\sigma \in \mathcal{I}_{|\Gamma^*|, |\hat{\Gamma}|}} \sum_{k=1}^{|\Gamma^*|} 1 - \mathcal{L}_{\text{signal}}^2(\hat{\gamma}_{\sigma(k)}, \gamma_k^*) & \text{if } |\Gamma^*| \leq |\hat{\Gamma}| \end{cases}, \quad (8)$$

$$\mathcal{L}_{\text{Intention}}^2 \in [0, 1]$$

where $\mathcal{I}_{n,m}$ denotes the set of all injections from $\llbracket 1, n \rrbracket$ to $\llbracket 1, m \rrbracket$. The injection constraint ensures that each Decoded Intention can only be matched to a unique Reference Intention, preventing multiple predictions from mapping to the same ground-truth Intention.

4.3 Intention for Workflow Generation

For Workflow Generation, we employ two distinct prompting strategies using an LLM. First, we generate Workflows based on the Intention Set $\hat{\Gamma}$, where each Intention object is individually provided as input to the LLM. This produces the Set of Workflows Decoded with Intention, denoted as $\hat{\mathcal{W}}_{\hat{\Gamma}}^k$. Independently, we generate directly from the original Mixed Intention Elicitation without providing any Intention information, forming the Set of Workflows Decoded without Intention, denoted as $\hat{\mathcal{W}}^k$. To assess the impact of Intention-aware Workflow Generation, both Decoded Sets are compared against the Reference Workflow Set $\mathcal{W}^{*,k}$.

Workflow Similarity Let s be a Workflow Similarity such that:

$$s \left\{ \begin{array}{l} \mathcal{W} \times \mathcal{W} \rightarrow [0, 1] \\ (\mathcal{W}_1, \mathcal{W}_2) \mapsto s(\mathcal{W}_1, \mathcal{W}_2) \\ s(\mathcal{W}_1, \mathcal{W}_2) = 1 \iff \mathcal{W}_1 = \mathcal{W}_2 \end{array} \right.$$

The distance s is a monotonically increasing function: as the similarity between two Workflows increases, s grows accordingly. Given two sets of Workflows $\mathcal{W}_1, \mathcal{W}_2$, we define the aggregated set-level Workflow Similarity S as:

$$S^2 = \begin{cases} 1 - \frac{1}{|\mathcal{W}_2|} \max_{\sigma \in \mathcal{I}_{|\mathcal{W}_1|, |\mathcal{W}_2|}} \sum_{j=1}^{|\mathcal{W}_1|} s^2(\mathcal{W}_{1,j}, \mathcal{W}_{2,\sigma(j)}) & \text{if } |\mathcal{W}_2| \geq |\mathcal{W}_1| \\ 1 - \frac{1}{|\mathcal{W}_1|} \max_{\sigma \in \mathcal{I}_{|\mathcal{W}_2|, |\mathcal{W}_1|}} \sum_{k=1}^{|\mathcal{W}_2|} s^2(\mathcal{W}_{1,\sigma(k)}, \mathcal{W}_{2,k}) & \text{if } |\mathcal{W}_2| \leq |\mathcal{W}_1| \end{cases} \quad (9)$$

$$S \in [0, 1]$$

This formulation finds the optimal pairing between Decoded and Reference Workflows to maximize total Similarity. The normalization by the cardinality of the smaller set penalizes missing or redundant Workflows. We employ multiple Workflow Similarity metrics, reporting the square root of certain squared metrics (such as squared Euclidean distances or squared losses), converting them back to their original units and improving comparability with standard similarity measures.

5 Evaluation Metrics

We employ two complementary types of evaluation metrics to compare Workflows, namely (1) semantic and structural metrics, which assess Workflow textual and structural similarity, and (2) LLM-based “judge” metrics, where LLMs are prompted to evaluate Workflows based on predefined criteria.

Semantic and Structural Metrics We use the following metrics to quantify similarity between Decoded Workflows and their Reference:

BLEU score [22]: Measures precision-based word and phrase overlap between generated and reference text. It penalizes extra words absent in the reference. The score ranges from 0 (no match) to 1 (perfect match).

ROUGE score [23]: Evaluates word and phrase overlap, focusing on recall. Key variants include ROUGE-1 (unigrams), ROUGE-2 (bigrams), and ROUGE-L (longest common subsequence).

METEOR score [24]: Extends BLEU by considering synonyms, stemming, and word forms, capturing near matches beyond exact overlap.

BERTScore [25]: Uses deep learning embeddings (BERT) to measure semantic similarity, rather than direct word matching. It computes Precision, Recall, and F1-score based on contextual embeddings.

Coverage Ratio: Quantifies word presence overlap, measuring the proportion of words in the reference that appear in the generated text.

Cosine Similarity: Measures semantic closeness by computing the cosine of the angle between text embeddings (computed from pre-trained transformer models). Scores range from 0 (opposite) to 1 (identical).

LLM-as-a-Judge Evaluation To approximate human expert assessment of Workflow quality, we prompt an LLM as an expert evaluator to compare each Decoded Workflow against its Reference counterpart. We use OpenAI’s GPT-4o [15] as a consistent evaluator in all experiments, leaving multi-model evaluation for future study. The LLM is prompted as an expert judge and provides numerical scores along four dimensions, all ranged from 0 to 10:

Coverage Score: Measures how comprehensively the Decoded Workflow includes all essential Tasks from the Reference. The LLM identifies missing elements, unnecessary additions, or incomplete implementations. Higher scores indicate full functional coverage, while lower scores reflect significant gaps.

Consistency Score: Evaluates the alignment of the logical flow and structure between the Decoded and Reference Workflows. The LLM assesses whether branches, sub-branches, and dependencies are correctly mapped, ensuring a coherent sequence of steps without contradictions, circular logic, or gaps. The score reflects the degree of structural and logical consistency, with higher scores indicating well-ordered Workflows, while lower scores denote misalignment or inconsistencies.

Integration Score: Measures how closely the Decoded Workflow replicates the transformation process(es) of the Reference Workflow. The LLM assesses whether the Input, Process, and Output components are correctly aligned, ensuring consistency in data flow and Task progression. The score reflects the degree of structural and functional alignment, where higher scores indicate well-matched, clearly defined transformations, and lower scores signal discrepancies or unclear process mappings.

Total Score: Provides an overall assessment of how well the Decoded Workflow matches the Reference Workflow in terms of completeness, clarity, and correctness. This score aggregates Integration, Coverage, and Consistency Scores, while also incorporating additional qualitative insights that may not be captured by individual metrics.

Both semantic similarity metrics and LLM-as-a-Judge scores present limitations when evaluating Workflow Generation. Semantic metrics, while providing useful signals, are limited to surface-level textual overlap and are not sufficient as the sole quantitative measure. LLM-based evaluation offers scalability and can approximate human judgment, but remains qualitative and is subject to model bias, prompt sensitivity, and limited transparency or reproducibility as models evolve. The concepts of Coverage, Consistency, and Integration provide an initial foundation for Workflow Evaluation, but further formalization is needed—especially to rigorously capture causal logic and the geometric or topological properties of Workflow structure. Developing more comprehensive, structure-aware, and quantitatively grounded metrics remains essential to establish robust Workflow Evaluation standards.

6 Results

This section presents the results of Signal Extraction, Intention Generation, and Workflow Generation, both with and without Intention guidance. We conduct experiments using 9 leading LLMs across 10 Mixed Intention Levels. Each Level corresponds to the number of Complete Intentions combined within an Intention Elicitation, simulating query complexity. For each Level n , 100 samples are generated, each representing a unique Intention Elicitation constructed from n Complete Intentions. Unless otherwise specified, all experiments include the following models: OpenAI’s GPT-4.5, GPT-4o, o3-mini, o1, Anthropic’s Claude 3.5 Opus, Claude 3.5 Sonnet, Claude 3.7 Sonnet, DeepSeek V3, and R1.

6.1 Signal Extraction

Model	Mixed Intention Level										Model
	1	2	3	4	5	6	7	8	9	10	
openai-gpt-4.5	0.194 (0.080)	0.161 (0.053)	0.133 (0.038)	0.134 (0.029)	0.132 (0.026)	0.129 (0.026)	0.134 (0.031)	0.141 (0.029)	0.133 (0.023)	0.132 (0.022)	0.142 (0.041)
openai-gpt-4o	0.213 (0.107)	0.179 (0.077)	0.178 (0.063)	0.186 (0.056)	0.179 (0.053)	0.167 (0.044)	0.182 (0.040)	0.194 (0.046)	0.181 (0.044)	0.180 (0.042)	0.184 (0.061)
openai-o1	0.177 (0.096)	0.163 (0.067)	0.148 (0.046)	0.163 (0.042)	0.164 (0.049)	0.153 (0.034)	0.162 (0.035)	0.153 (0.036)	0.147 (0.033)	0.155 (0.029)	0.159 (0.051)
openai-o3-mini	0.162 (0.083)	0.134 (0.057)	0.121 (0.034)	0.125 (0.032)	0.123 (0.033)	0.125 (0.028)	0.128 (0.031)	0.125 (0.028)	0.125 (0.026)	0.120 (0.025)	0.129 (0.042)
anthropic-claude-sonnet-3.5	0.243 (0.049)	0.176 (0.046)	0.143 (0.036)	0.125 (0.028)	0.115 (0.027)	0.108 (0.023)	0.113 (0.023)	0.119 (0.025)	0.106 (0.022)	0.107 (0.021)	0.136 (0.038)
anthropic-claude-sonnet-3.7	0.171 (0.064)	0.175 (0.050)	0.135 (0.038)	0.132 (0.031)	0.118 (0.034)	0.109 (0.025)	0.112 (0.023)	0.113 (0.024)	0.101 (0.022)	0.104 (0.022)	0.127 (0.038)
anthropic-claude-opus	0.310 (0.077)	0.211 (0.054)	0.176 (0.039)	0.154 (0.029)	0.151 (0.032)	0.137 (0.033)	0.142 (0.029)	0.144 (0.033)	0.130 (0.023)	0.131 (0.024)	0.168 (0.048)
deepseek-v3	0.251 (0.105)	0.206 (0.076)	0.171 (0.056)	0.146 (0.042)	0.134 (0.037)	0.125 (0.023)	0.131 (0.026)	0.128 (0.026)	0.116 (0.025)	0.115 (0.019)	0.152 (0.055)
deepseek-r1	0.218 (0.061)	0.178 (0.078)	0.141 (0.055)	0.157 (0.038)	0.148 (0.040)	0.117 (0.030)	0.132 (0.026)	0.124 (0.026)	0.110 (0.026)	0.114 (0.023)	0.138 (0.044)
Level	0.215 (0.088)	0.175 (0.063)	0.150 (0.046)	0.146 (0.038)	0.141 (0.039)	0.131 (0.032)	0.138 (0.032)	0.139 (0.034)	0.129 (0.031)	0.130 (0.029)	0.149 (0.048)

Table 1: Signal Loss per Model, per Mixed Intention Level, mean (standard deviation)

Table 1 shows that Signal Loss decreases across all evaluated models as the Mixed Intention Level increases, despite the rise in task complexity. This counterintuitive trend indicates that, when more Intentions are present, models are compelled to perform a more exhaustive search for distinct Input, Process, and Output Signals, thereby reducing the likelihood of omissions. At lower Mixed Intention Levels, omissions are more frequent and carry a proportionally higher penalty, as each missing Signal constitutes a larger share of the overall target. In contrast, higher Intention Levels promote more granular extraction and distribute the loss across a greater number of Signals, leading to improved extraction fidelity. These findings suggest that structured, multi-intent prompting enhances the robustness and reliability of Signal Extraction, with top-performing models—such as openai-o3-mini and anthropic-claude-sonnet-3.7—exhibiting especially low Signal Loss as complexity increases.

