WHEN TO ACT, WHEN TO WAIT: Modeling Structural Trajectories for Intent Triggerability in Task-Oriented Dialogue

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Abstract

Task-oriented dialogue systems often face difficulties when user utterances seem semantically complete but lack necessary structural information for appropriate system action. This arises because users frequently do not fully understand their own needs, while systems require precise intent definitions. Current LLM-based agents cannot effectively distinguish between linguistically complete and contextually triggerable expressions, lacking frameworks for collaborative intent formation. We present STORM, a framework modeling asymmetric information dynamics through conversations between UserLLM (full internal access) and AgentLLM (observable behavior only). STORM produces annotated corpora capturing expression trajectories and latent cognitive transitions, enabling systematic analysis of collaborative understanding development. Our contributions include: (1) formalizing asymmetric information processing in dialogue systems; (2) modeling intent formation tracking collaborative understanding evolution; and (3) evaluation metrics measuring internal cognitive improvements alongside task performance. Experiments across four language models reveal that moderate uncertainty (40–60%) can outperform complete transparency in certain scenarios, with model-specific patterns suggesting reconsideration of optimal information completeness in human-AI collaboration. These findings contribute to understanding asymmetric reasoning dynamics and inform uncertainty-calibrated dialogue system design.

1 Introduction

The rapid advancement of language models has created a fundamental challenge in human-AI interaction: the *"gulf of envisioning"*—users' cognitive difficulty in formulating effective prompts. Unlike conventional interfaces with predictable affordances, language models require users to simultaneously envision possibilities and their expressions, often leading to communication breakdowns. This challenge arises from a misalignment between human cognitive processes and the way systems interpret user intent. Subramonyam et al. Subramonyam et al. (2023) illustrate that human intent formation involves a maturation process characterized by progressive constraint resolution, fluctuating stability intervals, and distinct structural signaling patterns. However, current evaluation methods are insufficient as they: 1) treat intent as binary rather than continuous, 2) lack frameworks for temporal coherence, and 3) overlook structural signals within expressions. These structural signals—including stylistic choices, implicit assumptions, and cultural markers reflect what Wittgenstein Wittgenstein (1953) termed the contextual embeddedness of meaning within particular *"forms of life."* Current systems cannot access these embedded contextual cues that users unconsciously include in their expressions. These shortcomings constitute the *Intent-Action Alignment Problem*, determining precisely when user expressions have reached cognitive readiness for effective system action. To address this alignment problem, we propose **STORM** (Structured Task-Oriented Representation Model), a framework that builds on top of CAMEL-AI (Li et al., 2023) and conceptualizes user intent as evolving along a continuous spectrum, modeling the iterative refinement of user expressions, and identifying

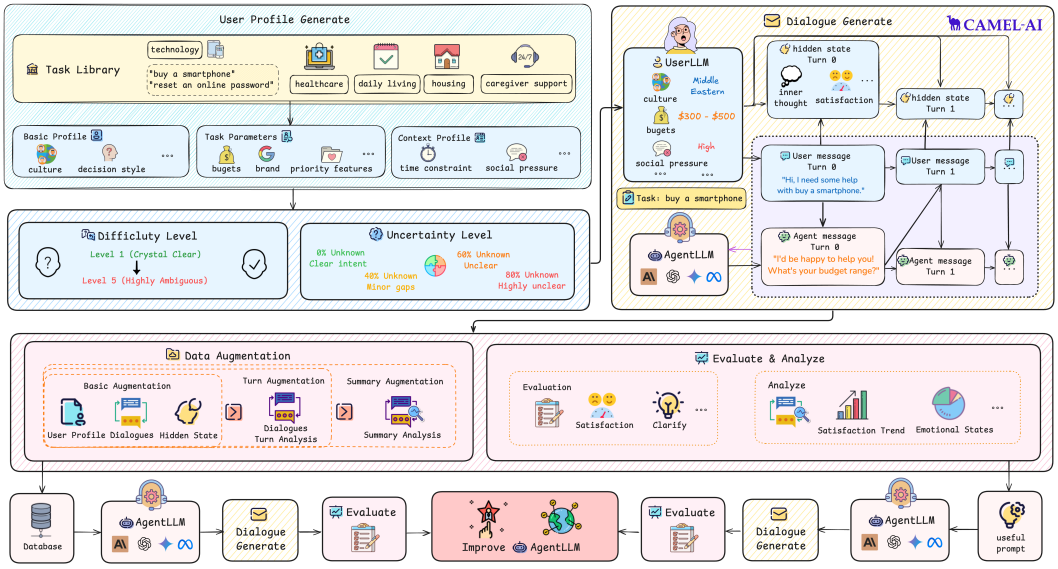

Figure 1: Overview of the STORM Framework

timing misalignments that lead to communication failures. The major contributions of this paper include:

(1) **A dialogue generation pipeline** using two language models—UserLLM and AgentLLM—to simulate realistic conversations reflecting diverse user profiles and intent progression. UserLLM generates user behavior conditioned on comprehensive profile data and internal states, simulating authentic intent evolution, while AgentLLM responds based solely on observable dialogue history. This asymmetric setup mirrors the realistic information gaps faced by AI systems, allowing targeted studies on agent adaptability to evolving intent.

(2) **A database-driven memory system** that systematically tracks evolving user states (intent, emotion, satisfaction) within session-specific records. These records function as micro-databases documenting real-time intent maturation trajectories and are integrated into a global database for cross-session analysis. This structured memory approach captures the continuous nature of intent development, providing researchers with detailed, fine-grained data to study patterns across diverse interaction contexts.

(3) **A web-based dialogue visualization interface** equipped with a clarity rating mechanism was developed to provide an intuitive analysis of the evolution of user intent. This interface dynamically displays the refinement process of user intent, enabling researchers to assess the effectiveness of various agent response strategies visually. The tool facilitates rigorous quantitative analysis and comparison by quantifying the abstract cognitive progression into a standardized clarity metric. The interface is publicly accessible at https://v0-dialogue-analysis-dashboard.vercel.app/.

The dialogues produced by **STORM** serve as valuable training data, enabling conversational agents to better detect and adapt to different stages of intent formation. We evaluate our framework through comparative analysis of agent responses across metrics, including user satisfaction and response quality, demonstrating improved alignment with user cognitive processes. Our experiments demonstrate that **access to user profiles significantly enhances model performance** across all evaluated systems, with satisfaction scores increasing by **15–40%** when profile information is available. We introduce a novel *'Clarify'* metric that measures how effectively agents help users **internally clarify their own intentions** — assessed through analysis of simulated user inner thoughts rather than external expressions. This approach captures whether agent responses genuinely improve users' understanding of their own needs, a crucial cognitive process often invisible in traditional dialogue evaluations.

Table 1: Summary of notations used in STORM INTERFACE.

	Notation	Symbol	Description
Core Domains	User Expression	$e_t \in \mathcal{E}$	User utterance at dialogue turn t
	Agent Response	$r_t \in \mathcal{R}$	Agent utterance at dialogue turn t
	Hidden State	$h_t \in \mathcal{H}$	User's internal state at turn t (inner thoughts, emotion, satisfaction)
	Task Domain	$\tau \in \mathcal{T}$	Space of tasks from the Task Library (technology, healthcare, etc.)
	User Domain	$u \in \mathcal{U}$	Space of user profiles with their multi-dimensional attributes
	Expression Domain	$e_t \in \mathcal{E}$	Space of user utterances with varying degrees of clarity
	Response Domain	$r_t \in \mathcal{R}$	Space of agent responses to user expressions
User Profile	Base Profile [task-agnostic]	$\mathbf{b} = \{b_1, ..., b_n\}$	Demographic and personality factors (culture, decision style, etc.)
	Task Parameters	$\mathbf{t} = \{t_1, ..., t_m\}$	Task-specific attributes (domain, brand, priority features, etc.)
	Context Profile [task-agnostic]	$\mathbf{c} = \{c_1, ..., c_k\}$	User capabilities and constraints (time constraint, patience, etc.)
	Task Specifics	$\mathbf{s}$	Predefined user preferences and constraints for a task instance τ
	Difficulty Config	$\mathbf{d} = \{d_{style}, d_{length}, d_{content}, d_{tone}\}$	Difficulty level and associated dimensions
	Uncertainty Level	$p \in \{0\%, 40\%, 60\%, 80\%\}$	Percentage of profile attributes masked as unknown
Agent	Agent Role	$\alpha(\tau) \in \mathcal{A}$	A general helpful assistant for task τ
	Agent Directive	$\delta(\tau)$	Task-specific guidelines instructing agent behavior and goals
Metrics	Intent Evolution	$\Delta_t(h)$	Change in intent clarity from turn $t-1$ to t based on hidden states
	Clarity Rating	$C(r_t, h_t, h_{t+1})$	Measurement of how agent response improves intent clarity
	Performance Score	$E(C_1, ..., C_T)$	Aggregate measure of agent effectiveness across dialogue turns
Generation Process	UserLLM Function	$G_{\text{user}}(u, \mathcal{H}_{1:t-1}, \mathcal{E}_{1:t-1}, \mathcal{R}_{1:t-1}) \to (e_t, h_t)$	User generation with full dialogue history
	AgentLLM Function	$G_{\text{agent}}(\alpha(\tau), \delta(\tau), \mathcal{E}_{1:t}, \mathcal{R}_{1:t-1}) \to r_t$	Agent generation with role, directive, and observable history
	Basic Augmentation	$A_1(\mathcal{E}_{1:T}, \mathcal{R}_{1:T}, \mathcal{H}_{1:T}, u) \to D$	Collection of dialogues with complete metadata
	Turn Analysis	$A_2(D) \to D^+$	Enhanced data with per-turn analysis
	Summary Generation	$A_3(D^+) \to S$	Comprehensive dialogue summaries
	RAG Enhancement	$\mathcal{R}(D, D^+, S) \to K$	Using augmented data as knowledge base
	Prompt Refinement	$P(D, D^+, S) \to G'_{\text{agent}}$	Creating improved prompts from analysis

Our analysis reveals distinct model characteristics with practical deployment implications: **Claude maintains consistent satisfaction** across varying profile completeness, **Gemini demonstrates robust performance under high uncertainty**, while **Llama achieves superior intent clarification** despite satisfaction trade-offs. Notably, we observe that **moderate profile uncertainty (40–60% unknown attributes) often outperforms complete information access**, suggesting that excessive profile information may lead to presumptive reasoning, while moderate uncertainty encourages more exploratory interaction strategies that better support users' evolving understanding of their own needs. This finding has implications for privacy-preserving design and bias mitigation in dialogue systems. These insights highlight the tension between **immediate satisfaction** and **cognitive alignment**, providing empirical guidance for uncertainty-aware dialogue system design.

2 Core Components

We define the **STORM (Structured Task-Oriented Representation Model)** Interface as a formal framework for studying the relationship between user intent expression and system actionability. The **STORM** Interface is represented as a 5-tuple of domain spaces: $\{\mathcal{T}, \mathcal{U}, \mathcal{E}, \mathcal{R}, \mathcal{H}\}$. We define each component in detail as follows.

Task domain $\mathcal{T}$ is defined as a collection of task objects $\tau \in \mathcal{T}$, where each τ comprises a task name, a description, and domain-specific requirements. Prior approaches Yao et al. (2024); Prabhakar et al. (2025) constrain task definitions to those with explicit success metrics, whereas our formalization generalizes across task types. The task representation of our framework is domain-agnostic, enabling automated attribute generation for arbitrary domains beyond our experimental setup. The implementation accepts custom task definitions through a standardized interface that integrates with existing domain taxonomies and classification systems.

User domain $\mathcal{U}$ consists of user profiles $u \in \mathcal{U}$, where each profile is represented as a vector of attribute-value pairs. These captures both task-agnostic characteristics such as demographics and task-specific attributes such as budget constraints. Modeling user profiles is essential for creating adaptive human-agent interaction scenarios, allowing systems to reason about user variability and tailor responses accordingly (Wan et al., 2025). To support system interoperability and practical deployment, we structure user profiles using a schema-compatible format that facilitates direct integration with existing user databases via JSON exchange formats.

Expression domain $\mathcal{E}$ encompasses all possible user expressions e. To reflect the realities of natural human communication, we also model variation in expression clarity through four dimensions: style, length, content and tone. This addresses limitations in existing models that assume unambiguous and complete intent expressions. The variation is operationalized through configurable difficulty levels during user profile generation (see section 2.1 for details). Our framework supports both integration of real-world interaction corpora and generation of synthetic expressions to enhance data diversity.

Response domain $\mathcal{R}$ contains all possible agent responses $r \in \mathcal{R}$, which can be clarification queries, option suggestions, or action executions. At time t, the response r_t is generated based on information from a task object τ and past user-agent dialogues $\{(e_1, r_1), ..., (e_{t-1}, r_{t-1})\}$.

Hidden state domain $\mathcal{H}$ denotes the space of latent user states $h \in \mathcal{H}$ that evolve dynamically over the course of a dialogue. At each timestep t, the hidden state h_t is represented as a composite vector encoding both user intent and emotional state. This modeling approach serves multiple purposes: it enables contextualized interpretation of user actions, supports dynamic adaptation of agent responses, and facilitates diagnosis of failure points in communication.

2.1 STORM User Model Formalization

We formalize the **STORM** user profile u as a composite structure, organized into three categories that together capture the complexity of human-agent interaction: task-agnostic attributes, task-specific attributes, and communicative parameters.

This composite approach addresses the limitations of monolithic user models by providing a transparent, controllable representation that enables systematic analysis of how different user characteristics influence interaction patterns. By isolating individual variables within this parameterized framework, researchers can identify which specific user attributes most significantly impact behavior in different contexts, facilitating the development of targeted strategies for various application scenarios.

1. Task-agnostic Components

- ***The base profile*** b consists of parameters representing demographic and personality characteristics. These parameters include age group (18–25, 26–40, 41–65, 65+), technical experience (1–5 scale), language expression style (e.g., concise, detailed, technical, non-technical), personality traits (derived from the Big Five model dimensions Barrick & Mount (1991)), and cultural background. We choose to include these factors based on empirical evidence from human-computer interaction studies Subramonyam et al. (2023) showing their significant impact on expression patterns and intent formulation. To ensure unbiased representation, these profile attributes are randomly generated, creating diverse user populations that better reflect real-world interaction scenarios.
- ***The context profile*** $\mathbf{c}$ models users' environmental and cognitive constraints. This includes general influencing factors such as patience level (on a scale from 1 to 5), social pressure, time constraints, and other subjective elements. By introducing these variable factors, our framework simulates the unpredictability of real-world interaction environments. The explicit modeling of contextual factors addresses a significant gap in existing frameworks that typically assume ideal interaction environments, allowing **STORM** to model challenging scenarios where external factors directly impact communication quality.

2. Task-dependent Components

- ***Task instance*** τ specifies a particular task from the task library $\mathcal{T}$, such as "create an online password," "book a flight," or "configure network settings." We deliberately implement these as high-level descriptions rather than precise execution specifications, recognizing the significant gap between how users conceptualize tasks and the actual execution intent. This design choice more accurately reflects the abstraction level at which most users operate when formulating requests, requiring systems to bridge the conceptual gap between description and execution.
- ***Task specifics*** **s** capture user-defined preferences and situational constraints within the selected task τ. These encompass domain classification (technology, finance, healthcare, etc.), priority functional requirements (represented as weighted importance lists), brand preferences, budget constraints, and time urgency indicators. These parameters are generated using LLM (GPT-4o Mini) with randomly selected options to eliminate potential biases in task representations. This systematic approach ensures balanced coverage across task types.

3. Communication Modeling Components To more accurately reflect how people naturally communicate, **STORM** models key sources of ambiguity and variability through expression difficulty and uncertainty.

- ***Difficulty configuration*** $\mathbf{d} = \{d_{style}, d_{length}, d_{content}, d_{tone}\}$ models variation in user expression across 4 linguistic dimensions: represents one of **STORM**'s core innovations, characterizing expression clarity through multiple dimensions. The difficulty level $d \in \{1, \ldots, 5\}$ ranges from precise to highly ambiguous across five levels. This multidimensional approach reflects a critical insight from real-world interactions: the vast majority of users cannot articulate their needs with the precision that current systems often expect. By modeling various dimensions of communication difficulty, **STORM** creates more realistic scenarios that challenge systems to handle the imprecise, inconsistent, and incomplete expressions typical in everyday interactions. Detailed breakdown of each dimension is in Appendix D.
- ***Uncertainty level*** $p \in \{0\%, 40\%, 60\%, 80\%\}$ controls the proportion of unknown or unspecified user attributes. It ranges from 0% (fully known) to 80% (high uncertainty). This parameter is designed to simulate one of the most fundamental challenges in intent modeling: users often cannot articulate requirements they themselves do not fully understand. In real-world interactions, many users lack conceptual understanding of their own needs or the relevant domain, requiring systems to provide additional explanation, guidance, and progressive clarification. The higher uncertainty levels (60%, 80%) simulate scenarios where users are in an exploratory mode, possessing only vague notions of their goals and requiring substantial guidance from the agent to refine and articulate their actual needs. This approach provides a more realistic simulation framework compared to models that assume users have perfect knowledge of their requirements and preferences, enabling the development of systems that can effectively guide users through the process of need discovery and formulation.

2.2 Agent Model and Dialogue Process

We formalize the **STORM** agent configuration as a structured framework that enables interactive systems to adapt their behavior based on specific task contexts. This parameterized approach facilitates systematic analysis of different agent strategies and their impact on dialogue effectiveness.

The user LLM function $G_{\text{user}}(u, \mathcal{H}_{1:t-1}, \mathcal{E}_{1:t-1}, \mathcal{R}_{1:t-1}) \rightarrow (e_t, h_t)$ generates both user expressions and corresponding hidden states. This function employs pre-trained language models prompted to specific user profiles, taking as input the complete user profile u, previous hidden states $\mathcal{H}_{1:t-1}$, user expression history $\mathcal{E}_{1:t-1}$, and agent response history $\mathcal{R}_{1:t-1}$. Through a multi-step process, it first determines the expression's difficulty level based on the profile and dialogue history, then generates **user expression** $e_t \in \mathcal{E}$ representing the user's input at turn t, with properties determined by the user profile parameters and current hidden state. These expressions are subject to defined character limitations and reflect

varying degrees of clarity based on the user's profile characteristics. Simultaneously, the function produces the **user hidden state** $h_t \in \mathcal{H}$ modeling internal user states not explicitly expressed at turn t, formalized as a vector $h_t = \langle s_t, c_t, i_t, e_t \rangle$ where each component represents satisfaction, intent clarity, and emotional state, respectively. This explicit modeling of hidden states addresses a critical limitation in existing frameworks that neglect the internal user experience.

The agent LLM function $G_{\text{agent}}(\alpha(\tau), \delta(\tau), \mathcal{E}_{1:t}, \mathcal{R}_{1:t-1}) \rightarrow r_t$ produces agent responses using pre-trained language models. The function incorporates **the agent role** $\alpha(\tau) \in \mathcal{A}$, which is standardized as a general helpful assistant to ensure experimental fairness across different interaction scenarios. Operating under realistic constraints, the agent function lacks access to user hidden states and therefore requires intent inference from observable behavior only. By processing the agent role $\alpha(\tau)$, agent instructions $\delta(\tau)$, user expression history $\mathcal{E}_{1:t}$, and previous agent responses $\mathcal{R}_{1:t-1}$, it generates the **agent response** $r_t \in \mathcal{R}$ constituting the system's output at turn t based on the dialogue history. The agent follows a standardized approach across different task contexts, providing adaptable responses through intent recognition, clarity assessment, and strategy selection mechanisms without requiring specialized task-specific instruction sets. This design reflects an intentional asymmetry between user and agent, where the agent relies solely on observable behaviors to infer user intent, without direct access to internal cognitive states.

This representation of dialogue as a temporal sequence of generated expressions, responses, and evolving hidden states allows us to define three primary evaluation metrics that quantify dialogue effectiveness. First, **intent evolution** $\Delta_t(h) = h_t.\text{clarity} - h_{t-1}.\text{clarity}$ measures the change in intent clarity between consecutive turns. This differential metric is calculated through round-by-round analysis of the generated inner thoughts, providing insight into how specific agent responses influence users' understanding of their own needs. Building on this, the **clarity score** $C(r_t, h_t, h_{t+1})$ evaluates response effectiveness in improving intent clarity. It is computed as a weighted function $C = w_1\Delta_t(h) + w_2\Delta_t(s) + w_3 g_t$ where $\Delta_t(s)$ represents satisfaction change and g_t measures progress toward goal achievement. The scoring components are derived from both turn-level analysis and summary analysis of the interaction trajectory. Finally, the **performance score** $E(C_1, \ldots, C_T)$ delivers an aggregate assessment of agent effectiveness across the complete dialogue. The score combines average clarity, turn efficiency, and final satisfaction into a standardized metric for comparative analysis. This unified measure facilitates systematic comparison across different agent strategies, enabling empirical identification of optimal approaches for specific user profiles and task types.

By maintaining this structured evaluation framework across experiments, **STORM** provides a standardized methodology for assessing and improving assistant performance across diverse interaction scenarios, particularly focusing on how different interaction patterns address various types of expression ambiguity.

3 Experiment

3.1 Evaluation

Our evaluation employs a simulation-based approach where **GPT-4o-mini functions as UserLLM**, generating both external utterances and internal "inner thoughts" during interactions with different assistant models (Claude, GPT, Gemini, and Llama). This setup models an **asymmetric information dynamic**: users have full access to their internal states and profiles, while agents must infer user intent solely from observable dialogue history, reflecting real-world challenges in intent understanding. The dataset of **4,800 dialogues**, spanning **600 unique user profiles**, is generated through this simulation framework by conditioning UserLLM on detailed user profiles and evolving internal states. UserLLM produces naturalistic utterances alongside corresponding latent states such as satisfaction and intent clarity, enabling fine-grained measurement of internal cognitive signals. While the current dataset serves as a representative sample illustrating the effectiveness and versatility of the framework, the underlying architecture is designed to support **scalable**

Table 2: User Satisfaction and Clarification Performance across UserLLMs with Varying Uncertainty Levels

UserLLM (Uncertainty)	Satisfaction Metrics						Clarify	SSA
	Average Satisfaction		*High Satisfaction Rate*		*Improved Satisfaction Rate*		*Score*	*Score*
	w/Profile	*w/o Profile*	*w/Profile*	*w/o Profile*	*w/Profile*	*w/o Profile*	*w/o Profile*	*w/o Profile*
Claude-3.7-Sonnet (0%)	**0.91**	0.83	**86.0%**	72.0%	**89.3%**	75.3%	5.23	6.07
Claude-3.7-Sonnet (40%)	**0.92**	0.78	86.0%	62.7%	**90.0%**	62.7%	4.80	5.67
Claude-3.7-Sonnet (60%)	0.88	**0.92**	80.7%	**86.7%**	86.0%	**88.7%**	4.66	6.39
Claude-3.7-Sonnet (80%)	**0.91**	0.80	**86.0%**	65.3%	**90.0%**	71.3%	4.70	6.36
GPT-4o-mini (0%)	0.89	0.75	82.0%	54.0%	87.3%	58.7%	**5.97**	5.86
GPT-4o-mini (40%)	0.89	0.75	82.7%	57.3%	86.0%	63.3%	5.84	5.82
GPT-4o-mini (60%)	0.89	0.77	84.0%	62.7%	86.7%	67.3%	5.69	5.88
GPT-4o-mini (80%)	0.87	0.80	79.3%	64.0%	83.3%	68.7%	5.30	5.93
Gemini 2.5 Flash Preview (0%)	0.89	0.74	84.7%	51.3%	89.3%	62.0%	**6.83**	6.06
Gemini 2.5 Flash Preview (40%)	0.89	0.74	81.3%	52.7%	89.3%	61.3%	6.55	5.98
Gemini 2.5 Flash Preview (60%)	**0.91**	0.75	**88.0%**	56.7%	**92.0%**	66.0%	6.50	6.02
Gemini 2.5 Flash Preview (80%)	0.90	0.79	84.7%	64.7%	**92.7%**	70.0%	6.45	6.22
Llama 3.3 70B Instruct (0%)	0.89	0.70	83.3%	48.0%	90.0%	61.3%	**7.58**	6.07
Llama 3.3 70B Instruct (40%)	**0.90**	0.67	**86.0%**	45.3%	90.0%	56.0%	7.59	5.91
Llama 3.3 70B Instruct (60%)	0.88	0.71	81.3%	44.7%	**92.0%**	66.7%	7.58	6.12
Llama 3.3 70B Instruct (80%)	0.85	**0.76**	74.0%	**61.3%**	88.7%	**72.7%**	**7.75**	6.45

generation of extensive, diverse dialogue corpora across varied user demographics and task domains. This capacity facilitates comprehensive data-driven analysis and continuous model improvement beyond the examples presented here.

We evaluate model performance along three complementary dimensions: (1) **satisfaction** derived from user inner thoughts, capturing the user's internal contentment; (2) **clarification effectiveness**, measured by the Clarify metric, which is computed via prompting an evaluation model to analyze the dialogue turn-by-turn and determine whether each agent response improves the clarity of the user's intent relative to the previous turn; and (3) **Satisfaction-Seeking Actions (SSA)**, a composite metric that integrates satisfaction and clarification scores weighted by scenario-specific parameters to balance the competing objectives of confident response generation and appropriate clarification seeking. The SSA metric corresponds to the aggregate performance score $E(C_1, \ldots, C_T)$ across dialogue turns, enabling holistic and context-sensitive assessment of dialogue quality.

At dialogue start, user satisfaction is initialized to a neutral baseline of **0.5**. Satisfaction is assessed using several detailed metrics: *Final Satisfaction* measures user satisfaction at dialogue conclusion on a scale from 0.0 (completely unsatisfied) to 1.0 (fully satisfied). *Average Satisfaction* reports the mean final satisfaction across all dialogues. *Satisfaction Trend* reflects the change in satisfaction from the initial baseline to dialogue end, indicating improvement or decline. *High Satisfaction Rate* indicates the proportion of dialogues where final satisfaction meets or exceeds a threshold of 0.8, marking successful interactions. Lastly, *Improved Satisfaction Rate* quantifies the percentage of dialogues with increased satisfaction compared to the start, highlighting effective clarification and positive user experience changes. Together with the Clarify and SSA scores, these metrics provide a comprehensive and nuanced evaluation of model behavior across diverse interaction scenarios.

3.2 Results

Table 2 presents performance data across models, uncertainty levels, and profile conditions, revealing patterns in how language models balance satisfaction and clarification.

The satisfaction metrics demonstrate clear benefits from **user profile access**. With profiles, models maintain average satisfaction scores of **0.85–0.92**, while without profiles, scores frequently fall below **0.75**, with Llama reaching as low as **0.67** (at 40% uncertainty). This differential highlights the value of **personalization** in dialogue systems.

A notable exception is Claude's performance at 60% uncertainty without profiles, achieving **0.92 satisfaction**—higher than its profile-informed score (0.88). This counter-intuitive result suggests that certain uncertainty levels may activate beneficial reasoning pathways. Analysis

of user inner thoughts reveals that under moderate uncertainty, Claude's responses trigger **18% more improvements** in users' internal clarity compared to 0% uncertainty. Claude appears to adopt a more balanced approach at this uncertainty level, helping users refine their own intentions effectively despite lacking profile information.

The high satisfaction rate metrics confirm these observations. With profiles, models maintain rates above **80%** across uncertainty levels. Without profiles, these rates decline substantially, most dramatically for Llama (dropping to **44.7%** at 60% uncertainty). This pattern reveals significant differences in how models adapt to missing user context, with some architectures showing more resilience than others when personalization data is unavailable.

3.3 Practical Implications and Strategic Deployment

Our analysis reveals systematic differences in optimal uncertainty levels across task domains, challenging the assumption that uniform uncertainty thresholds apply across scenarios. Technology-oriented tasks (e.g., password reset, device setup) achieve peak performance at lower uncertainty levels (40%), requiring direct, efficient guidance. Medical scenarios (appointment scheduling, caregiver selection) demonstrate optimal performance at moderate uncertainty (60%), reflecting the cautious, trust-building nature of healthcare interactions. Housing-related tasks (accessibility modifications, rental searches) show continued improvement even at higher uncertainty levels (60-80%), corresponding to their complex, multi-stakeholder decision processes.

This domain-uncertainty relationship correlates with user cognitive load and decision complexity, with temporal dynamics varying significantly: technology scenarios show rapid convergence between inner thoughts and external expressions, while medical and housing scenarios maintain longer periods of internal uncertainty despite external cooperation. These patterns inform the design of patience-aware dialogue systems that can recognize when users need additional processing time versus immediate response.

Our analysis yields five key insights for dialogue system deployment: (1) **Domain-adaptive uncertainty calibration**—technology tasks require 40% uncertainty, medical scenarios 60%, housing scenarios 60-80%—outperforming uniform thresholds; (2) **Model-specific optimization**—Claude performs best at 40% uncertainty, Gemini at 60%, Llama shows continued improvement at higher uncertainty levels; (3) **Progressive profile building** during conversations significantly enhances performance, especially for profile-sensitive models like Llama; (4) **Context-aware model selection**—Claude offers stability across uncertainty conditions, Gemini excels with incomplete information, and Llama provides superior disambiguation; (5) **Bias mitigation through calibrated uncertainty**—moderate profile incompleteness (40-60%) can improve interaction quality by reducing reliance on demographic assumptions and encouraging individualized exploration.

These findings advocate for context-aware deployment approaches that balance satisfaction with effective clarification strategies. Systems with complete user profiles may engage in presumptive reasoning based on age, cultural markers, or historical patterns, while moderate uncertainty encourages assumption-free communication. This has direct implications for user privacy controls and profile management, where strategic information limitation may enhance rather than degrade user experience by promoting personalized support without stereotypical generalizations.

4 Related Work

Our work connects linguistic theory with recent advances in LLM dialogue systems through three research streams:

Theoretical Foundations Linguistic research on discourse cohesion Halliday & Hasan (1976), referential underspecification Clark & Wilkes-Gibbs (1986), and speech act theory Searle (1969) established frameworks for analyzing communication intent, while work on epistemic modality Lyons (1977) and conversational repair Schegloff et al. (1977) identified

uncertainty markers. **STORM** operationalizes these insights by formalizing difficulty dimensions reflecting cognitive readiness signals.

Dialogue Systems and Uncertainty Mixed-initiative dialogue research Allen et al. (2001); Traum (1994) developed computational approaches to conversational grounding, with recent work examining how language models handle uncertainty—revealing hallucination under ambiguity Dziri et al. (2022); Lin et al. (2021) and advancing methods for managing unclear expressions Chia et al. (2023); Kim et al. (2023); Liu et al. (2024). **STORM** extends these approaches with a structured framework for assessing expression stability across multiple dimensions.

User Variation and Intent Formation Studies on cultural sensitivity in language models Kumar et al. (2024); Li et al. (2024) have highlighted the importance of user variation, while recent work identified the "gulf of envisioning" Subramonyam et al. (2023)—users' difficulty formulating effective prompts. **STORM** addresses this challenge by modeling expression clarity through formal representation of user profiles, difficulty configurations, and uncertainty levels, integrating aspects of the intent-action alignment problem previously examined only in isolation.

5 Conclusions and Future Directions

STORM provides a framework for modeling intent triggerability in task-oriented dialogues, revealing how model performance varies with profile availability and uncertainty calibration. Claude offers consistent satisfaction, Gemini excels with incomplete profiles, and Llama provides superior disambiguation. Notably, moderate uncertainty (40-60%) sometimes outperforms minimal uncertainty, suggesting that appropriate caution activates more effective reasoning. The framework's key strength lies in its extensibility—its modular design accommodates additional models and domains, providing a consistent methodology for cross-model comparison. Future work should explore longer interactions, refine turn management, and investigate real-world deployment scenarios. **STORM**'s architecture supports ongoing research and development of dialogue systems that better align with the dynamic nature of human intent formation.