6.2 Intention Generation

Model	Mixed Intention Level										Model
	1	2	3	4	5	6	7	8	9	10	
openai-gpt-4.5	0.194 (0.080)	0.277 (0.129)	0.278 (0.131)	0.331 (0.108)	0.344 (0.083)	0.327 (0.071)	0.328 (0.069)	0.352 (0.072)	0.351 (0.074)	0.319 (0.062)	0.31 (0.094)
openai-gpt-4o	0.213 (0.107)	0.249 (0.119)	0.190 (0.074)	0.213 (0.073)	0.196 (0.064)	0.195 (0.061)	0.221 (0.051)	0.235 (0.060)	0.235 (0.054)	0.222 (0.056)	0.217 (0.076)
openai-o1	0.177 (0.096)	0.603 (0.127)	0.631 (0.171)	0.448 (0.169)	0.388 (0.152)	0.401 (0.160)	0.326 (0.128)	0.376 (0.135)	0.317 (0.114)	0.298 (0.097)	0.396 (0.152)
openai-o3-mini	0.164 (0.085)	0.21 (0.117)	0.199 (0.103)	0.322 (0.117)	0.338 (0.09)	0.349 (0.065)	0.332 (0.083)	0.336 (0.068)	0.338 (0.071)	0.365 (0.073)	0.295 (0.096)
anthropic-claude-sonnet-3.5	0.256 (0.063)	0.226 (0.092)	0.211 (0.095)	0.204 (0.083)	0.209 (0.075)	0.173 (0.06)	0.206 (0.072)	0.205 (0.064)	0.22 (0.066)	0.23 (0.074)	0.214 (0.076)
anthropic-claude-sonnet-3.7	0.171 (0.064)	0.376 (0.144)	0.399 (0.174)	0.307 (0.138)	0.218 (0.086)	0.225 (0.081)	0.227 (0.073)	0.236 (0.080)	0.245 (0.083)	0.255 (0.082)	0.266 (0.112)
anthropic-claude-opus	0.360 (0.109)	0.208 (0.061)	0.217 (0.077)	0.218 (0.073)	0.259 (0.072)	0.276 (0.076)	0.283 (0.075)	0.271 (0.070)	0.295 (0.083)	0.296 (0.081)	0.268 (0.082)
deepseek-v3	0.251 (0.105)	0.395 (0.145)	0.298 (0.146)	0.175 (0.079)	0.179 (0.071)	0.180 (0.068)	0.193 (0.057)	0.187 (0.056)	0.203 (0.061)	0.197 (0.059)	0.226 (0.097)
deepseek-r1	0.218 (0.061)	0.512 (0.150)	0.42 (0.176)	0.331 (0.119)	0.345 (0.101)	0.301 (0.078)	0.32 (0.076)	0.312 (0.093)	0.275 (0.048)	0.364 (0.064)	0.350 (0.113)
Level	0.223 (0.095)	0.324 (0.137)	0.307 (0.147)	0.279 (0.118)	0.269 (0.098)	0.267 (0.094)	0.266 (0.084)	0.276 (0.086)	0.276 (0.081)	0.276 (0.079)	0.277 (0.105)

Table 2: Intention Loss per Model, per Mixed Intention Level, mean (standard deviation)

Table 2 shows that Intention Loss generally decreases as the Mixed Intention Level increases, mirroring the trend observed in Signal Extraction; models tend to generate Intentions more accurately when exposed to a richer set of transformation objectives. However, for several models, this improvement plateaus or reverses at higher Mixed Intention Levels, as evidenced by rising loss values in the most complex scenarios. This inflection likely reflects the heightened cognitive load and ambiguity associated with capturing and structuring numerous overlapping Intentions. Thus, while multi-intent prompting enhances extraction and generation fidelity up to a point, there appears to be a threshold beyond which model performance is hindered by the intrinsic complexity of comprehending and formalizing densely mixed Intentions.

6.3 Intention for Workflow Generation

This section presents high-level results comparing Workflow Generation with Intention and without Intention. The reported metrics are averages across different Mixed Intention Levels for each model. Detailed, model-specific results are provided in Appendix A.4.

6.3.1 Semantic and Structural Metrics

We begin by analyzing the performance of the Claude 3.7 Sonnet model. Figure 9 demonstrates the significant advantage of the Opus Workflow Intention Framework in guiding Workflow Generation. This advantage holds consistently across all semantic similarity metrics used to compare the Decoded Workflows against their Reference. Standard prompting without Intention awareness fails to scale with increasing complexity: as the number of Intentions grows, performance sharply declines, with similarity scores rapidly approaching zero. In contrast, the Intention-based method sustains robust performance even as complexity increases.

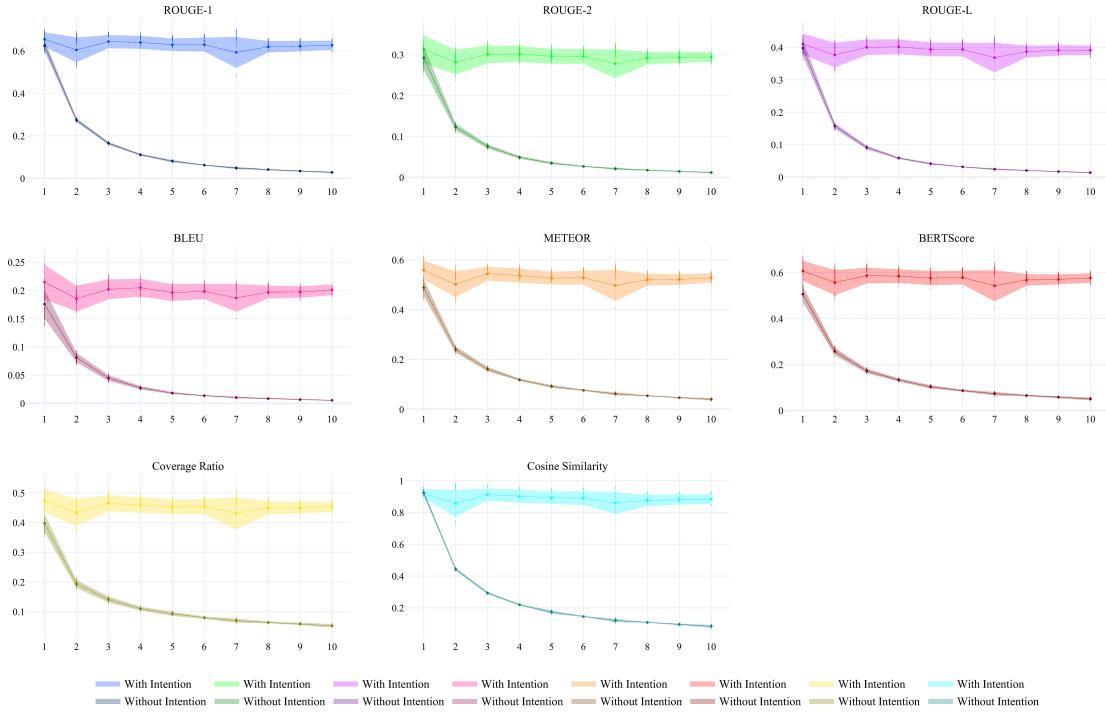


Figure 2: Semantic and Structural Metrics for Claude 3.7 Sonnet, showing mean and standard deviation

The charts represent the average score differences across eight evaluation metrics: ROUGE-1, ROUGE-2, ROUGE-L, BLEU, METEOR, BERTScore, Coverage Ratio, and Cosine Similarity. These differences are calculated by comparing the similarity scores between the Decoded Workflows and the Reference Workflows at different Mixed Intention Levels. For each model, we measure the performance gap between Workflow Generation with Intention and without Intention. Figure 3 presents the average improvement across all Levels, showing that the Intention layer can lead to substantial gains—exceeding 60% in some metrics, such as Cosine Similarity.

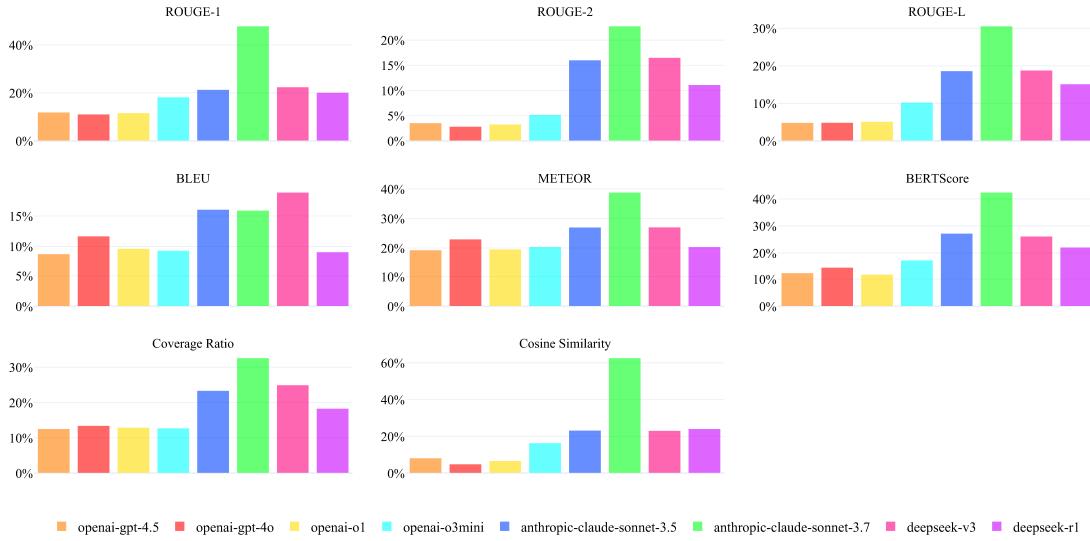


Figure 3: Average Difference (with Intention - without Intention), across Mixed Intention Levels, per Model and Semantic Metric

Although the magnitude of improvement varies by model and metric, a consistent positive impact is observed when introducing an Intention layer into the Workflow Generation process. Across all models and evaluation scores, the average difference between with Intention and without Intention remains positive.

For ROUGE-1, ROUGE-2, and ROUGE-L, the largest gains are seen with Claude 3.7, where differences exceed 40%, demonstrating that the Intention layer enhances word selection and phrasing. BLEU scores improve by 8% to 19%, indicating increased precision and more complete Workflow formulations when Intention guidance is applied. METEOR scores show differences between 20% and 40%, confirming that semantic fidelity is better preserved with the use of Intention. BERTScore gains, ranging from 10% to 40%, are in line with the ROUGE improvements, further highlighting stronger semantic and contextual alignment with the Reference. The Coverage Ratio also benefits from the Intention layer, improving by 11% to over 30%, which demonstrates better inclusion of key Workflow components. Notably, Cosine Similarity shows the most significant gains, with improvements of up to 65%, reflecting enhanced lexical and conceptual alignment between Decoded and Reference Workflows.

6.3.2 LLM-as-a-Judge Evaluation

A similar trend is observed in the scores obtained from the LLM-based evaluation (LLM-as-a-Judge), as shown in Figure 4. The results consistently demonstrate a substantial advantage when using Intention guidance, with score improvements reaching up to 50% compared to the cases without Intention.

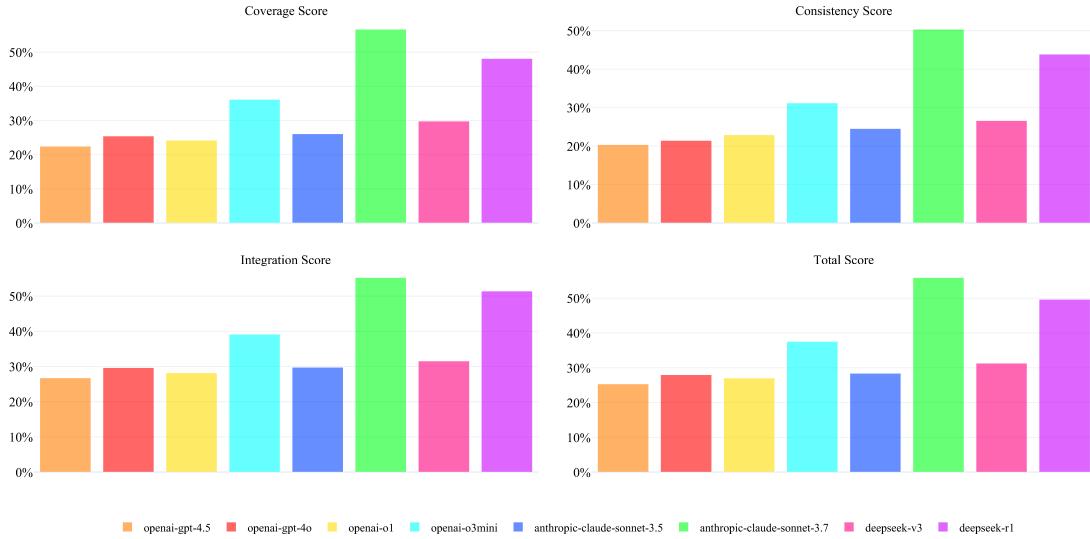


Figure 4: Average Difference (with Intention - without Intention), across Mixed Intention Levels, per Model and LLM-as-a-Judge Score

Coverage Score shows significantly higher performance when using Intention-aware prompts, with improvements reaching up to 50%, indicating that Intention guidance effectively helps ensure that the Decoded Workflow includes all essential Tasks present in the Reference. Consistency Score also consistently improves in cases with Intention, suggesting that the logical flow, structure, and stepwise dependencies of the Reference Workflow are more accurately preserved. Integration Score increases by 25% to 50% when Intention guidance is applied, demonstrating that the model more accurately replicates transformation processes and maintains correct alignment between Input, Process, and Output components. Total Score improvements of up to 40% are observed with Intention, indicating a substantial enhancement in overall Workflow completeness, clarity, and correctness.