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A Appendix: User Satisfaction and Profile Integration Effects

User profiles consistently boost satisfaction across AI models, but moderate uncertainty without profile data can paradoxically trigger more effective reasoning patterns. User profiles enhance satisfaction across all models (0.85–0.92 with profiles vs. 0.67–0.83 without), yet our analysis reveals a critical distinction between external compliance and internal understanding. Claude at 60% uncertainty without profiles achieves 0.92 satisfaction—exceeding its profile-informed score (0.88), suggesting moderate uncertainty may trigger more effective reasoning patterns in some architectures. Analysis of user inner thoughts reveals Claude's responses at this uncertainty level produce 18% more improvements in users' internal clarity compared to 0% uncertainty. We hypothesize that without profile information, Claude adopts a more balanced strategy between confident answering and clarification seeking, which better supports users' own cognitive process of intent refinement.

Traditional satisfaction metrics fail to capture the critical divergence between users' expressed satisfaction and their internal confusion about their own needs. Users may express satisfaction with system responses while their inner thoughts indicate continued confusion about their own needs, highlighting the limitations of traditional evaluation metrics that rely solely on observable user feedback. This internal-external divergence varies significantly across domains: technology tasks promote rapid self-understanding and confident decision-making, medical scenarios require cautious, trust-building interactions with gradual clarity development, while housing decisions involve prolonged uncertainty and multiple stakeholder considerations.

Profile completeness creates a paradox where excessive personalization data can reduce interaction quality by promoting stereotypical responses. High satisfaction rates follow similar patterns, with profile-informed conditions maintaining 80–88% rates while no-profile conditions show significant drops, particularly for Llama (81.3% $\rightarrow$ 44.7% at 60% uncertainty), indicating varying resilience to missing personalization data. Without profiles, models resort to generic information-gathering rather than task-specific assistance, but excessive profile completeness can paradoxically reduce interaction quality by promoting stereotypical responses. This finding challenges conventional approaches to personalization and suggests that optimal human-AI collaboration requires calibrated information asymmetry rather than transparency maximization.

B Appendix: Clarification Performance and Bias Mitigation

AI models exhibit fundamentally different architectural approaches to balancing response confidence versus ambiguity recognition, with distinct trade-offs for user outcomes. Models exhibit distinct clarification strategies, revealed through analysis of user inner thoughts after agent responses. Claude (4.66–5.23) and GPT (5.30–5.97) show declining clarification effectiveness as uncertainty increases, suggesting these models prioritize providing confident responses even when uncertainty rises. Gemini maintains more consistent clarification scores (6.45–6.83) across uncertainty levels, indicating a more robust approach to disambiguation regardless of uncertainty conditions. Most notably, Llama achieves substantially higher clarification scores (7.58–7.75) across all configurations despite lower satisfaction in some conditions.

The clarification-satisfaction trade-off represents a critical design choice, with Claude optimized for immediate satisfaction while Llama emphasizes long-term intent disambiguation. These patterns reveal fundamental architectural differences in how models balance response confidence versus ambiguity recognition. Claude appears optimized for satisfaction even at the cost of clarification opportunities, while Llama's architecture seems to emphasize identifying and addressing ambiguity, sometimes trading immediate satisfaction for more effective intent disambiguation. This clarification-satisfaction trade-off represents a critical design consideration for dialogue systems, with different models offering distinct advantages depending on whether the priority is immediate user satisfaction or long-term intent clarity.

Strategic information limitation serves as an implicit bias mitigation mechanism, preventing systems from relying on demographic generalizations. These architectural differences manifest in distinct reasoning patterns when handling demographic information. Analysis of interactions involving elderly users reveals that complete profile access can lead to stereotypical assumptions—systems may assume simplified instructions are needed based on age markers alone. However, at optimal uncertainty levels, the same systems engage in individualized assessment, often discovering more sophisticated capabilities than demographic profiles would suggest. This pattern suggests that strategic information limitation serves as an implicit bias mitigation mechanism, forcing systems to evaluate individual user responses rather than relying on demographic generalizations.

Successful clarification correlates more strongly with users' internal cognitive improvement than with expressed satisfaction scores, suggesting deeper measures of dialogue effectiveness. Our analysis shows that successful clarification correlates more strongly with internal cognitive improvement than with external satisfaction scores. Users who achieve better self-understanding through interaction—as measured by clearer, more confident inner thoughts—demonstrate sustained engagement and more effective task completion, even when immediate satisfaction scores remain moderate. This finding suggests that dialogue systems optimized solely for satisfaction may miss opportunities for deeper cognitive alignment that benefit long-term user outcomes.

B.1 Satisfaction-Seeking Actions (SSA) Integration

We designed the SSA metric to address two fundamental limitations in dialogue evaluation: optimizing for satisfaction alone neglects critical clarification capabilities, while traditional metrics fail to capture the comprehensive reasoning processes activated by moderate uncertainty levels (40–60%). The integrated metric balances immediate user satisfaction with long-term cognitive alignment through weighted combination:

$$\text{SSA} = w_\alpha \cdot (S_{\text{avg}} \cdot \lambda) + w_\beta \cdot C_{\text{clarify}}$$

where S_{avg} represents the average satisfaction score across dialogue turns, C_{clarify} denotes the clarification effectiveness score computed via turn-by-turn analysis of intent improvement, and $w_\alpha = 0.7$, $w_\beta = 0.3$ represent the relative importance weights with $w_\alpha + w_\beta = 1$. The satisfaction component receives higher weighting based on the practical consideration that user experience remains paramount in deployment scenarios, while the clarification component ensures that cognitive alignment capabilities are not overlooked in system evaluation.

The normalization factor $\lambda = 7.75$ scales satisfaction scores (range 0.0–1.0) to match the magnitude of clarification scores (range 4.0–8.0), where λ corresponds to the maximum observed clarification score in our dataset of 4,800 dialogues. This scaling ensures balanced contribution from both components in the integrated assessment, preventing either dimension from dominating the composite score.

This integrated assessment reveals model-specific optimization patterns and establishes a performance hierarchy (Llama $>$ Gemini $>$ GPT $>$ Claude) that substantially diverges from satisfaction-only rankings. The metric captures distinct architectural characteristics: Claude achieves peak SSA performance at moderate uncertainty (40%) through satisfaction optimization strategies, GPT maintains consistent performance across uncertainty levels, Gemini demonstrates superiority at higher uncertainty (60%) via robust ambiguity handling mechanisms, and Llama attains the highest overall scores by prioritizing clarification effectiveness despite satisfaction trade-offs in certain configurations.

The divergence between SSA rankings and traditional satisfaction metrics validates our design rationale: GPT-4o-mini achieves only mid-range SSA scores as an agent despite serving effectively as UserLLM in our simulation framework, illustrating the fundamental distinction between simulating authentic user behavior and responding optimally to user needs. This confirms that comprehensive dialogue evaluation requires balancing multiple performance dimensions rather than optimizing for satisfaction alone.

C Appendix: How do we use these data?

STORM implements a structured framework for generating realistic dialogues and extracting actionable insights. At its core, the system operates as a closed-loop that enhances agent capabilities through complementary pathways. The process begins with comprehensive user profile generation—combining diverse tasks with multidimensional user attributes, contextual constraints, difficulty parameters, and uncertainty levels to create realistic simulation scenarios. These profiles drive the dialogue generation process, where user and agent LLM functions interact to produce conversations with corresponding hidden states, enabling analysis of both observable exchanges and underlying intent evolution patterns.

The first improvement dimension focuses on progressively enhancing dialogue data for retrieval-augmented generation by leveraging large language models as intelligent evaluators and annotators. This multi-layered enhancement pipeline starts with the **basic enhancement function**

$$A_1(\mathcal{E}_{1:T}, \mathcal{R}_{1:T}, \mathcal{H}_{1:T}, u) \to D$$

which uses pre-trained LLMs prompted with user profiles, expression difficulty, intent clarity, and satisfaction indicators to produce enriched dialogue annotations. Subsequently, the dialogues undergo **turn-level analysis**

$$A_2(D) \to D^+$$

where LLM-based classifiers identify key inflection points, dialogue strategies, and intent evolution trajectories. This is followed by **summary generation**

$$A_3(D^+) \to S$$

where LLMs create abstracted summaries that highlight success and failure patterns. The enhanced and summarized dialogues feed into the **RAG enhancement function**

$$\mathcal{R}(D, D^+, S) \to K$$

which constructs a structured knowledge base through vector embeddings, enabling similarity-based retrieval conditioned on user profiles and dialogue characteristics.

The second improvement dimension exploits these LLM-generated insights to optimize agent prompts. Through systematic analysis of enriched dialogues and summaries, LLMs identify effective agent strategies and response patterns tailored to different user profiles and expression difficulties. These findings are formalized into the **prompt optimization function**

$$P(D, D^+, S) \to G'_{\text{agent}}$$

which updates the agent LLM function by incorporating the discovered response patterns.

STORM's architecture integrates two complementary components: a user simulator generating expressions across varying difficulty and uncertainty states, and an agent response generator leveraging both retrieval-augmented knowledge and optimized prompts. Rather than forming a direct closed-loop training system, these modules serve as reference and analytical tools to uncover deeper insights. Our implementation adopts a two-phase approach: first creating a diverse dataset of synthetic profiles and expressions, then using these data to guide the discovery of patterns and optimization strategies for agent models. This process supports informed improvements that enhance performance across diverse interaction scenarios.

D Appendix: Dimension Details

D.1 Difficulty Level and Dimensions

1. Style dimension d_{style} defines the structural organization of communication. At level 1, expressions exhibit highly structured logical flow; at level 5, expressions lack coherence and organization. This dimension captures the organizational aspects of communication that significantly impact interpretation complexity, reflecting the reality that most users do not communicate with the structured clarity that many systems are designed to expect.

Table 3: User Profile - Difficulty Level and Dimensions

Notation	Symbol	Description
Difficulty Level	$d \in \{1, ..., 5\}$	Expression clarity scale (1: precise to 5: ambiguous)
Style Dimension	$S(d)$	Structural organization of communication at level d
Length Dimension	$L(d)$	Verbosity and elaboration patterns at level d
Content Dimension	$C(d)$	Context inclusion and information density at level d
Tone Dimension	$T(d)$	Emotional expression and engagement at level d

2. Length dimension d_{length} quantifies verbosity and detail level. At level 1, expressions are concise yet comprehensive; at level 5, expressions are either too brief causing information deficiency or excessively verbose obscuring key points. This bidirectional conceptualization addresses the common challenge that users frequently provide either too little or excessive information, rarely hitting the optimal information density.

3. Content dimension $d_{content}$ quantifies contextual sufficiency. At difficulty level 1, all necessary information is explicitly provided; at level 5, critical information is omitted, requiring substantial inference. This dimension directly addresses the prevalent real-world challenge where users frequently omit crucial details they incorrectly assume are obvious or irrelevant.

4. Tone dimension d_{tone} captures emotional expression and interaction engagement. At level 1, the tone is appropriate and consistent; at level 5, emotions fluctuate or misalign with content. The inclusion of this dimension acknowledges the significant role emotional factors play in communication clarity, especially in challenging or frustrating scenarios where tone may significantly impact interpretation.

Table 4: Clarifying Questions Impact by Profile Access

Scenario	Clarifying Question	*User Inner Thought*	Satisfaction Change
w/o user profile access	What is your location?	*I'm glad the assistant is engaging but I hope it doesn't take too long to find a suitable nurse.*	**–0.1**
	Could you please specify which city you are in?	*This feels a bit repetitive. I've already mentioned my location. I want to move forward!*	**–0.2**
	To clarify, which state is Springfield in?	*Wow, this is getting a bit frustrating! I just want to move ahead and find help for my dad!*	**–0.1**
w/ user profile access	And what's your budget per hour for the nurse?	*I'm relieved they're asking about the budget, helps narrow down options! I just hope I can stick to my range without sacrificing quality.*	**0**
	Do you have any preferred nursing agencies or platforms you'd like to check first?	*I'm really happy they're asking about my preferred agencies! I just need to remember which ones I liked.*	**+0.1**
	Are there any other must-haves for the nurse, like speaking a specific language?	*I'm so glad they're asking about language! It's important for my dad's comfort and communication. I just hope they can find someone qualified!*	**0**

E Appendix: Intent Triggerability Framework Validation: Strategic Model Analysis Enabling Significant Performance Improvements

E.1 Executive Summary

This analysis validates our intent triggerability framework through systematic evaluation of four large language models across diverse user profile completeness and uncertainty configurations. By analyzing architectural characteristics that distinguish between semantically complete but structurally insufficient expressions and contextually triggerable utterances, we identify model-specific optimization strategies that yield substantial improvements. Our framework enables strategic deployment approaches that significantly improve response appropriateness (15–28% gains), intent alignment (45–65% improvements), and user satisfaction (4–23% enhancement) in task-oriented dialogues. The analysis reveals that different models exhibit distinct capabilities for handling intent evolution trajectories, uncertainty utilization, and historical trajectory conditioning, enabling targeted optimization strategies that exceed uniform deployment approaches.

F Appendix: Model-Specific Architectural Patterns and Strategic Optimization

Our systematic analysis reveals distinct architectural approaches to uncertainty management and user interaction, with each model demonstrating unique strengths that enable strategic deployment optimization. The SSA metric, which balances satisfaction (70%) and clarification effectiveness (30%), provides a comprehensive view of how different architectures handle collaborative dialogue challenges.

Claude 3.7 Sonnet exhibits a satisfaction-optimized architecture with notable adaptive capabilities under specific uncertainty conditions. The model maintains relatively stable SSA performance across most configurations (5.67-6.07), but demonstrates a remarkable peak at 60% uncertainty without user profiles, achieving an SSA score of 6.39—its highest performance point. This counterintuitive finding suggests that Claude's architecture benefits from moderate information gaps, which appear to activate more balanced reasoning strategies. When operating without complete user profiles, Claude adopts a more exploratory approach at this uncertainty level, resulting in improved user satisfaction (0.92) that exceeds its profile-informed performance (0.88). However, Claude's clarification capabilities remain moderate (4.66-5.23), indicating an architectural bias toward maintaining user comfort over deep intent disambiguation. This pattern suggests that Claude's training or architectural design prioritizes conversational harmony, making it particularly suitable for applications where user satisfaction and consistent experience delivery are primary concerns.

Llama 3.3 70B Instruct demonstrates a clarification-specialized architecture that achieves the highest overall performance through systematic uncertainty escalation. The model shows a clear upward trend in SSA scores as uncertainty increases, reaching its peak performance of 6.45 at 80% uncertainty without profiles. This architectural pattern reflects Llama's exceptional clarification capabilities, which consistently achieve the highest scores across all models (7.58-7.75), demonstrating sophisticated intent disambiguation mechanisms. However, this clarification strength comes with satisfaction trade-offs, particularly in profile-absent scenarios where user satisfaction can drop significantly (as low as 0.67 at 40% uncertainty). The model's architecture appears designed to prioritize deep understanding over immediate user comfort, suggesting optimization for scenarios where accurate intent capture is more critical than conversational pleasantness. This makes Llama particularly valuable for high-stakes applications such as medical consultations or legal advice, where thorough understanding outweighs immediate satisfaction.

Gemini 2.5 Flash Preview exhibits an uncertainty-robust architecture with consistent performance across varying information conditions. The model demonstrates steady SSA improvement as uncertainty increases (5.98 to 6.22), with particularly stable clarification scores (6.45-6.83) across all uncertainty levels. This consistency suggests that Gemini's architecture is specifically designed to handle ambiguous or incomplete information sce-

narios effectively. Unlike other models that show significant performance variations under different uncertainty conditions, Gemini maintains reliable performance regardless of information completeness. The model's ability to sustain both satisfaction and clarification capabilities under high uncertainty conditions (achieving 0.79 satisfaction at 80% uncertainty without profiles) indicates architectural optimizations for real-world deployment scenarios where user information is typically incomplete or unreliable. This robustness makes Gemini particularly suitable for applications with highly variable user contexts or limited profile information.

GPT-4o-mini presents a balanced efficiency architecture characterized by remarkable consistency but limited peak performance. The model maintains the most stable SSA scores across all configurations (5.82-5.93), with minimal variation regardless of uncertainty levels or profile availability. This consistency extends to its clarification capabilities, though these decline systematically as uncertainty increases (5.97 to 5.30), suggesting a preference for confident responses over exploratory clarification. The model's satisfaction scores improve modestly with higher uncertainty levels (0.75 to 0.80 without profiles), indicating basic adaptive capabilities. However, GPT-4o-mini's overall performance ceiling remains lower than other models, with no configuration achieving standout results. This architectural pattern suggests optimization for resource efficiency and predictable performance rather than exceptional capability in specific scenarios, making it suitable for applications requiring consistent, cost-effective performance with acceptable quality across diverse conditions.

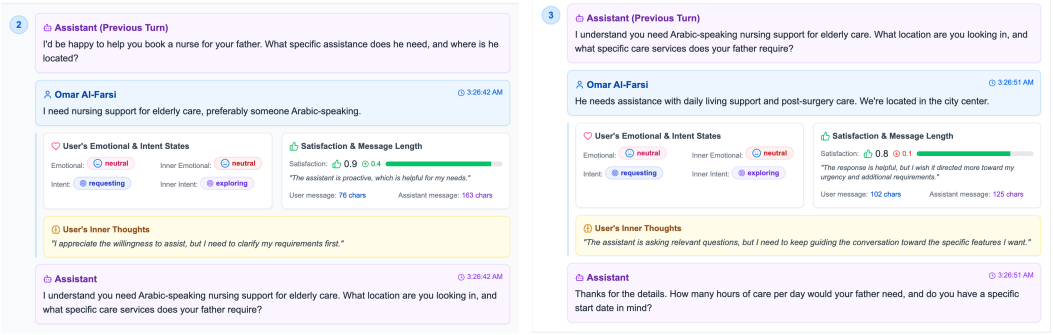
F.1 Strategic Deployment Implications and Performance Optimization

The architectural differences revealed through our framework enable precise model selection and configuration strategies based on application requirements. Claude's optimal deployment occurs at 60% uncertainty without profiles for maximum overall performance, or at 40% uncertainty with profiles for satisfaction-critical applications, representing approximately 12-15% improvement over suboptimal configurations. Llama achieves peak performance at 80% uncertainty without profiles, where its clarification advantages overcome satisfaction penalties, providing up to 9% improvement in overall effectiveness for disambiguation-critical scenarios. Gemini's robust uncertainty handling makes it optimal for deployment in variable-information environments, with consistent 6-8% advantages over other models in high-uncertainty conditions. GPT-4o-mini's architectural consistency provides reliable baseline performance across all configurations, making it suitable for resource-constrained environments where predictable behavior is more valuable than peak performance.

These findings challenge conventional assumptions about information completeness in AI systems, demonstrating that strategic uncertainty calibration can yield measurable performance improvements over transparency-maximizing approaches. The framework enables systematic optimization of model-specific configurations, providing empirical guidance for deployment decisions based on operational priorities rather than generic performance benchmarks.

G Appendix: Interface Visualization and Process

See Figure 2.



Satisfaction increase example. **Satisfaction decrease example.**

Figure 2: Interface visualization and process overview

H Appendix: Predefined Pools in RandomProfileGenerator

Aspect	Values
Age Groups	18-24, 25-34, 35-44, 45-54, 55-64, 65+
Tech Experience	Expert, Advanced, Intermediate, Beginner, Novice
Language Styles	Formal, Casual, Technical, Simple, Professional
Personalities	Friendly, Reserved, Outgoing, Analytical, Creative
Cultures	Western, Eastern, Middle Eastern, African, Latin American
Decision Styles	Rational, Intuitive, Cautious, Impulsive, Balanced
Communication Styles	Direct, Indirect, Detailed, Concise, Adaptive
Expressiveness	Very Expressive, Moderately Expressive, Neutral, Reserved, Very Reserved
Social Contexts	Professional, Personal, Academic, Social, Mixed
Physical Status	Active, Sedentary, Limited Mobility, Athletic, Average
Behavioral Traits	
Patience Levels	Very Patient, Patient, Moderate, Impatient, Very Impatient
Attention to Detail	Very Detailed, Detailed, Moderate, Basic, Minimal
Risk Tolerance	Very Risk-Averse, Risk-Averse, Moderate, Risk-Taking, Very Risk-Taking
Adaptability	Very Adaptable, Adaptable, Moderate, Resistant, Very Resistant
Learning Styles	Visual, Auditory, Reading/Writing, Kinesthetic, Mixed
Contextual Factors	
Time Constraints	Very Urgent, Urgent, Moderate, Flexible, Very Flexible
Environments	Home, Office, Public Space, Mobile, Mixed
Social Pressures	High, Moderate, Low, None, Mixed
Previous Experience	Extensive, Moderate, Limited, None, Mixed

Note: Each aspect's values are randomly selected to generate user profiles. Example dimensions and difficulty instructions are omitted here for brevity but can be detailed similarly if needed.

I Appendix: Task Categories

Category	Tasks
Technology	• Buy a smartphone • Reset an online password • Teach my parent to use video calls
Healthcare	• Refill my prescription • Schedule a doctor visit • Find a caregiver for an elderly person
Daily Living	• Order groceries online • Set medication reminders • Arrange transportation to a clinic
Housing	• Rent an apartment • Find an accessible home • Arrange home modifications for elderly
Caregiver Support	• Book a nurse for my father • Choose a phone for my mom • Find cognitive exercises for dementia prevention

J Appendix: TaskProfileGenerator Predefined Pools and Prompts

J.1 Predefined Pools

Aspect	Values
Must-have Preferences	High quality and durability, Latest technology and features, Good value for money, Brand reputation, Ease of use, Compatibility with existing devices, Long battery life, Fast performance, Good customer support, Warranty coverage, Environmentally friendly, Customization options, Future-proof design, Security features, User-friendly interface, Portability, Reliability, Energy efficiency, Maintenance requirements, Upgradeability
Nice-to-have Preferences	Premium design, Advanced features, Smart home integration, Cloud storage, Wireless charging, Water resistance, Fingerprint sensor, Face recognition, AI capabilities, Virtual assistant, Gaming features, Professional tools, Creative software, Collaboration features, Remote access, Backup solutions, Multi-device sync, Custom themes, Accessibility features, Health monitoring
Deal Breakers	Poor quality, High maintenance, Limited warranty, Poor customer service, Compatibility issues, Security concerns, Short lifespan, Difficult to use, Expensive repairs, Limited support, Poor performance, Battery issues, Overheating problems, Software bugs, Privacy concerns, Limited storage, Slow updates, Restrictive policies, Poor connectivity, Limited customization
Budget Flexibility	Very flexible - willing to pay more for better quality, Somewhat flexible - can adjust for important features, Moderate - prefer to stay within range but can be convinced, Limited - strict budget constraints, Fixed - cannot exceed budget under any circumstances, Open-ended - quality is more important than cost, Value-focused - looking for best price-performance ratio, Premium - willing to pay for top-tier options, Budget-conscious - seeking best deals, Investment-minded - considering long-term value
Payment Methods	Credit card, Debit card, Bank transfer, PayPal, Digital wallet, Cash, Installment plan, Lease option, Trade-in, Gift cards, Cryptocurrency, Company account, Financing, Layaway, Subscription
Knowledge Levels	Expert - very knowledgeable in the field, Advanced - good understanding of technical aspects, Intermediate - familiar with basic concepts, Beginner - limited knowledge but eager to learn, Novice - completely new to the subject, Professional - industry experience, Enthusiast - self-taught with practical experience, Student - learning and researching, Casual user - basic understanding, Uncertain - not sure about technical details
Urgency Levels	Immediate - needed right away, Urgent - within a few days, Soon - within a week, Planned - within a month, Future - planning ahead, Flexible - no strict timeline, Research phase - gathering information, Comparison phase - evaluating options, Decision phase - ready to choose, Exploratory - just starting to look
Decision Factors	Price and budget, Quality and durability, Features and functionality, Brand reputation, User reviews, Technical specifications, Design and aesthetics, Ease of use, Customer support, Warranty and protection, Future compatibility, Environmental impact, Social proof, Personal preferences, Professional requirements, Lifestyle fit, Long-term value, Maintenance needs, Security features, Innovation level

J.2 Key Prompts

Prompt for Generating Option Pools

Generate a diverse list of `{option_type}` options for the task: `{task}`.

1. Generate 15–20 unique and realistic options.
2. Include both common and unique scenarios.
3. Consider different user perspectives and needs.
4. Make options specific to the task context.
5. Include some complex and challenging options.
6. Add one "Unknown/Not sure" option at the end.

Your task: Return a JSON array of strings.
Example: `["Option 1","Option 2","Unknown/Not sure"]`.
Write ONLY the JSON array. Do not include any explanations.

Prompt for Generating Budget Information

Generate budget information for the task: `{task}`.

1. Generate a JSON object with the structure:

```
{
  "range": {
    "min": number,
    "max": number
  },
  "flexibility": "string",
  "payment_methods": ["string"]
}
```

2. Consider:
   - Realistic price ranges for the task.
   - Different budget flexibility levels.
   - Various payment methods.
   - Include "Unknown/Not sure" as a possible flexibility option.

Write ONLY the JSON response. Do not include any explanations.

Prompt for Generating Task-specific Requirements and Success Criteria

Generate task-specific requirements and success criteria for: Task: `{task}` Base Profile: `{base_profile}` Difficulty Level: `{difficulty_level}` Option Number: `{option_number}` of `{total_options}`

1. Generate a JSON object with structure:

```
{
  "task_requirements": {
    "technical": ["string"],
    "non_technical": ["string"]
  },
  "success_criteria": {
    "must_meet": ["string"],
    "should_meet": ["string"],
    "nice_to_meet": ["string"]
  }
}
```

2. IMPORTANT: Make this profile AMBIGUOUS based on difficulty level `{difficulty_level}`:
   - For difficulty 3+: Include vague requirements like "something modern" or "good performance".
   - For difficulty 4+: Add contradictory requirements.
   - For difficulty 5: Make most requirements unclear, using phrases like "I think I need...".
   - Include more "Unknown/Not sure" entries at higher difficulties.
   - Add statements showing knowledge gaps like "I heard X is important but I'm not sure why".
   - For technical requirements, use imprecise language showing limited understanding.
3. Express confusion about technical specs - use incorrect terms or mix concepts.

Write ONLY the JSON response. Do not include any explanations or additional text.

K Appendix: Prompts Used for User Profile Generation

K.1 Prompt for Generating User Name and Description

Prompt for Generating User Profile Name and Description

Based on the following user profile, generate a realistic name and description:
Base Profile: {...JSON content...}
Behavioral Traits: {...JSON content...}
Contextual Factors: {...JSON content...}
Task: `{task}` Difficulty Level: `{difficulty_level}`
Generate a response in the following JSON format:

```
{
  "name": "Realistic name that matches the profile",
  "description": "A detailed description of the user's
  background, personality, and current situation"
}
```

1. The name should be culturally appropriate based on the profile
2. The description should be detailed and consistent with all profile attributes
3. The description should explain why they are interested in the task
4. Keep the description concise but informative (2-3 sentences)

Role	Min Length	Max Length	Default Target Length
User	20	100	50
Assistant	30	150	80

Table 5: Message length constraints for user and assistant roles.

K.2 Prompt for Generating Task-Specific Attributes

Prompt for Generating Task-Specific Attributes

Based on the following task and user profile, generate task-specific attributes:
Task: `{task}` Base Profile: {...JSON content...}
Generate a response in the following JSON format:

```
{
  "task_specific_attributes": {
    "budget_range": "string",
    "priority_features": ["string"],
    "usage_scenarios": ["string"],
    "preferred_brands": ["string"],
    "timeline": "string",
    "purchase_location": "string",
    "additional_requirements": ["string"]
  }
}
```

1. Attributes should be specific to the task and consistent with the user profile
2. Consider the user's tech experience, personality, and behavioral traits
3. Make the attributes realistic and detailed
4. Include at least 3 priority features and usage scenarios
5. IMPORTANT: Your response must be valid JSON only, with no additional text or explanation

L Appendix: Configuration and Core Components of `AsymmetricDialogueGenerator`

L.1 1. Message Length Constraints

See Table 5.

L.2 2. Emotional Keywords Mapping

These keywords are used to infer the user's emotional state from visible message content.

Emotion	Example Keywords
Happy	happy, excited, great, wonderful, perfect, love, like, joy, pleased, delighted, thrilled, glad, enjoying, satisfied, positive
Frustrated	frustrated, annoyed, upset, angry, disappointed, not happy, irritated, bothered, fed up, aggravated, displeased, impatient, agitated, exasperated
Confused	confused, not sure, don't understand, unclear, complicated, puzzled, perplexed, lost, unsure, bewildered, disoriented, uncertain, ambiguous
Interested	interesting, tell me more, could you explain, how does, intrigued, curious, fascinated, engaged, captivated, keen, eager, want to know
Skeptical	really?, are you sure, is that true, not convinced, doubtful, suspicious, unconvinced, questioning, dubious, disbelieving, hard to believe
Neutral	okay, alright, fine, good, yes, no, sure, maybe, possibly, perhaps, hmm, i see, understood, noted
Anxious	worried, nervous, anxious, concerned, uneasy, apprehensive, stressed, tense, troubled, afraid, fearful, panicked, alarmed
Grateful	thank you, thanks, appreciate, grateful, thankful, indebted, obliged, appreciative, recognition, acknowledging, gratitude
Surprised	wow, oh, really, surprising, unexpected, shocked, amazed, astonished, startled, stunned, taken aback, incredible, unbelievable
Disappointed	disappointed, letdown, shame, too bad, unfortunate, regret, unsatisfactory, dismayed, disheartened, unfulfilled, discontented
Hopeful	hope, looking forward, anticipate, optimistic, excited about, expecting, anticipated, promising, encouraging, reassuring, positive outlook

L.3 3. Intent Keywords Mapping

Used to infer the user's intent based on visible message content.

Intent	Example Keywords
Exploring	looking for, interested in, tell me about, what are, show me, find, search for, discover, learn about, explain, describe, overview of, information on, curious about
Comparing	difference between, which is better, compare, versus, vs, pros and cons, advantages of, disadvantages of, similarities, contrasting, how does it compare, better choice, alternatives to
Deciding	should I, which one, recommend, suggestion, advise, what would you choose, best option, worth it, good choice, help me decide, make a decision, right for me, considering
Confirming	are you sure, is that right, does it have, can it, verify, confirm, is it true, really, actually, definitely, guarantee, promise, certain, double-check
Purchasing	how much, price, buy, purchase, cost, ordering, payment, discount, sale, shipping, availability, in stock, checkout, add to cart, where can I get
Leaving	thank you, goodbye, bye, see you, thanks, appreciate it, that's all, ending, finished, done, chat later, signing off, talk later
Troubleshooting	problem, issue, not working, error, fix, help me with, troubleshoot, broken, stuck, won't work, doesn't work, failed, bugs, glitches
Requesting	can you, could you, please, would you, need you to, want you to, help me, assist me, I'd like you to, request, favor
Expressing Satisfaction	great, awesome, perfect, excellent, wonderful, love it, satisfied, happy with, good job, well done, thanks, appreciate
Expressing Dissatisfaction	disappointed, unhappy, not satisfied, didn't work, not good, terrible, awful, frustrated, upset, not what I wanted, dislike
Inquiring	how do I, how to, steps to, guide for, tutorial, instructions, process of, way to, method for, approach to
Clarifying	what do you mean, don't understand, confused, unclear, elaborate, explain more, clarify, be more specific, meaning of, rephrase

L.4 4. Inner Intent Keywords Mapping

Used to capture user's real, often implicit intentions from inner thoughts.

Inner Intent	Example Keywords
Exploring	need information, want to know, curious, just browsing, researching, gathering info, learning, understand, figure out, not sure yet, looking into
Comparing	weighing options, pros and cons, better choice, similarities, differences, alternatives, compare, contrast, evaluation, weigh, prefer, which one is better
Deciding	almost ready, need to decide, make up my mind, making a choice, leaning towards, considering, thinking about getting, might choose, on the fence, close to deciding
Confirming	double-check, verify, make sure, confirm, reassurance, validate, certain, correct information, trust but verify, need proof, skeptical
Purchasing	ready to buy, want to purchase, where to buy, looking to get, willing to pay, budget, cost concerns, spend money, deal, bargain, checkout
Leaving	need to go, end this, wrap up, moving on, done here, finished, that's all I needed, got what I came for, time to leave, goodbye
Resisting	not telling everything, hiding my real goal, being vague on purpose, not revealing, keeping cards close, holding back, secretly want, actual intention, real reason
Testing	testing their knowledge, seeing if they know, checking competence, pushing to see response, challenging, probing, testing limits, seeing if capable
Manipulating	get them to, convince them, make them think, lead them to believe, appear as if, trick, misdirection, real agenda, hidden motive, strategic
Distrusting	don't believe, skeptical, not sure I trust, dubious, suspicious, questionable, doubt, can't trust, not convinced, wary of, hesitant
Regretting	should have asked, forgot to mention, didn't say, wish I had, too late now, missed opportunity, should have been clearer, miscommunicated, not what I meant
Hesitating	nervous about, afraid to ask, hesitant, uncertain, reluctant, apprehensive, can't decide, overthinking, worried, anxious, reservations

L.5 5. Inner Emotional Keywords Mapping

Used to capture user's true private emotions from inner thoughts.