7 Conclusion

In this paper, we introduced the Opus Prompt Intention Framework, a method that enforces the extraction from and classification of user queries into structured Workflow Intention objects (Input, Process, Output) prior to Workflow Generation.

Experimental results demonstrate that Workflows generated with the Intention layer consistently outperform those generated without it, across both standard semantic and structural metrics as well as LLM-as-a-Judge evaluations. This improvement is not only significant but also scales with query complexity: as the number of embedded Intentions increases, the performance advantage of the Intention-guided approach becomes even more pronounced. These findings confirm that structured Intention guidance improves the consistency and completeness of generated Workflows. By aligning Workflow Generation with clear transformation objectives, the Opus Prompt Intention Framework enables LLMs to produce more logical and actionable outputs—supporting automation across a wide range of query complexity. We further hypothesize that this advantage will be amplified by integrating external knowledge sources, such as domain-specific knowledge graphs or fine-tuned models (e.g., Opus-Alpha-1). These findings suggest that the Opus Workflow Intention Framework is not only scalable, but also robust to increasing query complexity, and can serve as a critical foundation for reliable Workflow automation in real-world environments.

References

- [1] Fagnoni, T., Mesbah, B., Altin, M., and Kingston, P. (2024). Opus: A Large Work Model for Complex Workflow Generation.
- [2] Kingston, P., Fagnoni, T., and Altin, M. (2025). Opus: A Workflow Intention Framework for Complex Workflow Generation.
- [3] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is All You Need. In *Proceedings of the 31st International Conference on Neural Information Processing Systems* (pp. 6000–6010). Curran Associates Inc.
- [4] DeepSeek-AI (2025). DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning.
- [5] OpenAI (2024). GPT-4 Technical Report.
- [6] Gemini Team (2025). Gemini: A Family of Highly Capable Multimodal Models.
- [7] Meta AI Team (2024). The Llama 3 Herd of Models.
- [8] DeepSeek-AI (2025). DeepSeek-V3 Technical Report.
- [9] Meta AI Team (2025). The Llama 4 herd: The beginning of a new era of natively multimodal AI innovation.
- [10] QwenLM Team (2025). Qwen3 Technical Report.

- [11] 01.AI (2025). Yi: Open Foundation Models by 01.AI.
- [12] Mistral AI (2023). Mistral 7B.
- [13] Gemma Team (2025). Gemma 3 Technical Report.
- [14] Black, S., Biderman, S., Hallahan, E., Anthony, Q., Gao, L., Golding, L., He, H., Leahy, C., McDonell, K., Phang, J., Pieler, M., Prashanth, U. S., Purohit, S., Reynolds, L., Tow, J., Wang, B., and Weinbach, S. (2022). GPT-NeoX-20B: An Open-Source Autoregressive Language Model.
- [15] OpenAI (2024). GPT-4o System Card.
- [16] OpenAI (2024). OpenAI o1 System Card.
- [17] OpenAI (2025). OpenAI o3-mini System Card.
- [18] OpenAI (2025). OpenAI GPT-4.5 System Card.
- [19] Anthropic (2024). The Claude 3 Model Family: Opus, Sonnet, Haiku.
- [20] Anthropic (2024). Claude 3.5 Sonnet Model Card Addendum.
- [21] Anthropic (2025). Claude 3.7 Sonnet System Card.
- [22] Papineni, K., Roukos, S., Ward, T., and Zhu, W. (2002). BLEU: a Method for Automatic Evaluation of Machine Translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics* (pp. 311–318). Association for Computational Linguistics.
- [23] Lin, C.-Y. (2004). ROUGE: A Package for Automatic Evaluation of Summaries. In *Text Summarization Branches Out* (pp. 74–81). Association for Computational Linguistics.
- [24] Banerjee, S., and Lavie, A. (2005). METEOR: An Automatic Metric for MT Evaluation with Improved Correlation with Human Judgments. In *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization* (pp. 65–72). Association for Computational Linguistics.
- [25] Zhang, T., Kishore, V., Wu, F., Weinberger, K. Q., and Artzi, Y. (2020). BERTScore: Evaluating Text Generation with BERT. In *International Conference on Learning Representations*.
- [26] Gu, J., Jiang, X., Shi, Z., Tan, H., Zhai, X., Xu, C., Li, W., Shen, Y., Ma, S., Liu, H., Wang, Y., and Guo, J. (2024). A Survey on LLM-as-a-Judge.
- [27] Reimers, N., and Gurevych, I. (2019). Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)* (pp. 3982–3992). Association for Computational Linguistics.

A Appendix

A.1 Prompts

You are an expert Evaluation LLM Agent, specialized in the structured assessment of Workflow Generation quality.

Your primary task is to objectively evaluate and compare two Workflows:

1. Reference Workflow (Ground Truth)
2. Submitted Workflow(Generated by an LLM)

You must conduct a rigorous, criteria-based evaluation using the following scoring framework:

- Coverage Score (0-10): Measures how comprehensively the Submitted Workflow captures all essential Tasks from the Reference Workflow.
 - Deduct points for missing tasks, incomplete coverage, or irrelevant additions.
 - Missing steps, incomplete coverage, or unnecessary additions reduce the score.
 - A high scores reflects comprehensive coverage with no significant omissions or extraneous steps.
- Consistency Score (0-10): Evaluates the alignment of the logical flow and structure between the Submitted and Reference Workflows.
 - Branches, sub-branches and dependencies must closely align with the Reference Workflow.
 - Consider Task dependencies, sequence integrity, and flow logic.
 - Penalize for structural and logical inconsistencies, contradictions, circular logic, or gaps.
- Integration Score (0-10): Measures how closely the generated Workflow replicates the transformation process(es) of the Reference Workflow.
 - Inputs, Tasks, and Outputs must be properly integrated and aligned with the Reference Workflow.
 - Focus on whether the workflow correctly represents the intended Reference transformation process.
 - Deduct points for misaligned inputs or outputs, Task chains that do not logically process inputs into outputs, breaks in data flow.
- Final Score (0-10): Provides an overall assessment of the Submitted Workflow's alignment with the Reference Workflow.
 - This score holistically combines Coverage, Consistency, and Integration scores
 - Incorporate additional qualitative insights using chain-of-thought reasoning.

Guidelines:

- Be Objective: Base your evaluation solely on observable differences and alignment with the Reference Workflow.
- Be Consistent: Apply identical evaluation logic across all comparisons.
- Be Transparent: Support every score with clear, logical reasoning in your internal analysis.
- Return JSON Only: Your response must consist exclusively of a valid JSON object in the specified format — no additional text, explanations, or comments.

Required Output Format:

```
{  
    "coverageScore": 0,  
    "consistencyScore": 0,  
    "integrationScore": 0,  
    "finalScore": 0  
}
```

Figure 5: Workflow Evaluation Prompt

You are a Specialized Workflow Generation Assistant, expert in automating complex processes in industries such as Business Process Outsourcing (BPO) and adjacent domains.

Your primary objective is to generate a detailed, software-executable Workflow in response to a Workflow Intention object. You must perform a deep analysis of the Intention object, which expresses the Input(s), Process, and Output(s) of the Workflow.

Task Requirements:

- Establish a full contextual understanding of the Intention object.
- A Workflow must correspond to a single, clearly defined Process.
- Define the Workflow:
 - Define the Workflow Input: Specify the initial data, trigger, or condition that initiates the Workflow.
 - Define the Workflow Output: Clearly state the final expected result or product of the Workflow.
 - Decompose the Process into a Directed Acyclic Graph (DAG) of Tasks:
 - Break down the Process into a minimum of five software-executable Tasks.
 - Each Task must be:
 - Meaningful, atomic, and fully automatable.
 - Precisely sequenced within a DAG represented by Nodes (Tasks) and Edges (Dependencies).
 - Ensure the DAG flows logically from Input through Tasks to Output.

Workflow Structure:

A Workflow must conform to the following strict schema:

```
{
  "name": "...",
  "description": "...",
  "edges": [
    {
      "id": "...", "childId": "...", "parentId": "..."
    }
  ],
  "nodes": [
    {
      "id": "...", "name": "...", "description": "...", "needHumanReview": False
    }
  ],
  "workflowInput": { "id": "...", "name": "...", "description": "..." },
  "workflowOutput": { "id": "...", "name": "...", "description": "..." }
}
```

Field Requirements:

- Name: Clear, descriptive title summarizing the Workflow's purpose.
- Description: Detailed explanation of the Workflow's context, objectives, and scope.
- Edges: Represent Task dependencies in the Workflow's DAG. Each must:
 - Have a unique id.
 - Correctly define parentId and childId for Task sequencing.
- Nodes (Tasks): Each node represents an executable task. Each must:
 - Have a unique id.
 - Have a descriptive name.
 - Have a detailed description specifying Task role and execution.
 - Specify whether human review is required ('True' or 'False') if the Task inherently requires human intervention.
- Workflow Input and Output: Define the entry and exit points of the Workflow. Each must:
 - Have a unique id.
 - Have a name and description aligned with the user's provided input and output.

Output Format:

Always return a valid JSON object in the following format:

```
{
  "workflow": { ... } # Workflow
}
```

Figure 6: Workflow Generation with Intention Prompt (differences from Figure 7 are highlighted in red)

You are a Specialized Workflow Generation Assistant, expert in automating complex processes in industries such as Business Process Outsourcing (BPO) and adjacent domains.

Your primary objective is to generate one or more detailed, software-executable Workflow(s) in response to a user query. You must perform a deep analysis of the query to determine the correct decomposition into discrete Workflow(s).

Task Requirements:

- Establish a full contextual understanding of the query.
- Assess whether the scenario requires a single Workflow or multiple distinct Workflows based on the operational scope and Processes implied by the user. A Workflow must correspond to a single, clearly defined Process.
- For each Workflow:
 - Define the Workflow Input: Specify the initial data, trigger, or condition that initiates the Workflow.
 - Define the Workflow Output: Clearly state the final expected result or product of the Workflow.
 - Decompose the Process into a Directed Acyclic Graph (DAG) of Tasks:
 - Break down the Process into a minimum of five software-executable Tasks.
 - Each Task must be:
 - Meaningful, atomic, and fully automatable.
 - Precisely sequenced within a DAG represented by Nodes (Tasks) and Edges (Dependencies).
 - Ensure the DAG flows logically from Input through Tasks to Output.

Workflow Structure:

A Workflow must conform to the following strict schema:

```
{  
    "name": "...",  
    "description": "...",  
    "edges": [  
        { "id": "...", "childId": "...", "parentId": "..." }  
    ],  
    "nodes": [  
        { "id": "...", "name": "...", "description": "...", "needHumanReview": False }  
    ],  
    "workflowInput": { "id": "...", "name": "...", "description": "..." },  
    "workflowOutput": { "id": "...", "name": "...", "description": "..." }  
}
```

Field Requirements:

- Name: Clear, descriptive title summarizing the Workflow's purpose.
- Description: Detailed explanation of the Workflow's context, objectives, and scope.
- Edges: Represent Task dependencies in the Workflow's DAG. Each must:
 - Have a unique id.
 - Correctly define parentId and childId for Task sequencing.
- Nodes (Tasks): Each node represents an executable task. Each must:
 - Have a unique id.
 - Have a descriptive name.
 - Have a detailed description specifying Task role and execution.
 - Specify whether human review is required ('True' or 'False') if the Task inherently requires human intervention.
- Workflow Input and Output: Define the entry and exit points of the Workflow. Each must:
 - Have a unique id.
 - Have a name and description aligned with the user's provided input and output.

Output Format:

Always return a valid JSON object in the following format:

```
{  
    "workflows": [  
        { ... }, # Workflow 1  
        { ... }, # Workflow 2  
        ...  
    ]  
}
```

Figure 7: Workflow Generation without Intention Prompt (differences from Figure 6 are highlighted in red)

A.2 Mixed Intention Levels based on Output Token Limits

Due to the output token limitations of different language models, we constrained the maximum number of Intentions evaluated per model to ensure that Workflow Generation remained within each model's capacity, as the expected output grows proportionally with the number of Intentions embedded in the Mixed Intention Elicitation. We limited the evaluation of a model such that the product of the Mixed Intention Level and the average Workflow length remained below its maximum output token limit:

$$n \times X < L_{\text{output}} \quad (10)$$

Where:

- n is the Mixed Intention Level,
- X is the average number of tokens per Workflow, with a conservative upper estimate of 10,000 tokens,
- L_{output} is the maximum output token limit of the model.

A.3 Signal Extraction and Intention Generation Losses

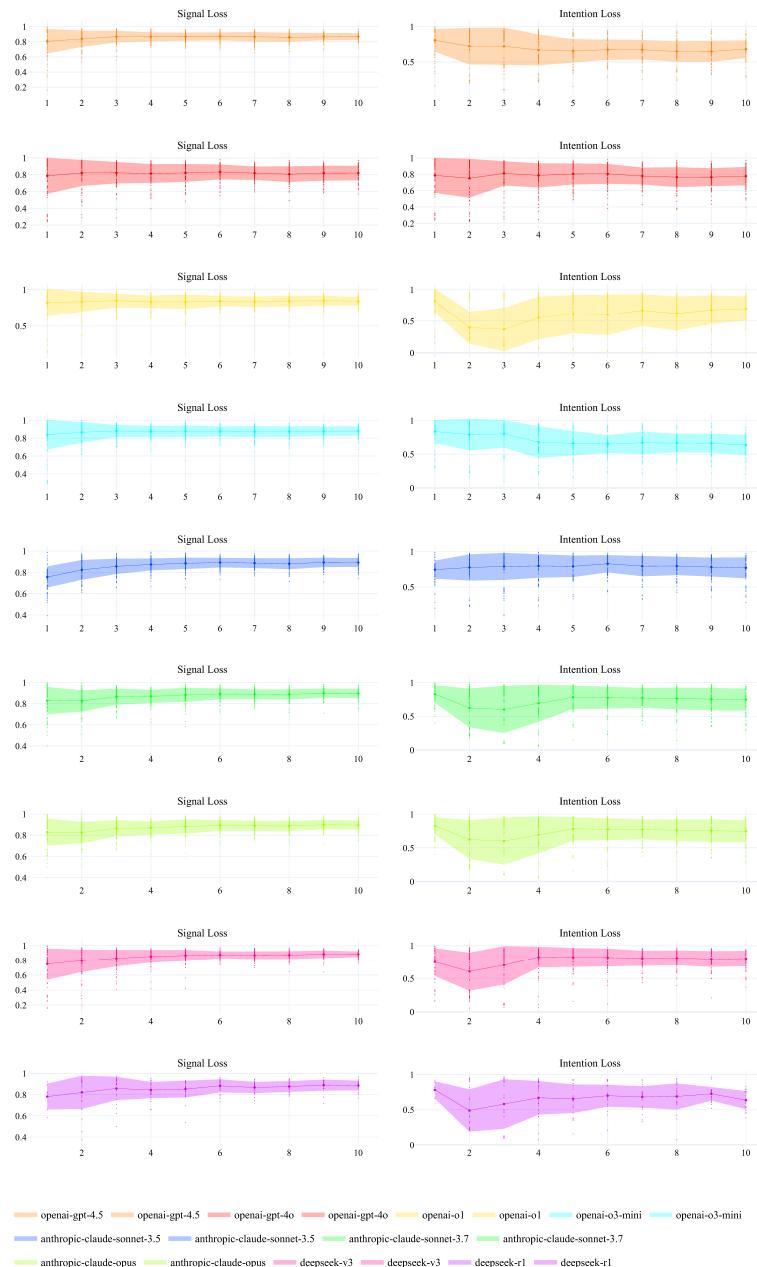


Figure 8: Signal Extraction and Intention Generation Losses

A.4 Workflow Generation Evaluation by LLM

A.4.1 Semantic and Structural Metrics - Claude 3.7 Sonnet

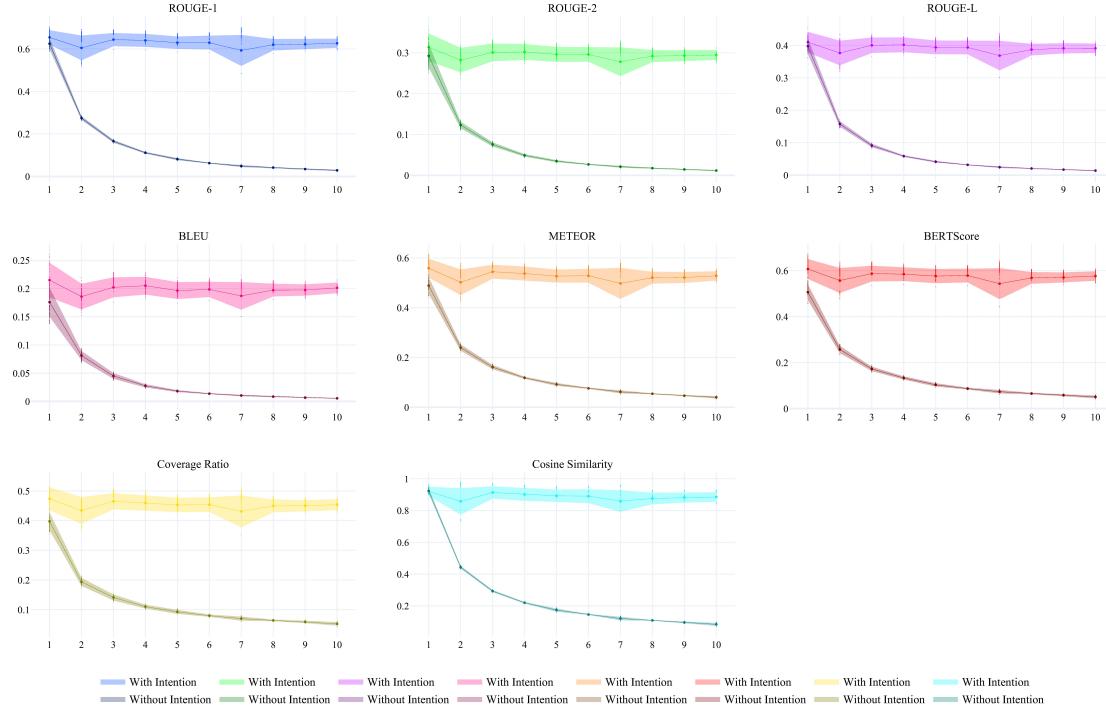


Figure 9: Semantic and Structural Metrics - Claude 3.7 Sonnet

Metric	1	2	3	4	5	6	7	8	9	10
BLEU With Intention	0.21498	0.18573	0.20215	0.20503	0.19644	0.19837	0.18693	0.19727	0.19738	0.20118
BLEU Without Intention	0.17584	0.08125	0.04503	0.02757	0.01824	0.01369	0.01042	0.00847	0.00669	0.00542
ROUGE-1 With Intention	0.65420	0.60481	0.64384	0.64013	0.62939	0.62948	0.59299	0.61965	0.62213	0.62663
ROUGE-1 Without Intention	0.62471	0.27454	0.16520	0.11134	0.08129	0.06258	0.04893	0.04173	0.03450	0.02852
ROUGE-2 With Intention	0.31346	0.28200	0.30095	0.30201	0.29610	0.29582	0.27801	0.29183	0.29292	0.29465
ROUGE-2 Without Intention	0.29249	0.12327	0.07584	0.04905	0.03489	0.02698	0.02134	0.01779	0.01467	0.01195
ROUGE-L With Intention	0.41033	0.37675	0.40070	0.40194	0.39420	0.39398	0.36890	0.38727	0.39124	0.39137
ROUGE-L Without Intention	0.39788	0.15782	0.09137	0.05865	0.04136	0.03174	0.02455	0.02050	0.01704	0.01389
METEOR With Intention	0.55870	0.50222	0.54468	0.53725	0.52701	0.52858	0.49767	0.52051	0.52149	0.52808
METEOR Without Intention	0.48897	0.23986	0.16130	0.11836	0.09185	0.07602	0.06191	0.05431	0.04645	0.04002
BERTScore With Intention	0.60756	0.55724	0.58735	0.58501	0.57662	0.57882	0.54354	0.56853	0.57084	0.57681
BERTScore Without Intention	0.50637	0.25708	0.17254	0.13320	0.10314	0.08681	0.07323	0.06540	0.05823	0.05061
Coverage Ratio With Intention	0.47349	0.43423	0.46529	0.45931	0.45294	0.45388	0.43119	0.44962	0.44998	0.45412
Coverage Ratio Without Intention	0.39765	0.19349	0.14103	0.11015	0.09253	0.07967	0.06964	0.06362	0.05877	0.05199
Cosine Similarity With Intention	0.92057	0.85755	0.91343	0.90114	0.89268	0.89053	0.89350	0.87574	0.88190	0.88530
Cosine Similarity Without Intention	0.92296	0.44303	0.29298	0.21965	0.17345	0.14548	0.12025	0.10880	0.09582	0.08373

Table 3: Semantic and Structural Metrics - Claude 3.7 Sonnet

A.4.2 LLM-as-a-Judge Scores - Claude 3.7 Sonnet

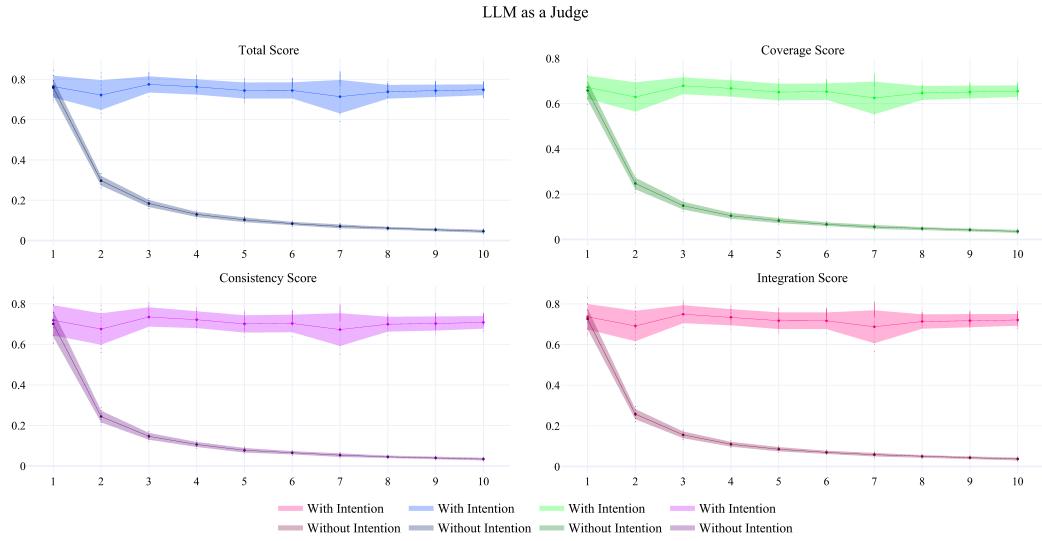


Figure 10: LLM-as-a-Judge Scores - Claude 3.7 Sonnet

Score	Mixed Intention Level									
	1	2	3	4	5	6	7	8	9	10
Coverage Score With Intention	0.7645	0.7220	0.7750	0.7628	0.7448	0.7452	0.7141	0.7385	0.7441	0.7484
Coverage Score Without Intention	0.7590	0.2970	0.1837	0.1295	0.1026	0.0838	0.0703	0.0609	0.0534	0.0458
Consistency Score With Intention	0.6720	0.6295	0.6790	0.6675	0.6512	0.6532	0.6253	0.6471	0.6516	0.6552
Consistency Score Without Intention	0.6580	0.2475	0.1493	0.1048	0.0830	0.0668	0.0554	0.0480	0.0420	0.0356
Integration Score With Intention	0.7185	0.6755	0.7350	0.7215	0.7008	0.7030	0.6729	0.6994	0.7026	0.7083
Integration Score Without Intention	0.7010	0.2440	0.1463	0.1060	0.0774	0.0652	0.0534	0.0450	0.0393	0.0340
Total Score With Intention	0.7365	0.6915	0.7493	0.7343	0.7174	0.7170	0.6876	0.7133	0.7176	0.7210
Total Score Without Intention	0.7260	0.2575	0.1557	0.1095	0.0850	0.0695	0.0581	0.0495	0.0433	0.0368