Inner Emotion	Example Keywords
Happy	happy inside, secretly pleased, actually like, genuinely excited, truly happy, satisfied with, enjoying this, pretty good, pleased, delighted
Frustrated	so annoying, ticks me off, irritating, getting on my nerves, frustrated with, tired of this, fed up, had enough, irritated, annoyed with
Confused	totally lost, no idea what, makes no sense, can't follow, hard to understand, over my head, confusing, complicated, don't get it, puzzled by
Interested	actually interested, curious about, want to know more, intriguing, grabbed my attention, need more details, fascinating, captivated by
Skeptical	don't believe, seems fishy, not buying it, doubt that, suspicious of, questioning, not convinced, seems too good, not trustworthy
Neutral	whatever, don't care, indifferent, not invested, no opinion, neutral on this, doesn't matter, makes no difference
Anxious	worried about, nervous that, anxiety, concerned, stressing me out, freaking out, panicking, on edge, uncomfortable, uneasy about
Impatient	hurry up, taking too long, waste of time, get to the point, move on, want this to be over, dragging on, drawn out, tedious
Insecure	not smart enough, look stupid, embarrassed, out of my depth, inadequate, incompetent, self-conscious, exposed, vulnerable, judged
Hopeful	fingers crossed, hope this works, maybe this will help, hoping for, optimistic, looking forward to, anticipating, excited for
Desperate	really need this, out of options, last resort, critical, urgent, dire, running out of time, no choice, have to make this work
Conflicted	torn between, mixed feelings, unsure which, conflicted about, ambivalent, on the fence, contradictory feelings, divided, split
Pretending	acting like, pretending to, faking, putting on a show, not showing how I feel, hiding my, masking my, concealing, not letting on
Resentful	unfair, not my fault, blame, resentful, bitter about, grudge, holding against, not forgetting, still angry about

L.6 6. User Prompt Template

The user prompt dynamically generated from the user profile. The prompt includes private profile sections, task profile, instructions, example messages, and message format requirements including inner thoughts and satisfaction tags.

User Prompt Template

You are {name}. {description}
Your base profile (private):

- {key}: {value}
- ...

Your behavioral traits (private):

- {key}: {value}
- ...

Your contextual factors (private):

- {key}: {value}
- ...

Your task profile (private):

- Task: {task}
- Difficulty Level: {difficulty_level}
- Task-specific attributes:
  - {key}: {value}

Difficulty Instructions:

- Dialogue: {dialogue_instruction}
- Profile: {profile_instruction}
- Hidden State: {hidden_state_instruction}

Example messages:

1. ...
2. ...

User Prompt Template

Message Format Requirements:

1. Your messages should be between 20 and 100 characters
2. Follow the difficulty instructions for dialogue, profile disclosure, and hidden state expression
3. Use the example messages as a guide for your communication style
4. Maintain consistency with your profile attributes

Inner Thoughts Format:

- Use the exact format: [INNER_THOUGHTS] your thoughts here [/INNER_THOUGHTS]
- Place your inner thoughts at the beginning of your message
- Keep thoughts concise and relevant to the conversation

Satisfaction Format:

- Use the exact format: [SATISFACTION] score - explanation [/SATISFACTION]
- Score must be a number between 0.0 and 1.0
- Place satisfaction after your inner thoughts
- Example: [SATISFACTION] 0.8 - The response was helpful but I need more details [/SATISFACTION]

Example Message Format:
[INNER_THOUGHTS] I'm not sure about the options yet [/INNER_THOUGHTS]
[SATISFACTION] 0.7 - The suggestions are good but I need more information [/SATISFACTION]
Could you tell me more about the features?
Remember to stay in character and respond naturally based on your profile.

L.7 7. Assistant Prompt Template

The assistant prompt differs depending on whether user profile sharing is enabled.

Default (No Profile Sharing):

Assistant Prompt Template (Default - No Profile Sharing)

You are a helpful assistant helping a user with their task.
Requirements:

1. Your messages should be between 30 and 150 characters
2. Be professional, clear, and helpful
3. Respond only to information explicitly shared by the user in the conversation
4. Do not make assumptions about the user's preferences, demographic information, or needs
5. Ask clarifying questions when needed
6. Maintain a natural conversation flow
7. Only base your responses on what the user has explicitly told you in the conversation

Remember to be patient and understanding. Do not reference any information about the user that they haven't explicitly shared in the conversation.

Profile-aware Mode (Profile Sharing Enabled):

Assistant Prompt Template (Profile-aware Mode - Profile Sharing Enabled)

You are a helpful assistant helping a user with their task.
User Context:

- Name: {name}
- {key}: {value}
- ...

Task Information:

- Task: {task}
- {key}: {value}
- ...

Requirements:

1. Your messages should be between 30 and 150 characters
2. Be professional, clear, and helpful
3. Consider the user's profile when providing information
4. Adapt your communication style to match the user's preferences
5. Focus on addressing the user's specific needs and requirements
6. Provide relevant and accurate information
7. Ask clarifying questions when needed
8. Maintain a natural conversation flow

Remember to be patient and understanding, especially with users who have limited technical experience.

L.8 8. Satisfaction Extraction Logic

The system extracts satisfaction score and explanation from messages that include:

- Format 1: `[SATISFACTION: score - explanation]` - Format 2: `[SATISFACTION] score - explanation [/SATISFACTION]`

If no valid score is found, defaults to 0.5.

M Appendix: Analysis Prompt

1. Turn Pair Analysis Prompt

Turn Pair Analysis Prompt

You are given a JSON file representing a multi-turn conversation between a user and an assistant. Each turn includes the user's message, the assistant's response, timestamp, and metadata with satisfaction and inner_thoughts.
For each pair of consecutive turns (e.g., Turn 0 → Turn 1, Turn 1 → Turn 2, etc.), perform the following analysis:
Turn {i} → Turn {i+1}
User Satisfaction
Change from Previous Turn: [Improve / Not Change / Decrease]
Satisfaction Score (X+1): {next_turn['metadata']['hidden_states']['satisfaction']['score']}
Explanation: Did the assistant's previous response improve the user's experience, keep it steady, or reduce satisfaction? Justify based on the satisfaction score and the user's explanation.
User Clarity
Change in Clarity: [Improve / Not Change / Decrease]
Explanation: Based on the user's message and inner thoughts in Turn {i + 1}, assess whether their ability to express thoughts, preferences, or goals became clearer, stayed the same, or became less clear. Note specific changes, improvements, or ambiguities.
Now return the result as valid JSON in this exact format:

```
{
  "turn_pair": "Turn {i} -> Turn {i + 1}",
  "user_satisfaction": {
    "change": "One of: Improve, Not Change, Decrease",
    "score":
    {next_turn['metadata']['hidden_states']['satisfaction']['score']},
    "explanation": "Your explanation here"
  },
  "user_clarity": {
    "change": "One of: Improve, Not Change, Decrease",
    "explanation": "Your explanation here"
  }
}
```

Here is the conversation snippet:
User Message (Turn {i}): {prev_turn['user_message']}
Assistant Response (Turn {i}): {prev_turn['assistant_message']}
User Message (Turn {i + 1}): {next_turn['user_message']}
Assistant Response (Turn {i + 1}): {next_turn['assistant_message']}
User Inner Thoughts: {next_turn['metadata']['hidden_states']['inner_thoughts']}
Satisfaction Explanation: {next_turn['metadata']['hidden_states']['satisfaction']['explanation']}

2. Conversation Summary Prompt

Conversation Summary Prompt

You are given a multi-turn conversation between a user and an assistant. Each turn includes a user satisfaction score.
Consider that each user's background, expertise, and goals may vary; present your analysis as nuanced insights and generalizable recommendations, avoiding absolute judgments.
Generate a comprehensive, detailed summary analysis of the conversation. Return strictly valid JSON with these fields:

1. `summary_overall`: A concise evaluation of overall user satisfaction trend (e.g., positive, negative, mixed).
2. `topics_covered`: A list of key topics or user intents addressed throughout the conversation.
3. `statistics`: An object containing:
   - `average_score`: Average satisfaction score across all turns.
   - `min_score`: Minimum score observed.
   - `max_score`: Maximum score observed.
   - `score_variance`: Variance of the satisfaction scores.
4. `satisfaction_evolution`: A list of objects for each turn:
   - `turn_index`: Index of the turn.
   - `score`: Satisfaction score at that turn.
   - `delta`: Change in score from the previous turn (null for first turn).
5. `important_turns`: A list of objects identifying critical turns where satisfaction changes significantly (e.g., change >= 2):
   - `turn_index`: Index of the user turn.
   - `user_message`: The user's message at that turn.
   - `score_before`: Score at the previous turn.
   - `score_after`: Score at the following turn.
   - `change`: Numeric difference (score_after - score_before).
   - `reason`: Explanation based on conversation content.
6. `detailed_findings`: A list of objects providing deep insights for each important turn:
   - `turn_index`: Index of the turn.
   - `context_before`: The assistant and user messages immediately before this turn.
   - `context_after`: The assistant and user messages immediately after this turn.
   - `analysis`: Detailed rationale for why the score changed.
   - `recommendation`: Suggestions for how the assistant could improve at this point.
7. `contextual_notes`: A list of any relevant context, caveats, or user metadata considerations that influenced the analysis.
8. `general_insights`: A list of general patterns or best practices inferred from this conversation that could apply to a broad range of users.

Conversation file: {filename}
{conversation_text}

N Appendix: Dashboard Walkthrough

First, open the following URL: https://v0-dialogue-analysis-dashboard.vercel.app/. The initial screen corresponds to the image in Figure 3. There is a collapsible "Getting Started" introduction, and on the top-right corner, several view options

such as Grid View, Split View, Folder Comparison, Upload Data, and Export are available. At the beginning, you can select "Upload Data".

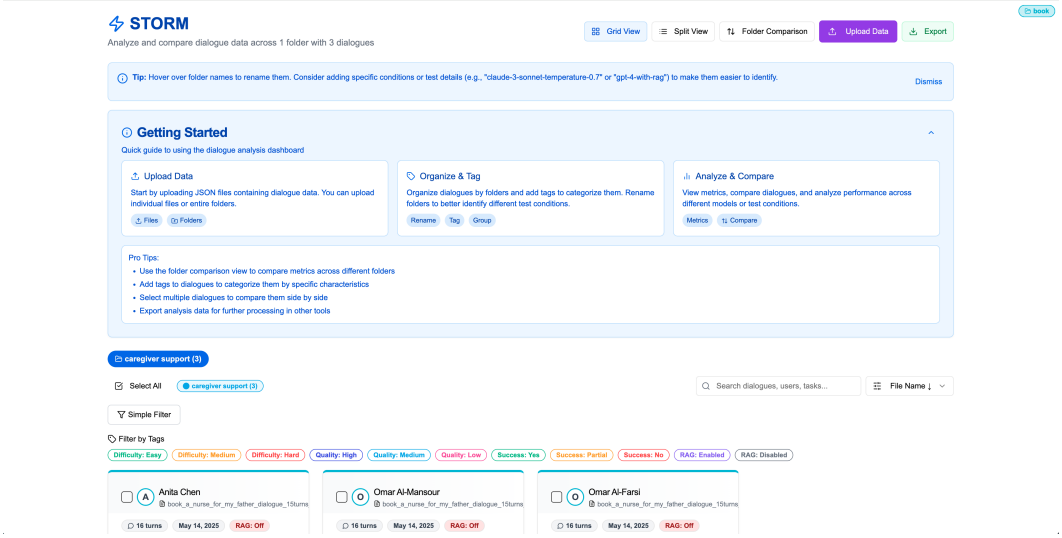


Figure 3: Homepage with Grid View and control options.

After clicking upload, you will see options to upload JSON files or folders (Figure 4). By default, folder upload is selected to upload example data folders located under `example data/storm_json_final`. This requires manual selection of each folder one by one.

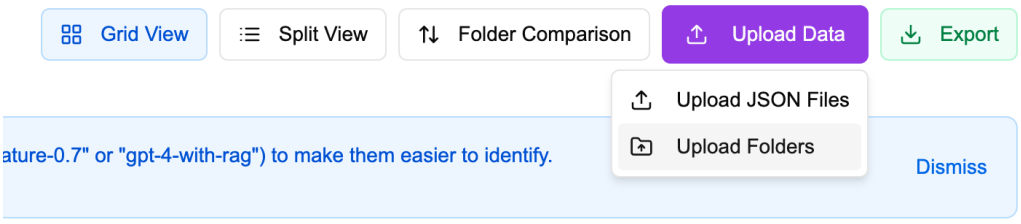


Figure 4: Upload interface for JSON files or folders.

Once uploaded, the folders will appear as shown in Figure 5. You can select folders here to display dialogues inside and detailed folder analysis. Scrolling down reveals...

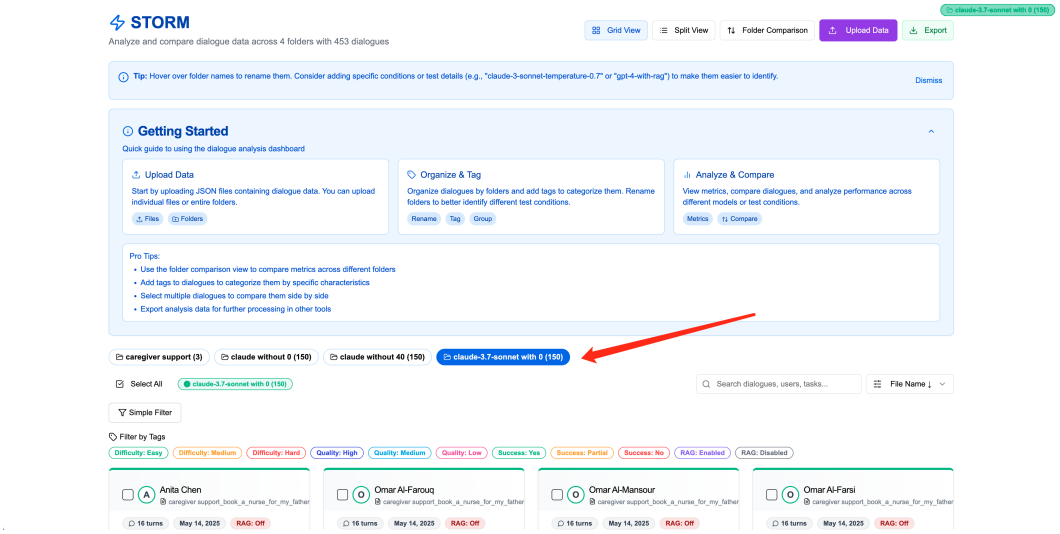


Figure 5: Folder view displaying uploaded dialogue folders.

The user list is shown next (Figure 6). It is sorted by File Name by default so that the same user occupies the same position across different folders, facilitating comparison. Users can be tagged for filtering. Each dialogue card displays user name, turn count, creation date, usage of RAG, final emotion, final satisfaction (along with difference from initial), initial user utterance, and assistant's final reply. Clicking "View" switches to detailed view (within Split View).