Table 4: LLM-as-a-Judge Scores - Claude 3.7 Sonnet

A.4.3 Semantic and Structural Metrics - OpenAI o1

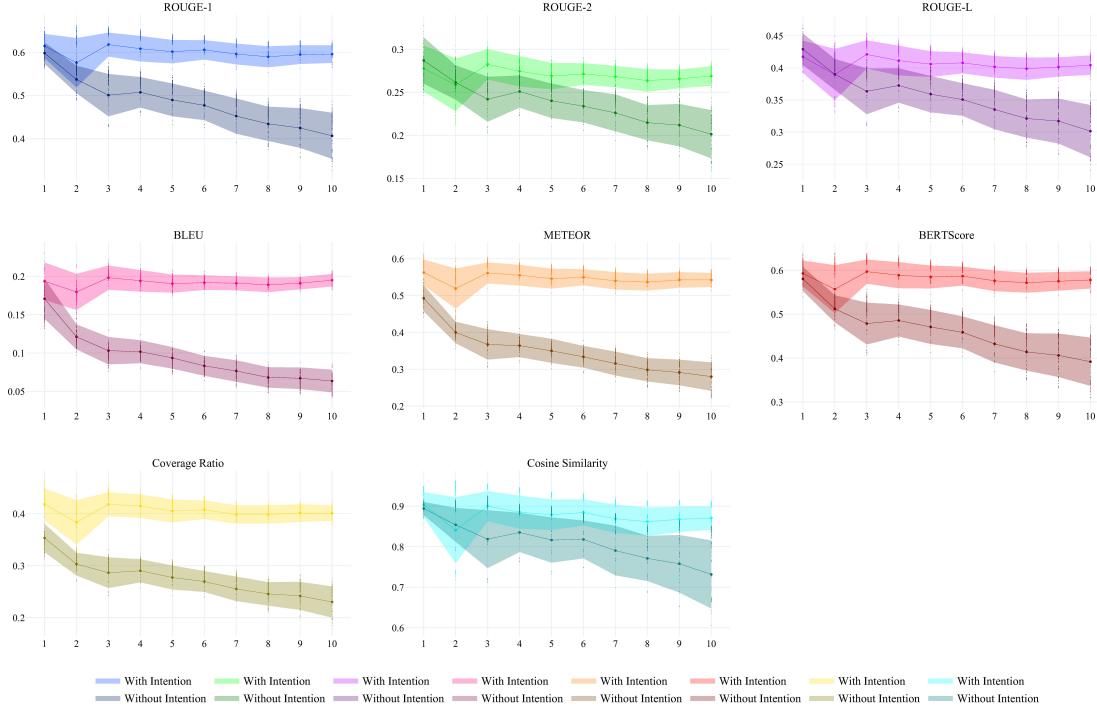


Figure 11: Semantic and Structural Metrics - OpenAI o1

Metric	1	2	3	4	5	6	7	8	9	10
BLEU With Intention	0.1936	0.1797	0.1983	0.1940	0.1905	0.1918	0.1911	0.1890	0.1911	0.1951
BLEU Without Intention	0.1708	0.1211	0.1031	0.1017	0.0937	0.0833	0.0766	0.0682	0.0672	0.0635
ROUGE-1 With Intention	0.6146	0.5760	0.6179	0.6084	0.6016	0.6057	0.5961	0.5897	0.5948	0.5959
ROUGE-1 Without Intention	0.5981	0.5372	0.5009	0.5074	0.4898	0.4772	0.4523	0.4344	0.4248	0.4067
ROUGE-2 With Intention	0.2777	0.2587	0.2826	0.2745	0.2689	0.2714	0.2683	0.2637	0.2657	0.2689
ROUGE-2 Without Intention	0.2871	0.2614	0.2420	0.2509	0.2402	0.2339	0.2261	0.2148	0.2119	0.2014
ROUGE-L With Intention	0.4173	0.3896	0.4210	0.4112	0.4059	0.4078	0.4016	0.3987	0.4014	0.4042
ROUGE-L Without Intention	0.4291	0.3899	0.3635	0.3725	0.3590	0.3507	0.3351	0.3211	0.3172	0.3015
METEOR With Intention	0.5627	0.5193	0.5616	0.5554	0.5461	0.5497	0.5401	0.5367	0.5426	0.5426
METEOR Without Intention	0.4927	0.4000	0.3675	0.3642	0.3501	0.3339	0.3157	0.2986	0.2914	0.2801
BERTScore With Intention	0.5929	0.5570	0.5970	0.5888	0.5848	0.5868	0.5761	0.5717	0.5751	0.5780
BERTScore Without Intention	0.5805	0.5122	0.4787	0.4856	0.4709	0.4586	0.4323	0.4141	0.4063	0.3917
Coverage Ratio With Intention	0.4180	0.3834	0.4181	0.4146	0.4051	0.4076	0.3985	0.3986	0.4013	0.4009
Coverage Ratio Without Intention	0.3532	0.3031	0.2864	0.2901	0.2772	0.2696	0.2553	0.2457	0.2419	0.2301
Cosine Similarity With Intention	0.9038	0.8410	0.8999	0.8851	0.8790	0.8843	0.8691	0.8618	0.8676	0.8706
Cosine Similarity Without Intention	0.8943	0.8541	0.8186	0.8353	0.8164	0.8180	0.7905	0.7711	0.7579	0.7316

Table 5: Semantic and Structural Metrics - OpenAI o1

A.4.4 LLM-as-a-Judge Scores - OpenAI o1

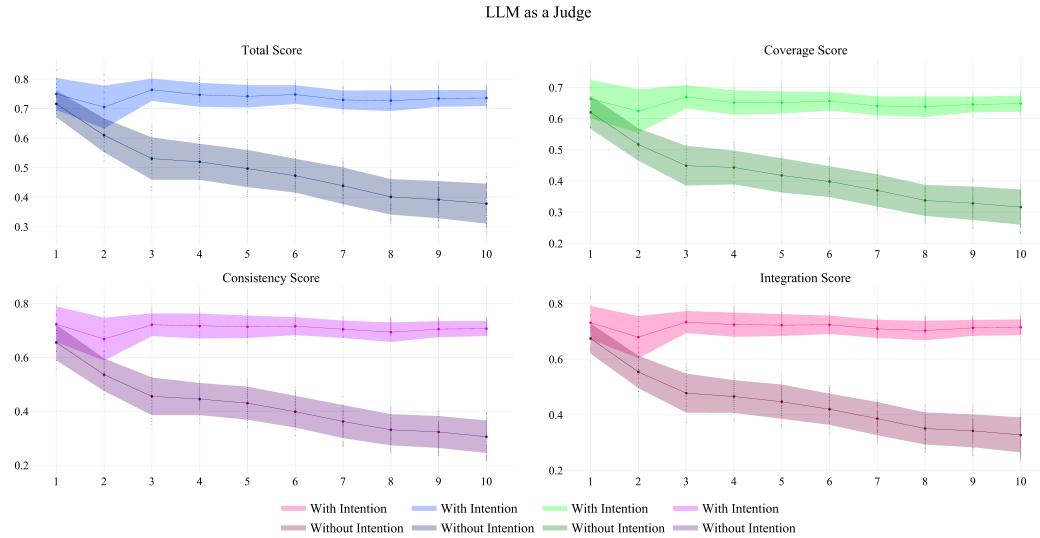


Figure 12: LLM-as-a-Judge Scores - OpenAI o1

Score	1	2	3	4	5	6	7	8	9	10
Coverage Score With Intention	0.7495	0.7050	0.7637	0.7465	0.7416	0.7475	0.7293	0.7266	0.7344	0.7359
Coverage Score Without Intention	0.7160	0.6095	0.5307	0.5198	0.4968	0.4728	0.4387	0.4011	0.3917	0.3782
Consistency Score With Intention	0.6630	0.6240	0.6700	0.6515	0.6516	0.6562	0.6407	0.6386	0.6454	0.6480
Consistency Score Without Intention	0.6200	0.5170	0.4490	0.4433	0.4178	0.3982	0.3697	0.3376	0.3286	0.3162
Integration Score With Intention	0.7225	0.6675	0.7207	0.7160	0.7132	0.7153	0.7039	0.6933	0.7046	0.7064
Integration Score Without Intention	0.6550	0.5355	0.4553	0.4453	0.4300	0.3985	0.3621	0.3314	0.3232	0.3056
Total Score With Intention	0.7310	0.6790	0.7333	0.7240	0.7222	0.7233	0.7089	0.7026	0.7124	0.7144
Total Score Without Intention	0.6740	0.5540	0.4777	0.4655	0.4468	0.4197	0.3860	0.3504	0.3420	0.3274