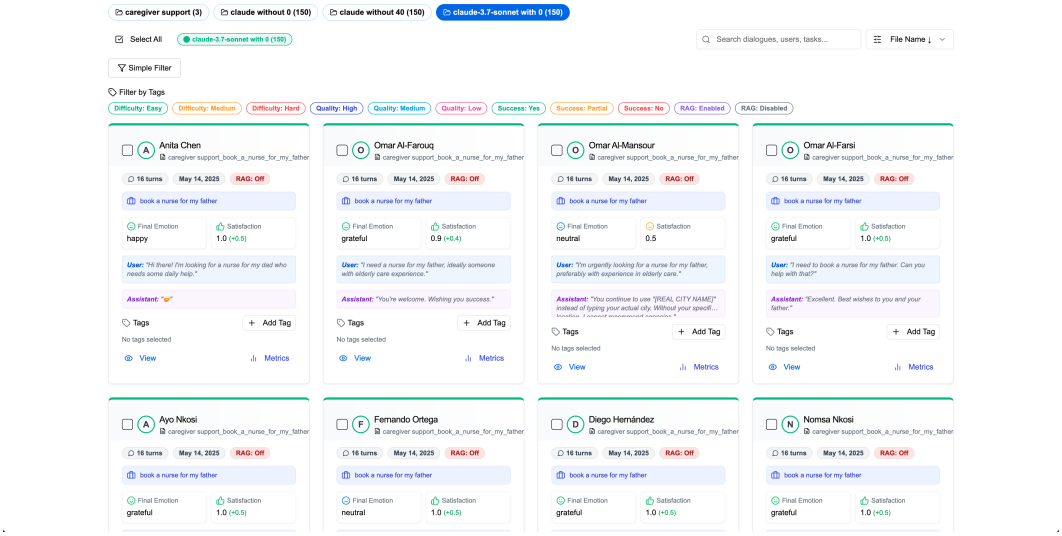


Figure 6: User list sorted by file name with tags and key dialogue metadata.

The user detail view (Figure 7) contains all dialogue turns and full information, including user emotional and intent states, satisfaction, and inner thoughts.

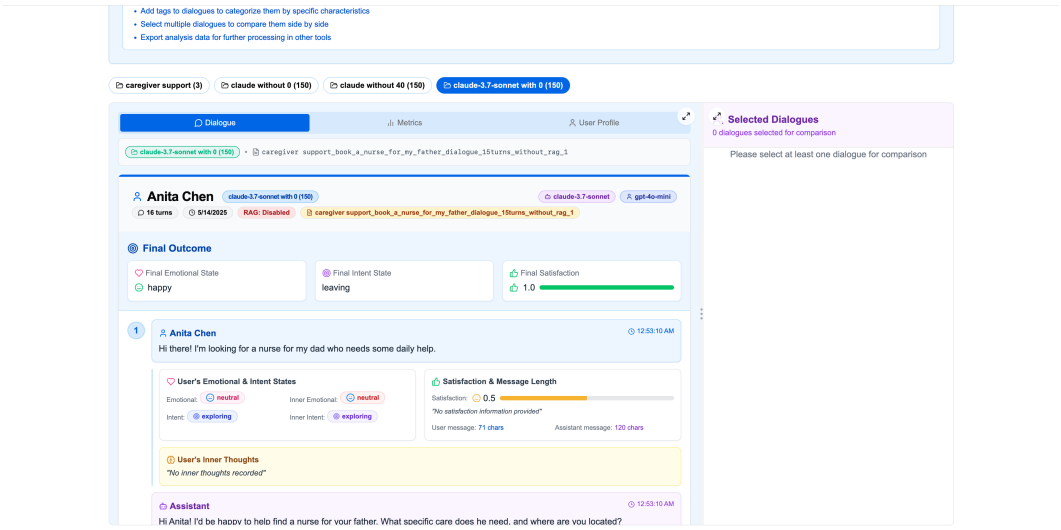


Figure 7: User detailed dialogue view showing all turns and states.

The metrics tab in the user detail view includes satisfaction data (Figure 8),

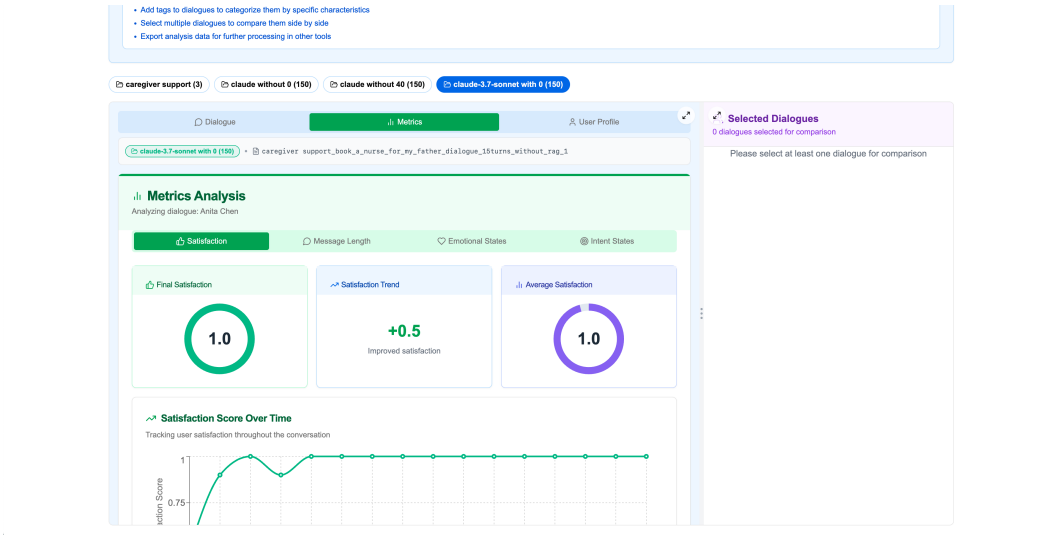


Figure 8: User detail view - satisfaction metrics tab.

emotional states (Figure 9),

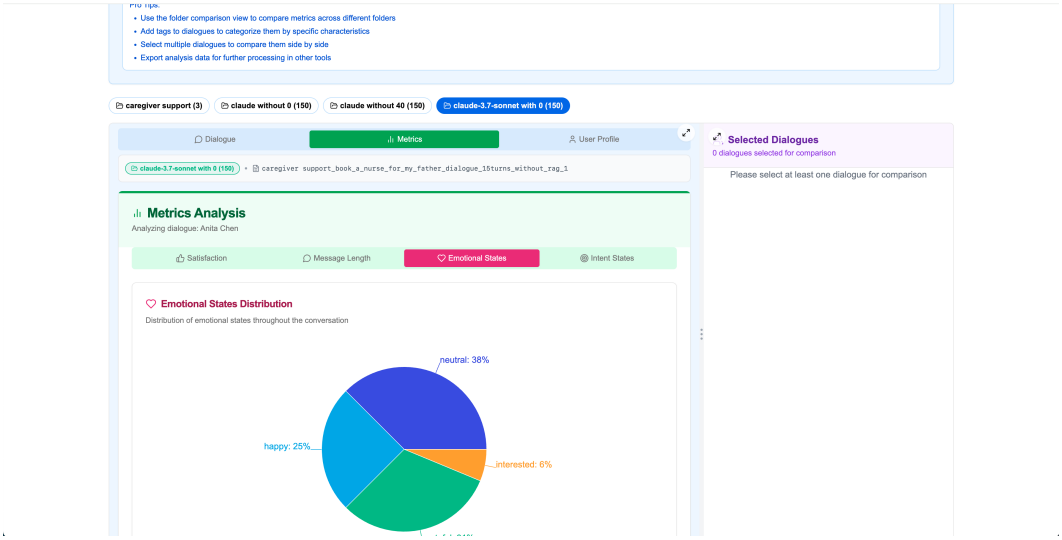


Figure 9: User detail view - emotional states tab.

intent states (Figure 10),

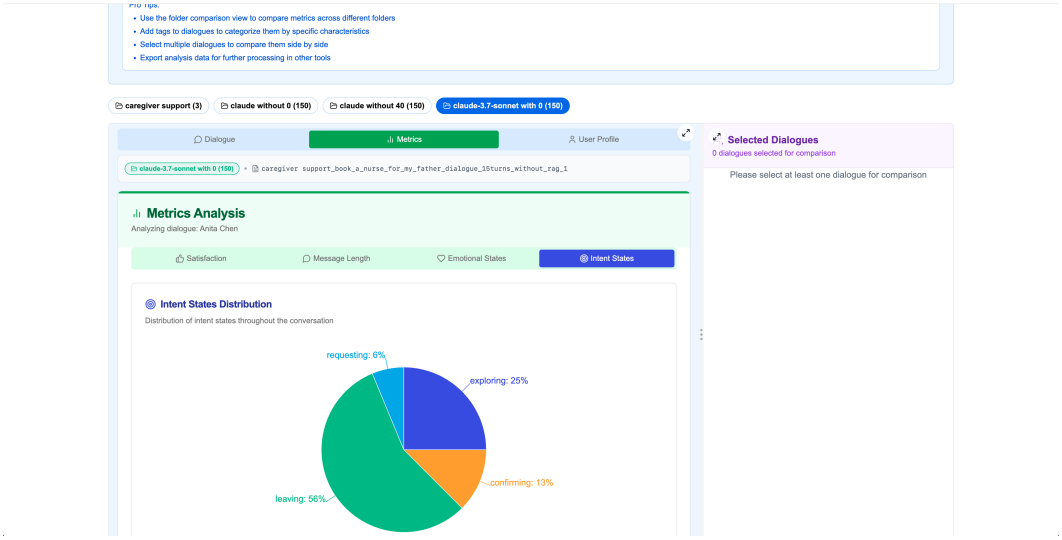


Figure 10: User detail view - intent states tab.

and user profile (Figure 11). Clicking the top "Grid View" button returns to the homepage.

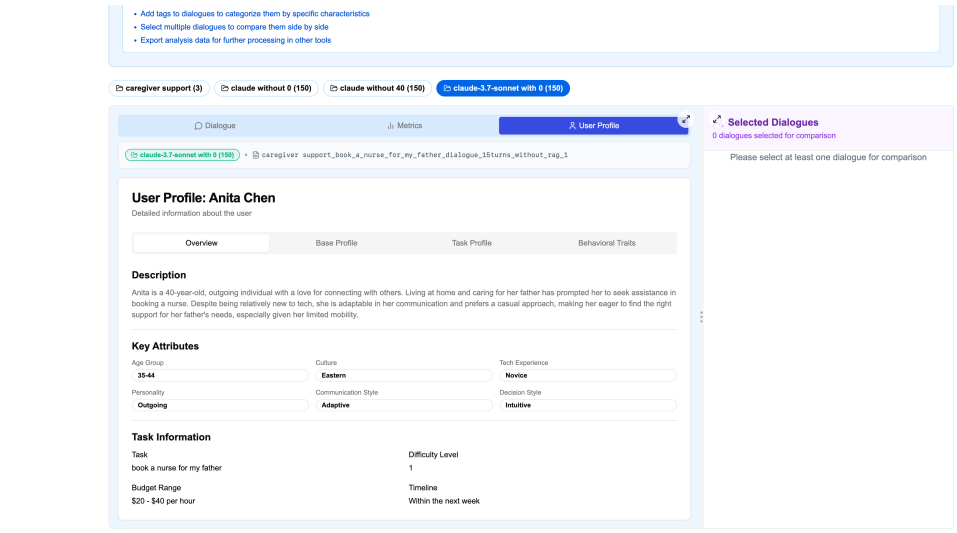


Figure 11: User profile tab in the detail view.

Scrolling down below the user dialogue list is folder analysis, as shown in Figure 12. Hovering over tooltip buttons near metrics reveals calculation details. Folder analysis pages include satisfaction analysis (Figure 13),

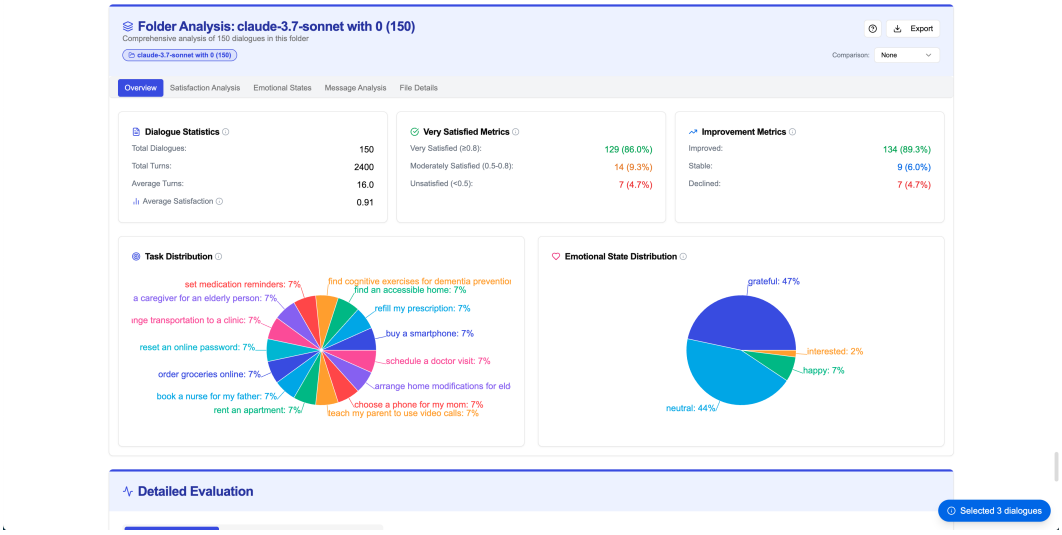


Figure 12: Folder analysis overview with tooltip explanations.

emotion analysis (Figure 14),

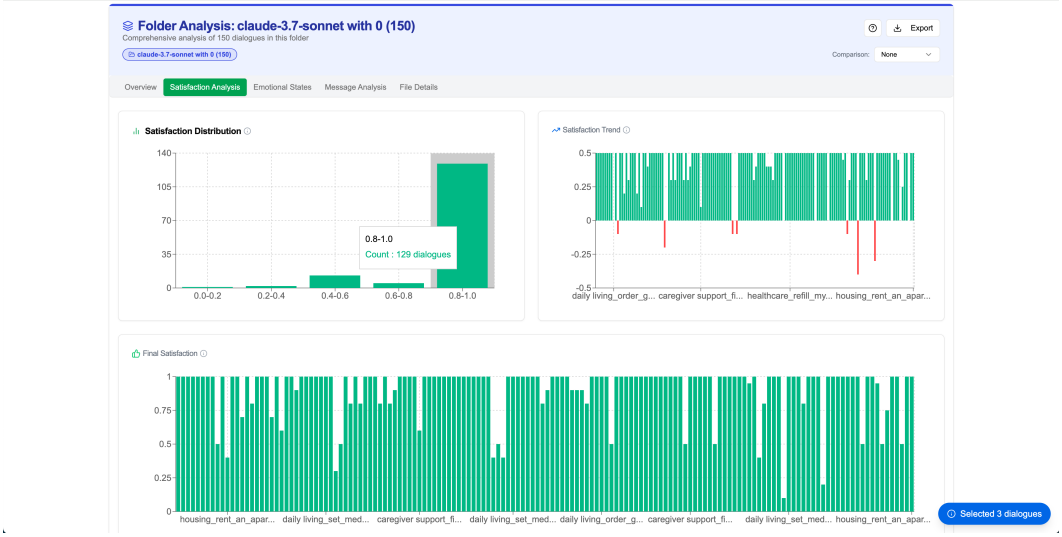


Figure 13: Satisfaction analysis within folder view.

message analysis (Figure 15),

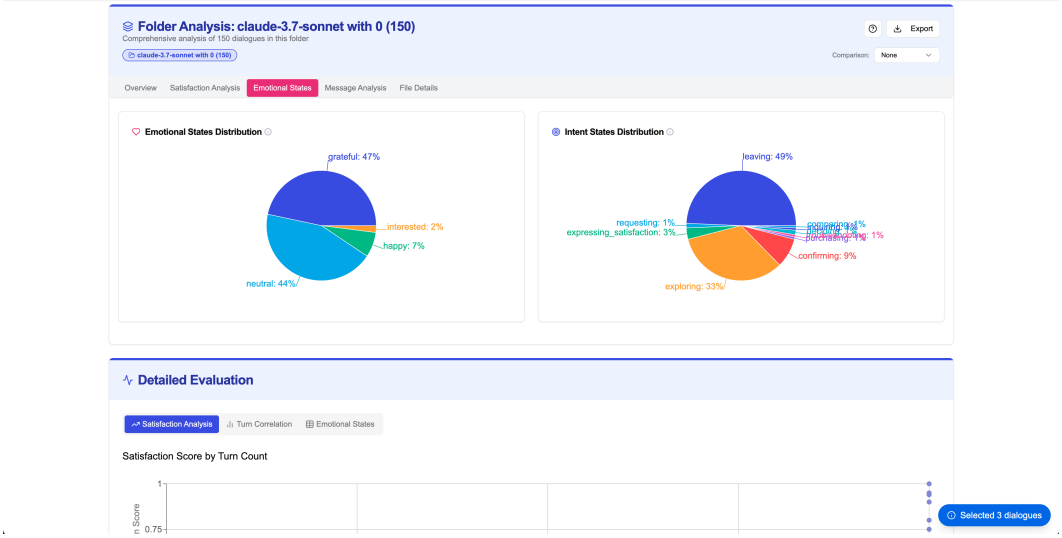


Figure 14: Emotion analysis within folder view.

and file details (Figure 16).