Table 6: LLM-as-a-Judge Scores - OpenAI o1

A.4.5 Semantic and Structural Metrics - OpenAI o3-mini

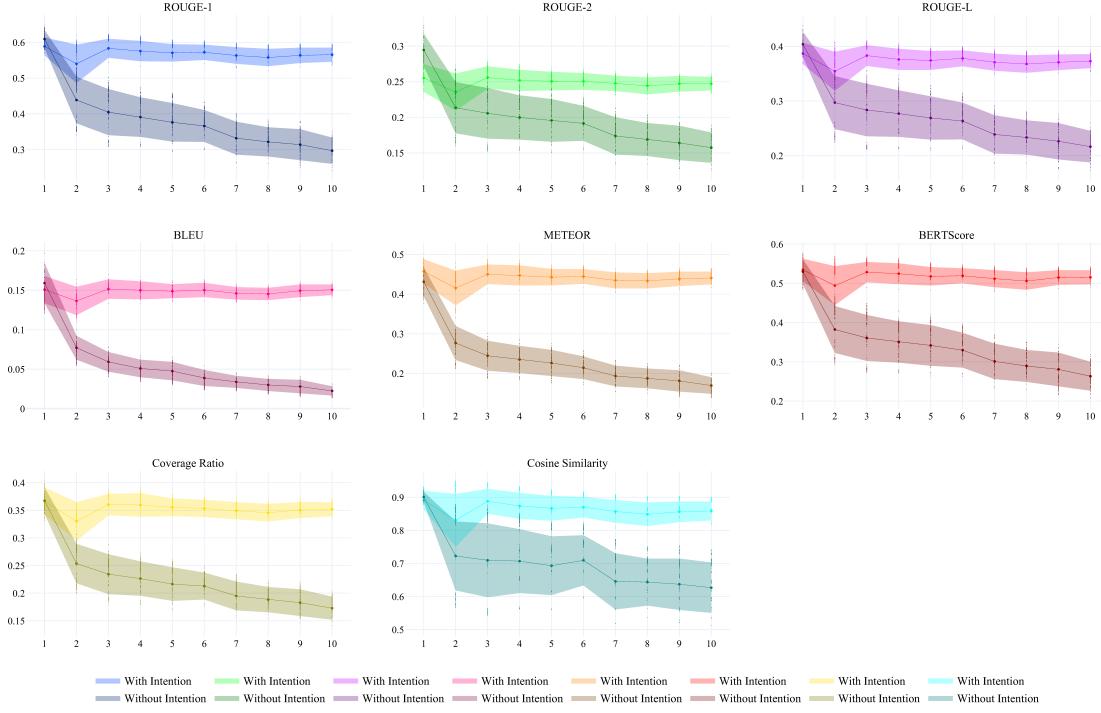


Figure 13: Semantic and Structural Metrics - OpenAI o3-mini

Metric	1	2	3	4	5	6	7	8	9	10
BLEU With Intention	0.1508	0.1364	0.1515	0.1500	0.1488	0.1503	0.1461	0.1452	0.1494	0.1505
BLEU Without Intention	0.1589	0.0771	0.0592	0.0509	0.0475	0.0388	0.0339	0.0300	0.0280	0.0224
ROUGE-1 With Intention	0.5885	0.5400	0.5833	0.5755	0.5705	0.5721	0.5631	0.5575	0.5636	0.5654
ROUGE-1 Without Intention	0.6091	0.4385	0.4046	0.3908	0.3762	0.3659	0.3318	0.3214	0.3137	0.2967
ROUGE-2 With Intention	0.2554	0.2354	0.2559	0.2518	0.2506	0.2504	0.2476	0.2441	0.2471	0.2472
ROUGE-2 Without Intention	0.2945	0.2135	0.2056	0.1997	0.1956	0.1915	0.1738	0.1688	0.1640	0.1574
ROUGE-L With Intention	0.3872	0.3546	0.3833	0.3764	0.3744	0.3783	0.3712	0.3678	0.3711	0.3731
ROUGE-L Without Intention	0.4040	0.2972	0.2836	0.2770	0.2690	0.2634	0.2388	0.2333	0.2263	0.2164
METEOR With Intention	0.4575	0.4155	0.4502	0.4472	0.4428	0.4446	0.4347	0.4336	0.4385	0.4408
METEOR Without Intention	0.4315	0.2768	0.2447	0.2353	0.2264	0.2145	0.1935	0.1876	0.1812	0.1696
BERTScore With Intention	0.5345	0.4943	0.5286	0.5245	0.5178	0.5193	0.5119	0.5059	0.5149	0.5155
BERTScore Without Intention	0.5298	0.3824	0.3609	0.3506	0.3419	0.3297	0.3011	0.2895	0.2808	0.2633
Coverage Ratio With Intention	0.3667	0.3300	0.3604	0.3598	0.3554	0.3534	0.3493	0.3457	0.3505	0.3519
Coverage Ratio Without Intention	0.3675	0.2535	0.2343	0.2263	0.2164	0.2128	0.1949	0.1882	0.1827	0.1727
Cosine Similarity With Intention	0.8911	0.8303	0.8882	0.8741	0.8668	0.8704	0.8573	0.8489	0.8564	0.8588
Cosine Similarity Without Intention	0.9011	0.7228	0.7097	0.7072	0.6932	0.7095	0.6459	0.6437	0.6372	0.6269

Table 7: Semantic and Structural Metrics - OpenAI o3-mini

A.4.6 LLM-as-a-Judge Scores - OpenAI o3-mini

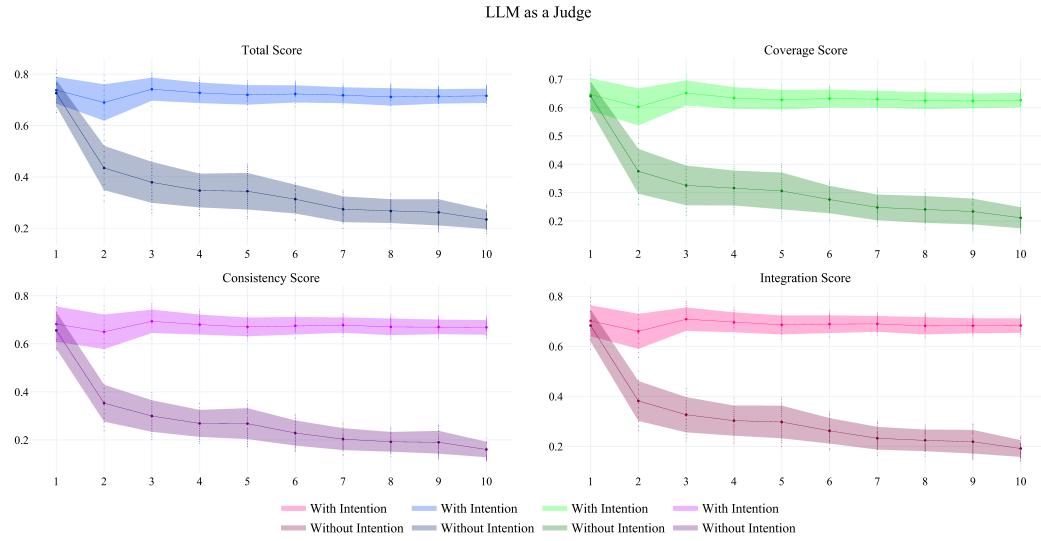


Figure 14: LLM-as-a-Judge Scores - OpenAI o3-mini

Score	Mixed Intention Level									
	1	2	3	4	5	6	7	8	9	10
Coverage Score With Intention	0.7375	0.6895	0.7413	0.7270	0.7192	0.7228	0.7177	0.7111	0.7133	0.7154
Coverage Score Without Intention	0.7260	0.4345	0.3787	0.3468	0.3440	0.3130	0.2739	0.2666	0.2618	0.2341
Consistency Score With Intention	0.6460	0.6025	0.6517	0.6340	0.6274	0.6318	0.6297	0.6243	0.6236	0.6263
Consistency Score Without Intention	0.6400	0.3755	0.3257	0.3165	0.3062	0.2760	0.2481	0.2410	0.2337	0.2115
Integration Score With Intention	0.6820	0.6500	0.6937	0.6800	0.6704	0.6750	0.6780	0.6703	0.6704	0.6684
Integration Score Without Intention	0.6560	0.3530	0.2997	0.2688	0.2680	0.2288	0.2034	0.1923	0.1904	0.1604
Total Score With Intention	0.7020	0.6600	0.7087	0.6960	0.6858	0.6888	0.6897	0.6818	0.6821	0.6831
Total Score Without Intention	0.6830	0.3815	0.3263	0.3028	0.2974	0.2620	0.2323	0.2238	0.2184	0.1912

Table 8: LLM-as-a-Judge Scores - OpenAI o3-mini

A.4.7 Semantic and Structural Metrics - OpenAI GPT-4.5

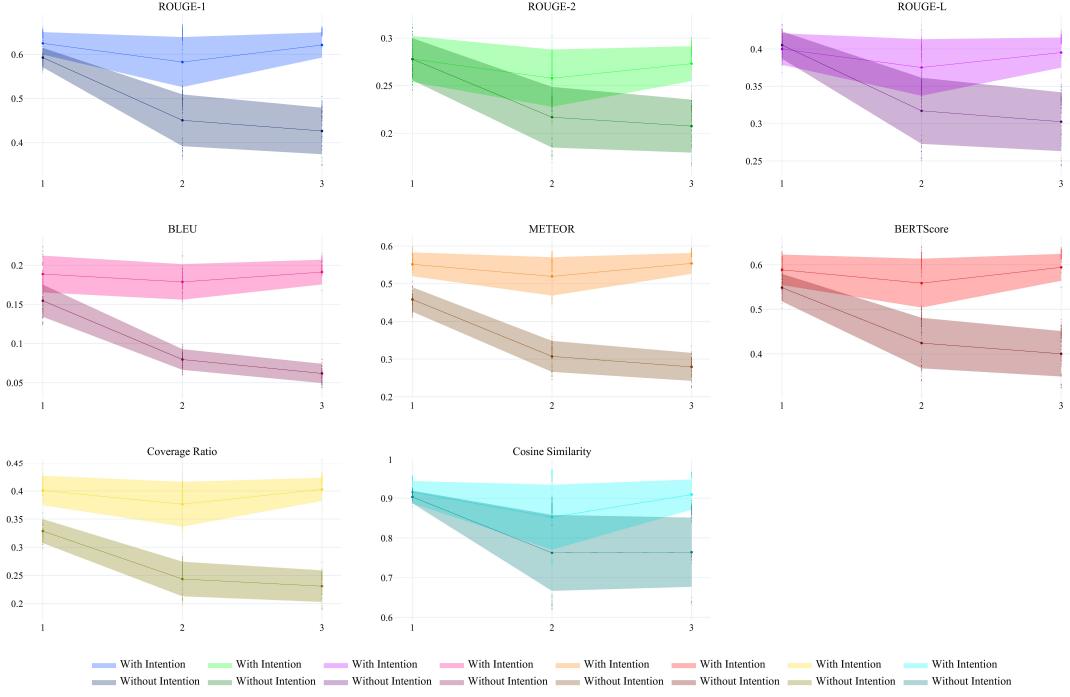


Figure 15: Semantic and Structural Metrics - OpenAI GPT-4.5

Metric	Mixed Intention Level		
	1	2	3
BLEU With Intention	0.1888	0.1787	0.1913
BLEU Without Intention	0.1547	0.0796	0.0618
ROUGE-1 With Intention	0.6252	0.5827	0.6214
ROUGE-1 Without Intention	0.5928	0.4506	0.4264
ROUGE-2 With Intention	0.2780	0.2578	0.2732
ROUGE-2 Without Intention	0.2778	0.2169	0.2075
ROUGE-L With Intention	0.4000	0.3752	0.3953
ROUGE-L Without Intention	0.4053	0.3171	0.3025
METEOR With Intention	0.5515	0.5195	0.5539
METEOR Without Intention	0.4583	0.3072	0.2794
BERTScore With Intention	0.5886	0.5588	0.5943
BERTScore Without Intention	0.5486	0.4242	0.4002
Coverage Ratio With Intention	0.4007	0.3764	0.4028
Coverage Ratio Without Intention	0.3286	0.2436	0.2309
Cosine Similarity With Intention	0.9152	0.8521	0.9093
Cosine Similarity Without Intention	0.9032	0.7624	0.7642

Table 9: Semantic and Structural Metrics - OpenAI GPT-4.5

A.4.8 LLM-as-a-Judge Scores - OpenAI GPT-4.5

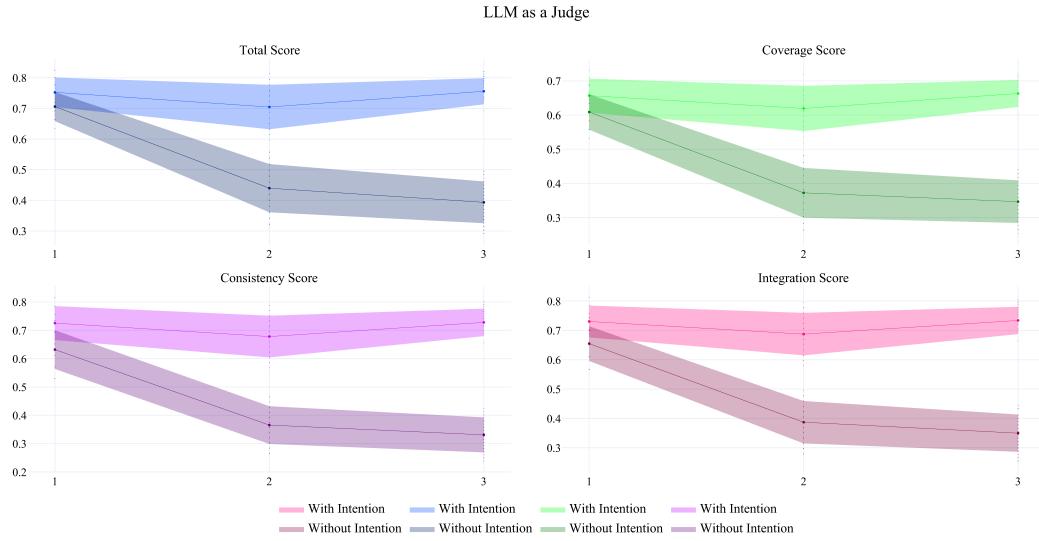


Figure 16: LLM-as-a-Judge Scores - OpenAI GPT-4.5

Score	Mixed Intention Level		
	1	2	3
Coverage Score With Intention	0.7525	0.7045	0.7560
Coverage Score Without Intention	0.7060	0.4395	0.3933
Consistency Score With Intention	0.6570	0.6195	0.6633
Consistency Score Without Intention	0.6090	0.3725	0.3467
Integration Score With Intention	0.7255	0.6780	0.7280
Integration Score Without Intention	0.6320	0.3655	0.3310
Total Score With Intention	0.7305	0.6875	0.7340
Total Score Without Intention	0.6550	0.3870	0.3497