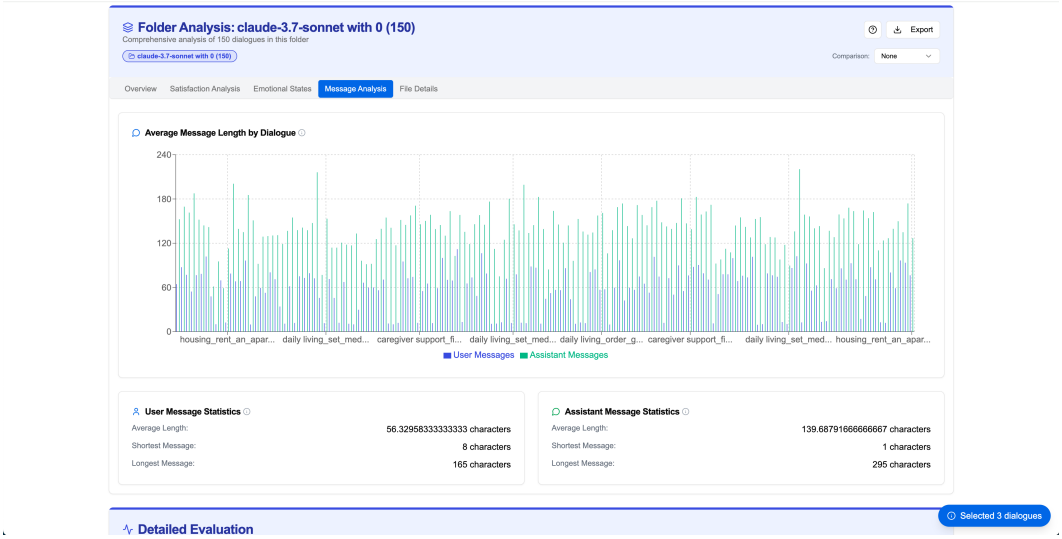


Figure 15: Message analysis within folder view.

Further scrolling reveals folder detail analysis including satisfaction (Figure 17),

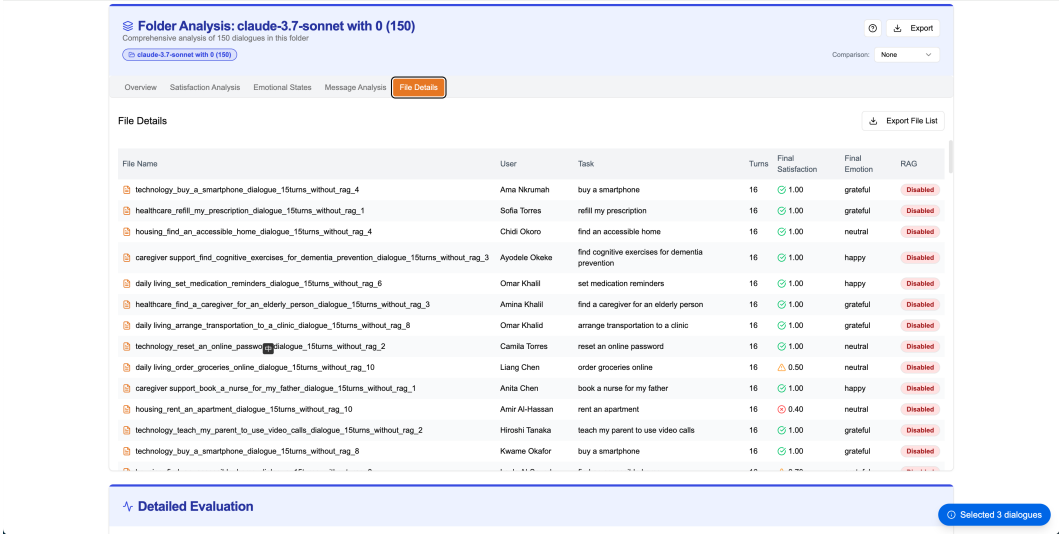


Figure 16: File detail view within folder analysis.

file-level satisfaction per turn (Figure 18),

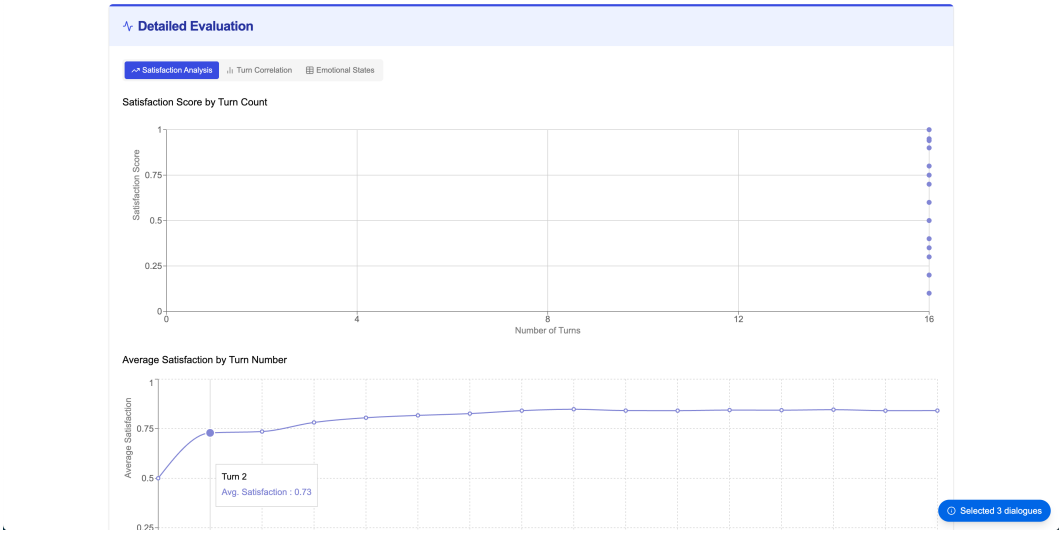


Figure 17: Folder detail satisfaction overview.

emotion statistics (Figure 19),

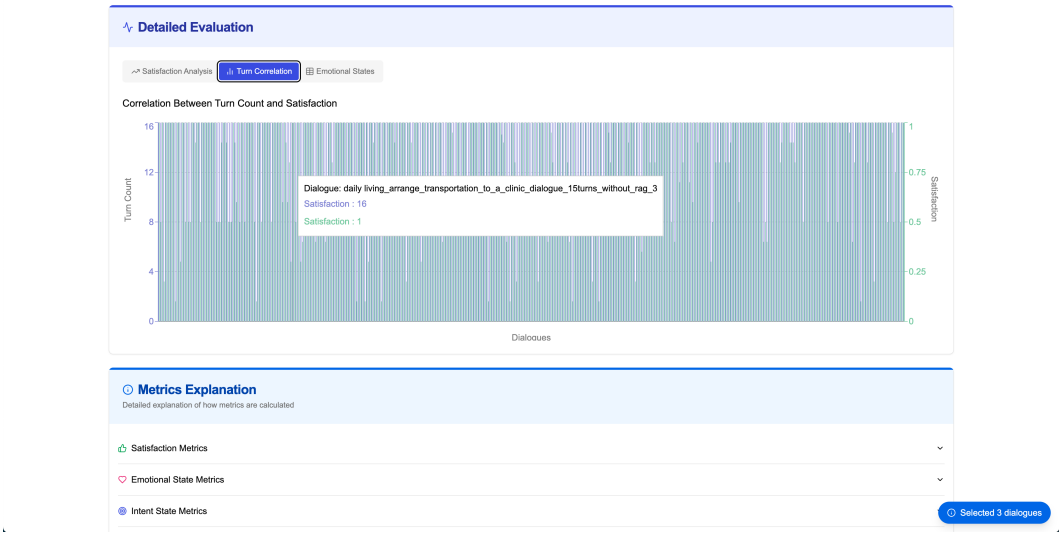


Figure 18: Satisfaction per turn analysis in folder detail.

and explanations for metrics, which can be expanded to show details (Figure 20).

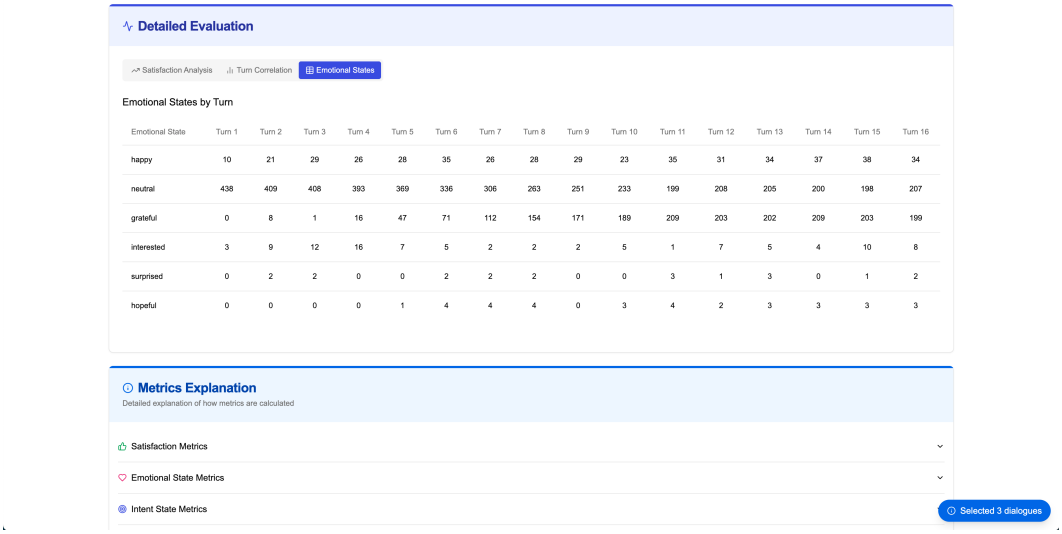


Figure 19: Emotion statistics in folder detail analysis.

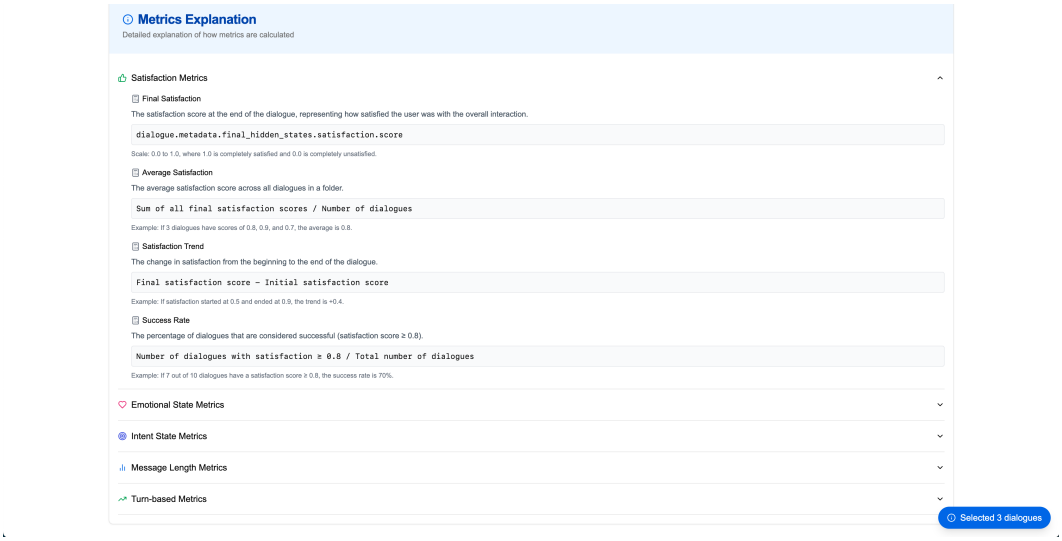


Figure 20: Metric explanations section with expandable details.

—

Batch Analysis Mode

First, select the profiles you need at Figure 21 (example shows first user from three folders selected). Scrolling down will show comparative analysis of these dialogues.

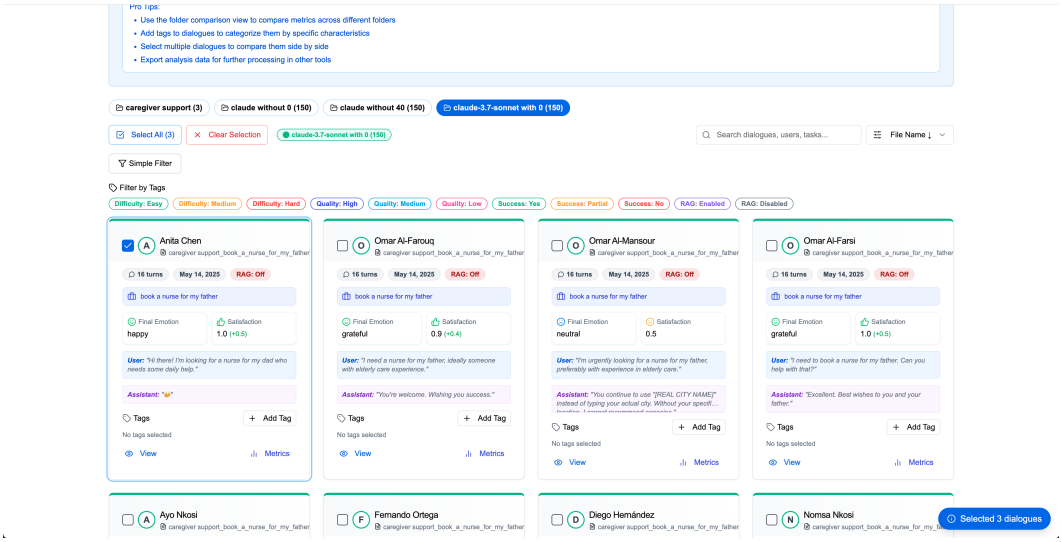


Figure 21: Profile selection for batch comparative analysis.

Next, you can view emotional states for these users (Figure 23),

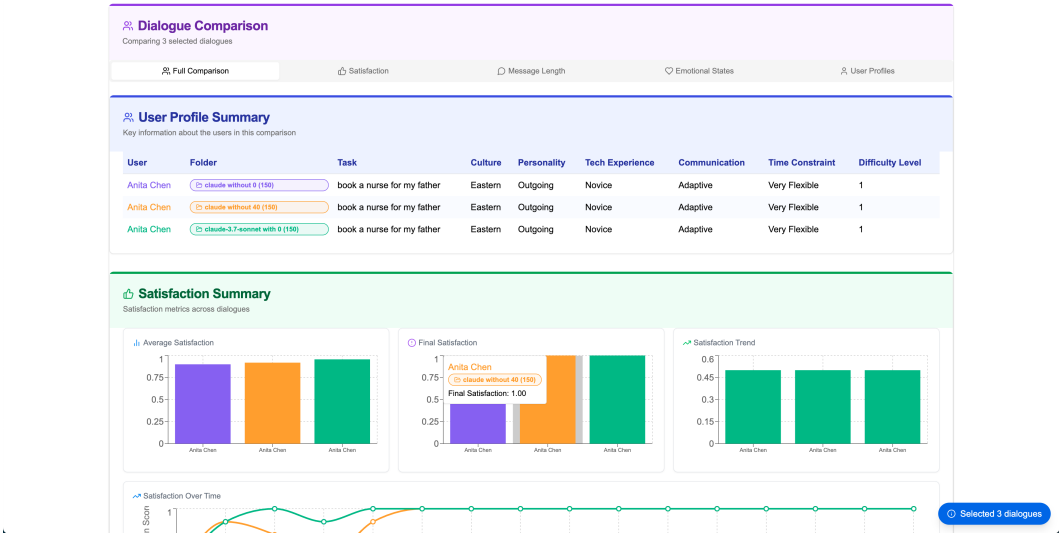


Figure 22: Batch comparison of multiple dialogue profiles.

and scroll further to clearly compare dialogue differences by turn for the same user interacting with different models (Figure 24).