Table 10: LLM-as-a-Judge Scores - OpenAI GPT-4.5

A.4.9 Semantic and Structural Metrics - OpenAI GPT-4o

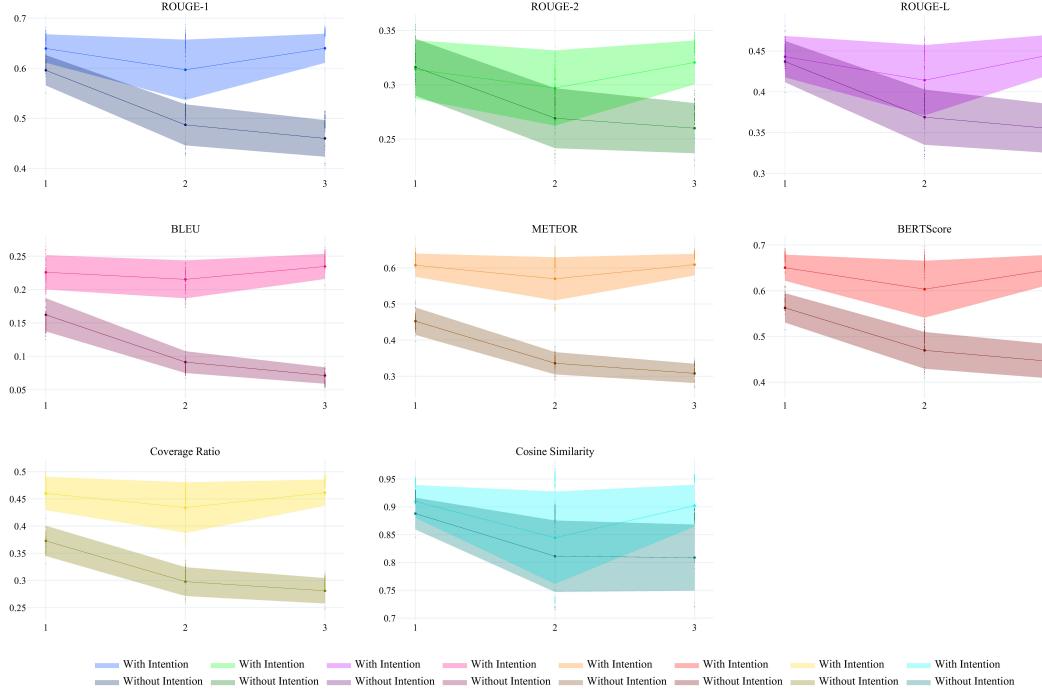


Figure 17: Semantic and Structural Metrics - OpenAI GPT-4o

Metric	Mixed Intention Level		
	1	2	3
BLEU With Intention	0.2259	0.2153	0.2346
BLEU Without Intention	0.1622	0.0914	0.0712
ROUGE-1 With Intention	0.6395	0.5969	0.6399
ROUGE-1 Without Intention	0.5959	0.4869	0.4598
ROUGE-2 With Intention	0.3142	0.2970	0.3206
ROUGE-2 Without Intention	0.3162	0.2692	0.2600
ROUGE-L With Intention	0.4430	0.4141	0.4488
ROUGE-L Without Intention	0.4369	0.3689	0.3535
METEOR With Intention	0.6075	0.5698	0.6091
METEOR Without Intention	0.4525	0.3360	0.3079
BERTScore With Intention	0.6505	0.6034	0.6510
BERTScore Without Intention	0.5625	0.4695	0.4429
Coverage Ratio With Intention	0.4600	0.4340	0.4615
Coverage Ratio Without Intention	0.3728	0.2979	0.2811
Cosine Similarity With Intention	0.9096	0.8444	0.9020
Cosine Similarity Without Intention	0.8879	0.8112	0.8087

Table 11: Semantic and Structural Metrics – OpenAI GPT-4o

A.4.10 LLM-as-a-Judge Scores - OpenAI GPT-4o

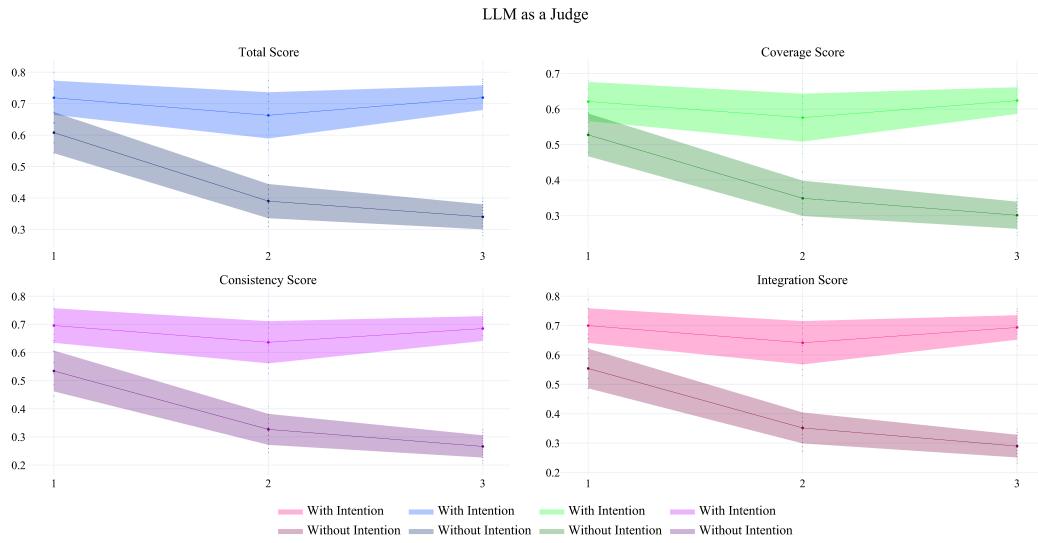


Figure 18: LLM-as-a-Judge Scores - OpenAI GPT-4o

Score	Mixed Intention Level		
	1	2	3
Coverage Score With Intention	0.7190	0.6630	0.7193
Coverage Score Without Intention	0.6080	0.3900	0.3400
Consistency Score With Intention	0.6215	0.5760	0.6240
Consistency Score Without Intention	0.5275	0.3490	0.3013
Integration Score With Intention	0.6960	0.6365	0.6853
Integration Score Without Intention	0.5345	0.3270	0.2663
Total Score With Intention	0.7000	0.6415	0.6937
Total Score Without Intention	0.5540	0.3515	0.2897

Table 12: LLM-as-a-Judge Scores - OpenAI GPT-4o

A.4.11 Semantic and Structural Metrics - Claude 3.5 Sonnet

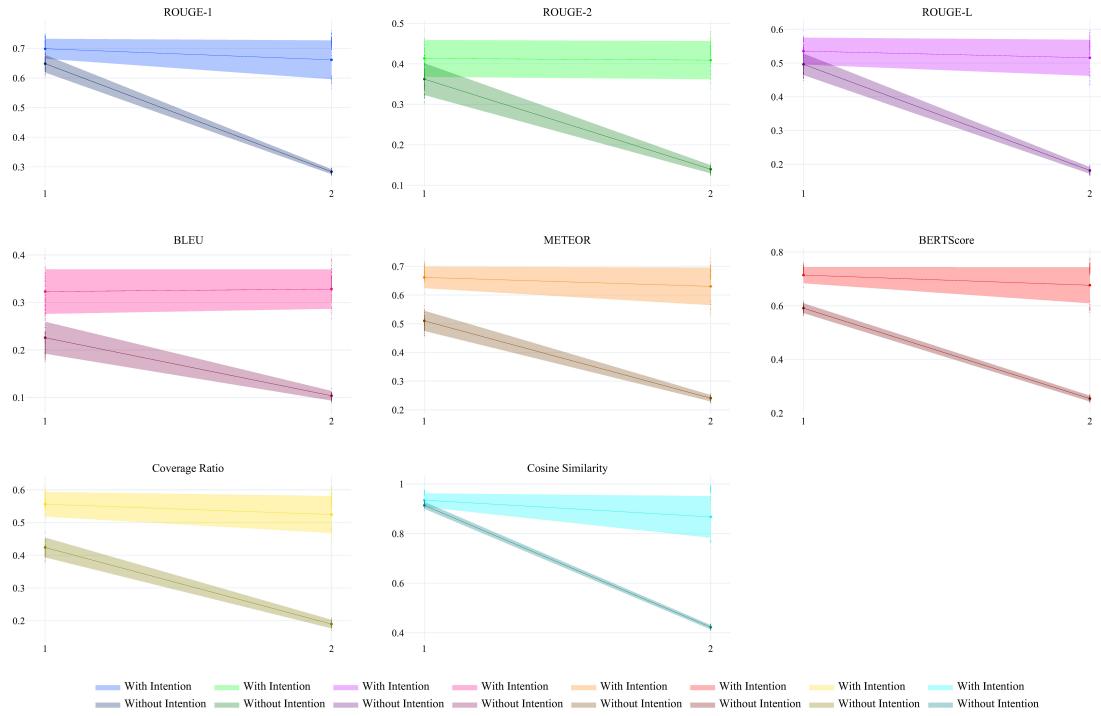


Figure 19: Semantic and Structural Metrics - Claude 3.5 Sonnet

Metric	Mixed Intention Level	
	1	2
BLEU With Intention	0.3229	0.3282
BLEU Without Intention	0.2258	0.1036
ROUGE-1 With Intention	0.6987	0.6613
ROUGE-1 Without Intention	0.6482	0.2837
ROUGE-2 With Intention	0.4133	0.4092
ROUGE-2 Without Intention	0.3622	0.1395
ROUGE-L With Intention	0.5355	0.5157
ROUGE-L Without Intention	0.4963	0.1816
METEOR With Intention	0.6617	0.6303
METEOR Without Intention	0.5102	0.2405
BERTScore With Intention	0.7139	0.6762
BERTScore Without Intention	0.5908	0.2542
Coverage Ratio With Intention	0.5561	0.5246
Coverage Ratio Without Intention	0.4238	0.1895
Cosine Similarity With Intention	0.9347	0.8671
Cosine Similarity Without Intention	0.9137	0.4225

Table 13: Semantic and Structural Metrics - Claude 3.5 Sonnet

A.4.12 LLM-as-a-Judge Scores - Claude 3.5 Sonnet

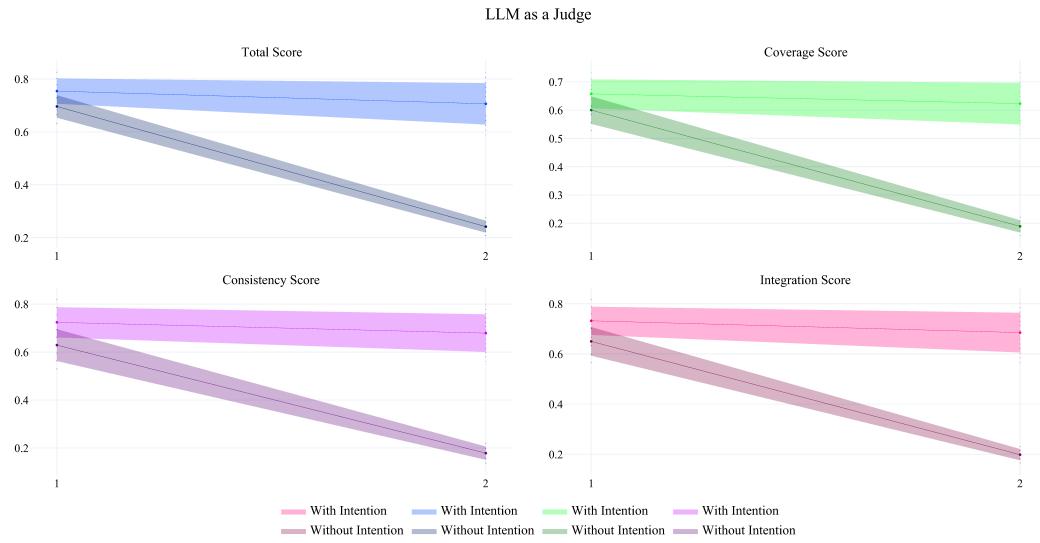


Figure 20: LLM-as-a-Judge Scores - Claude 3.5 Sonnet

Score	Mixed Intention Level	
	1	2
Coverage Score With Intention	0.7540	0.7060
Coverage Score Without Intention	0.6960	0.2415
Consistency Score With Intention	0.6575	0.6230
Consistency Score Without Intention	0.6000	0.1890
Integration Score With Intention	0.7240	0.6790
Integration Score Without Intention	0.6290	0.1785
Total Score With Intention	0.7320	0.6850
Total Score Without Intention	0.6500	0.1985