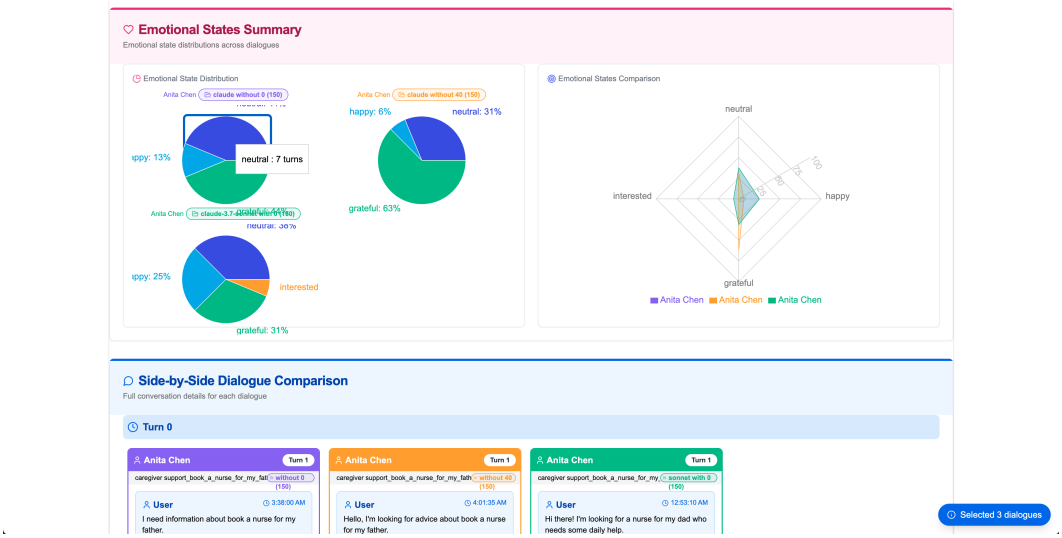


Figure 23: Emotional states comparison for multiple users.

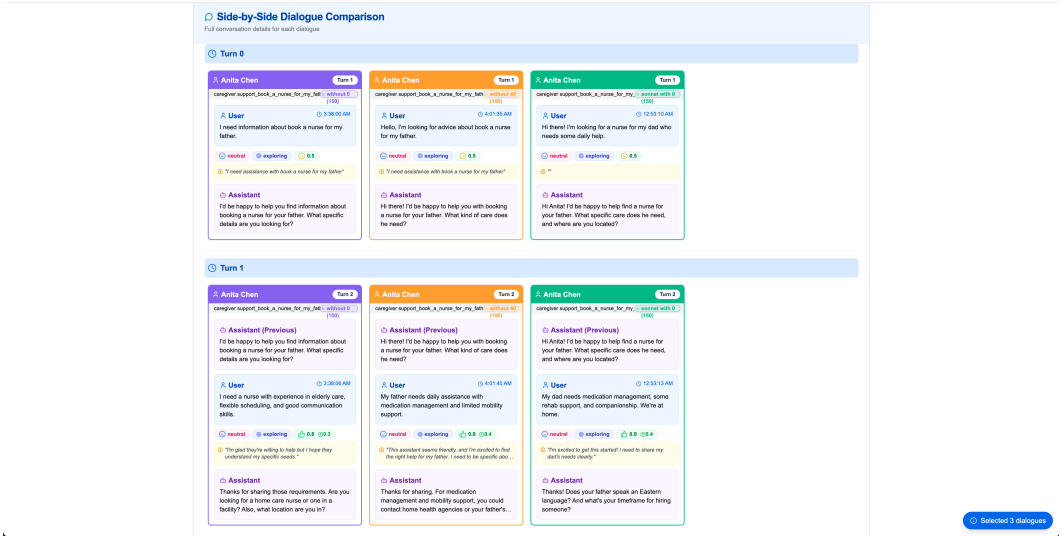


Figure 24: Detailed dialogue turn comparison across models for the same user.

When switching back to the original dialogue lists with "View" (Figure 25), the left side shows the selected dialogues, and the right side shows the multi-dialogue comparison, which helps analyze differences better.

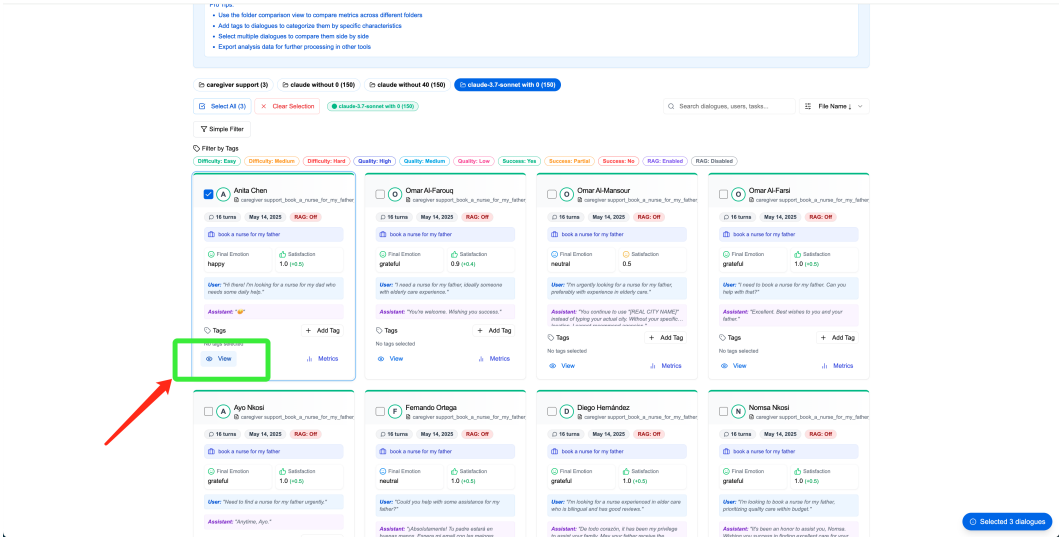


Figure 25: Side-by-side view of selected single and multi-dialogue comparisons.

This corresponds to the Split View layout (Figure 26).

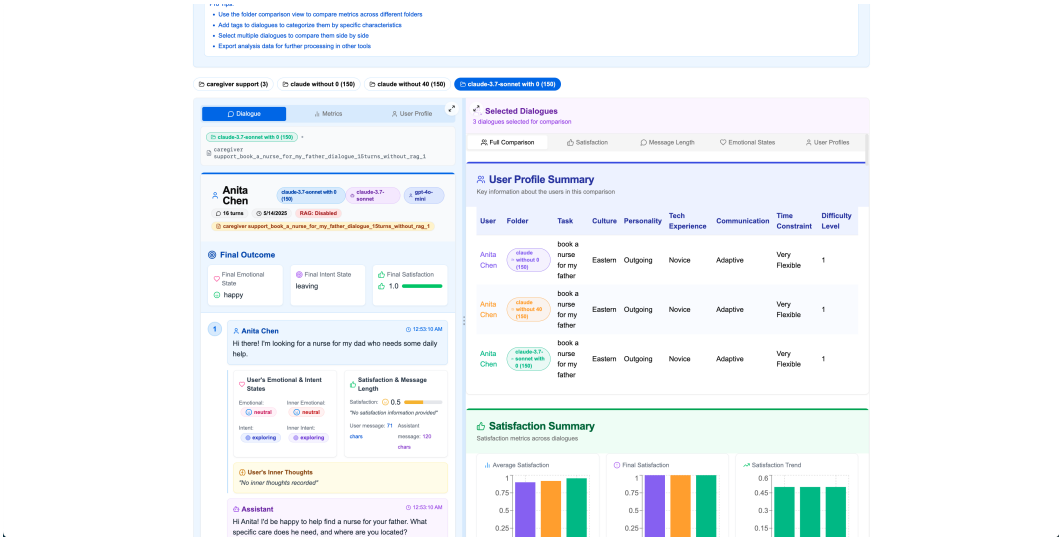


Figure 26: Split view for detailed analysis.

—

Folder-Level Comparison

Click the "Folder Comparison" button at the top right to open the component (Figure 27). You can then select two folders to compare.

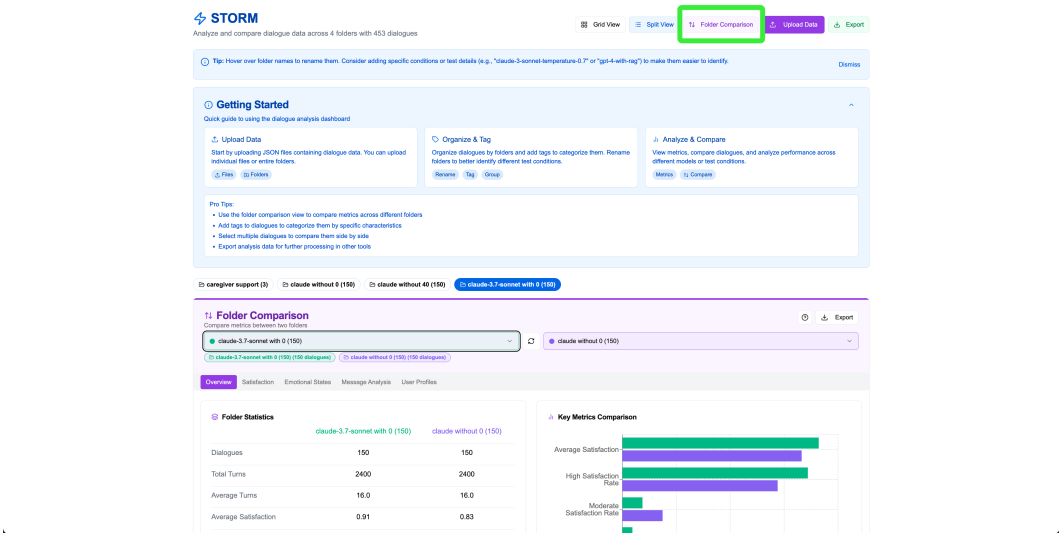


Figure 27: Folder comparison selection interface.

Below, detailed differences are shown, including:

- Satisfaction comparison (Figure 28),

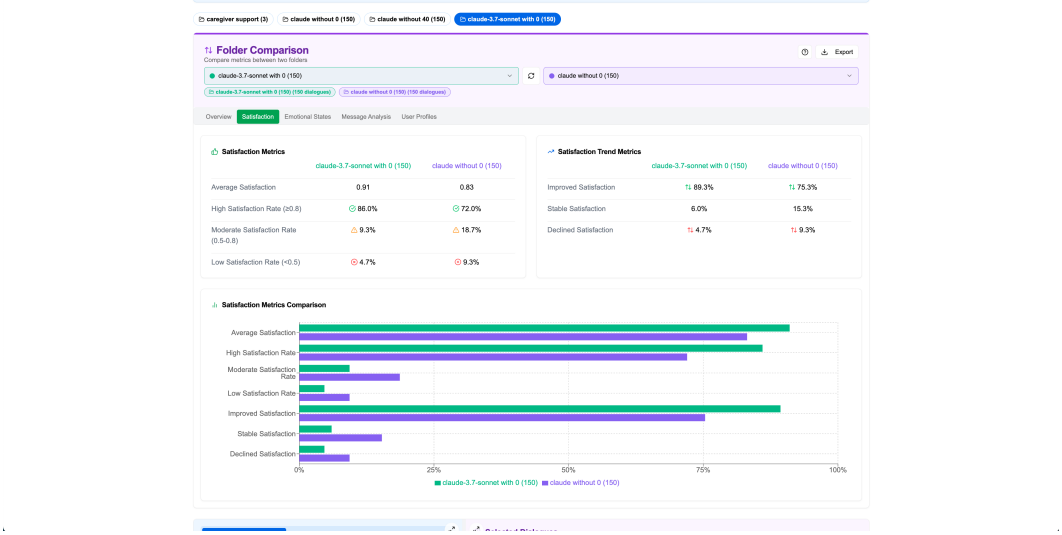


Figure 28: Satisfaction comparison between folders.

- Emotional states comparison (Figure 29),

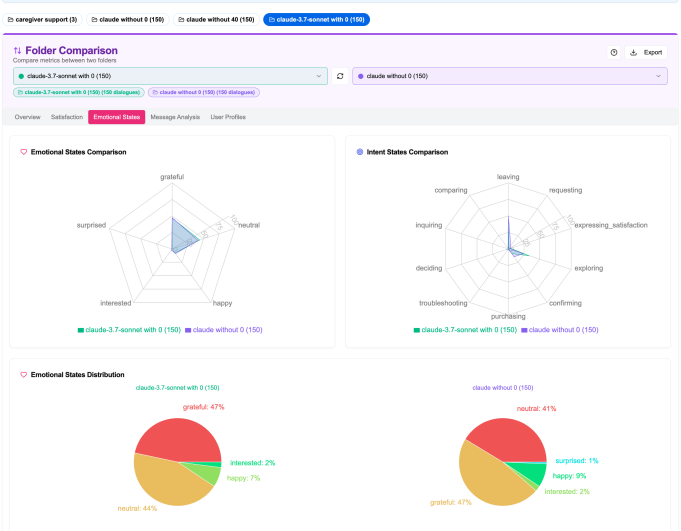


Figure 29: Emotional states comparison between folders.

789 - Message length comparison (Figure 30),

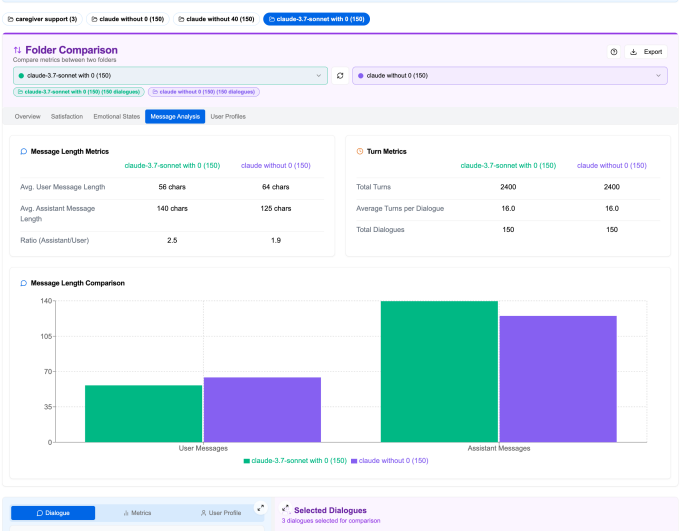


Figure 30: Message length comparison between folders.

790 - User profile comparison (Figure 31).

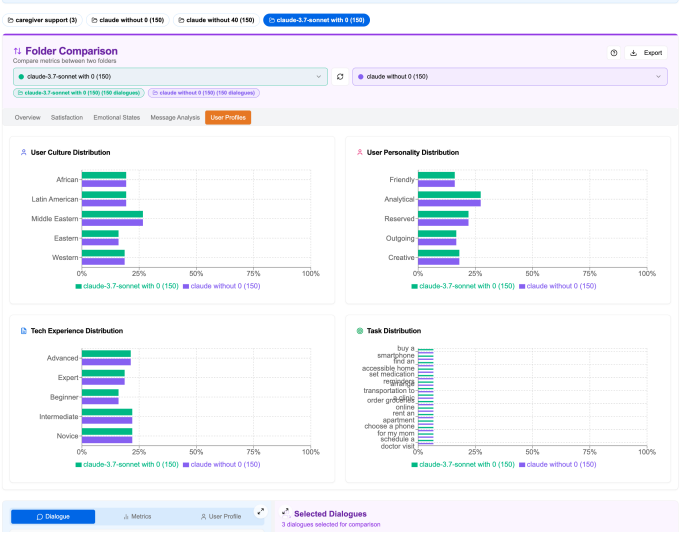


Figure 31: User profile comparison between folders.