Table 14: LLM-as-a-Judge Scores - Claude 3.5 Sonnet

A.4.13 Semantic and Structural Metrics - DeepSeek-V3

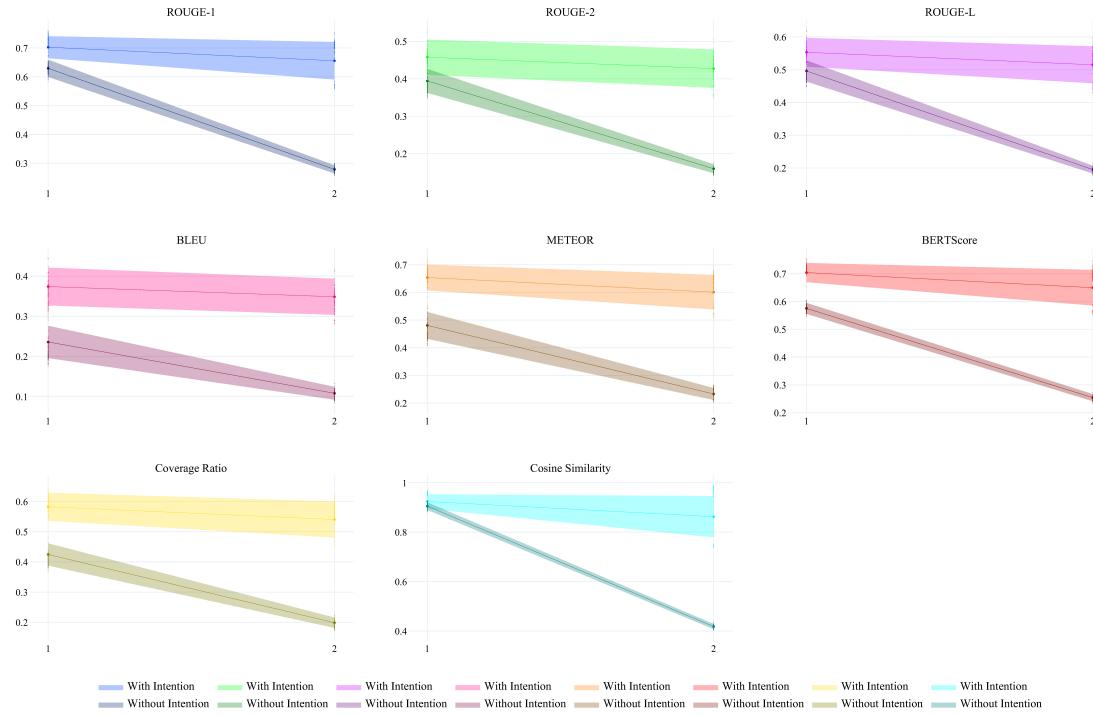


Figure 21: Semantic and Structural Metrics - DeepSeek-V3

Metric	Mixed Intention Level	
	1	2
BLEU With Intention	0.3741	0.3486
BLEU Without Intention	0.2362	0.1083
ROUGE-1 With Intention	0.7027	0.6557
ROUGE-1 Without Intention	0.6294	0.2790
ROUGE-2 With Intention	0.4578	0.4272
ROUGE-2 Without Intention	0.3944	0.1596
ROUGE-L With Intention	0.5532	0.5151
ROUGE-L Without Intention	0.4961	0.1953
METEOR With Intention	0.6541	0.6010
METEOR Without Intention	0.4808	0.2329
BERTScore With Intention	0.7041	0.6496
BERTScore Without Intention	0.5753	0.2541
Coverage Ratio With Intention	0.5826	0.5405
Coverage Ratio Without Intention	0.4247	0.1987
Cosine Similarity With Intention	0.9241	0.8625
Cosine Similarity Without Intention	0.9050	0.4182

Table 15: Semantic and Structural Metrics - DeepSeek-V3

A.4.14 LLM-as-a-Judge Scores - DeepSeek-V3

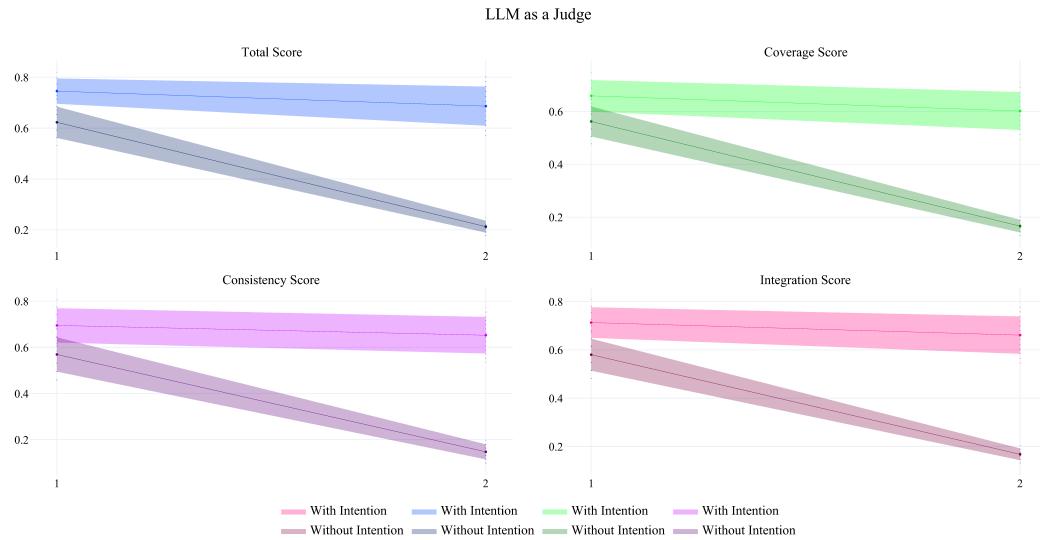


Figure 22: LLM-as-a-Judge Scores - DeepSeek-V3

Score	Mixed Intention Level	
	1	2
Coverage Score With Intention	0.7455	0.6865
Coverage Score Without Intention	0.6230	0.2125
Consistency Score With Intention	0.6590	0.6015
Consistency Score Without Intention	0.5620	0.1660
Integration Score With Intention	0.6950	0.6525
Integration Score Without Intention	0.5690	0.1470
Total Score With Intention	0.7130	0.6610
Total Score Without Intention	0.5800	0.1675

Table 16: LLM-as-a-Judge Scores - DeepSeek-V3

A.4.15 Semantic and Structural Metrics - DeepSeek-R1

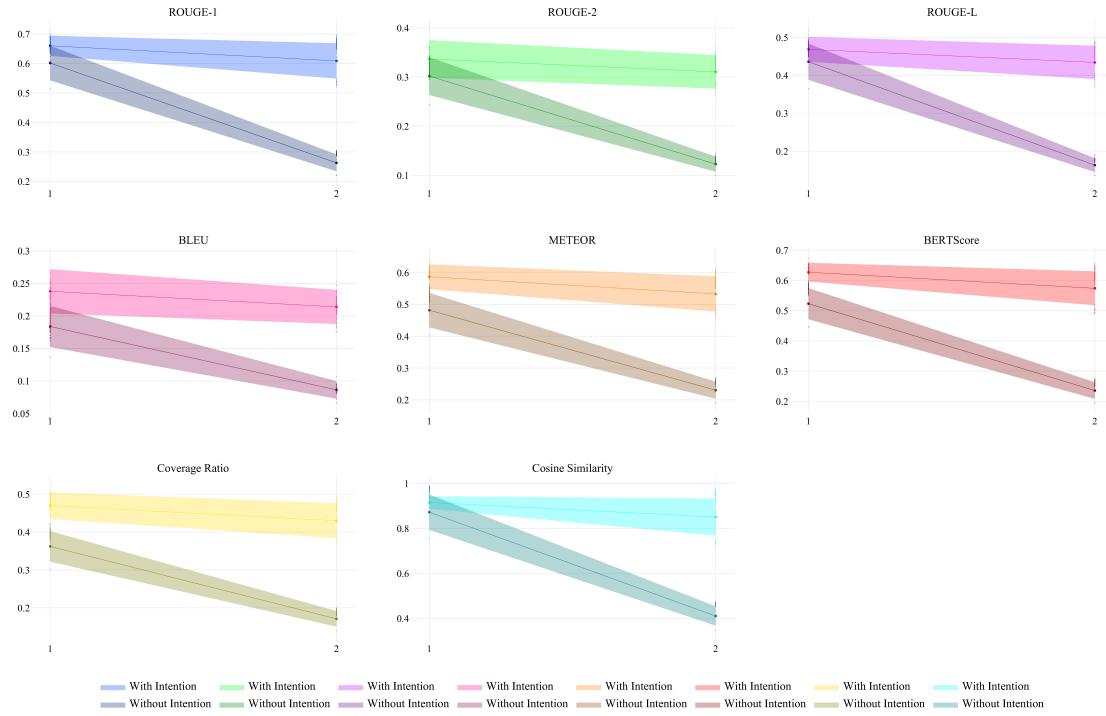


Figure 23: Semantic and Structural Metrics - DeepSeek-R1

Metric	Mixed Intention Level	
	1	2
BLEU With Intention	0.2379	0.2139
BLEU Without Intention	0.1837	0.0863
ROUGE-1 With Intention	0.6600	0.6088
ROUGE-1 Without Intention	0.6015	0.2628
ROUGE-2 With Intention	0.3368	0.3106
ROUGE-2 Without Intention	0.3019	0.1228
ROUGE-L With Intention	0.4686	0.4340
ROUGE-L Without Intention	0.4358	0.1630
METEOR With Intention	0.5872	0.5331
METEOR Without Intention	0.4820	0.2303
BERTScore With Intention	0.6274	0.5740
BERTScore Without Intention	0.5231	0.2355
Coverage Ratio With Intention	0.4695	0.4299
Coverage Ratio Without Intention	0.3621	0.1710
Cosine Similarity With Intention	0.9152	0.8504
Cosine Similarity Without Intention	0.8720	0.4103

Table 17: Semantic and Structural Metrics - DeepSeek-R1

A.4.16 LLM-as-a-Judge Scores - DeepSeek-R1

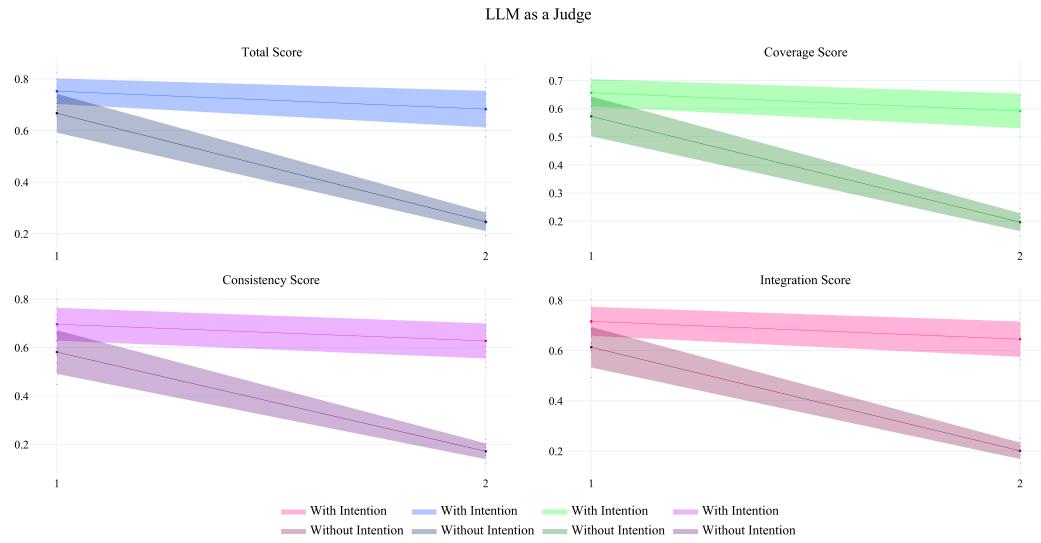


Figure 24: LLM-as-a-Judge Scores - DeepSeek-R1

Score	Mixed Intention Level	
	1	2
Coverage Score With Intention	0.7525	0.6830
Coverage Score Without Intention	0.6670	0.2460
Consistency Score With Intention	0.6570	0.5920
Consistency Score Without Intention	0.5730	0.1965
Integration Score With Intention	0.6960	0.6270
Integration Score Without Intention	0.5810	0.1715
Total Score With Intention	0.7160	0.6450
Total Score Without Intention	0.6130	0.2010

Table 18: LLM-as-a-Judge Scores - DeepSeek-R1