HOW CAN WE ASSESS HUMAN-AGENT INTERACTIONS? CASE STUDIES IN SOFTWARE AGENT DESIGN

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Paper under double-blind review

ABSTRACT

LLM-powered agents are both a promising new technology and a source of complexity, where choices about models, tools, and prompting can affect their usefulness. While numerous benchmarks measure agent accuracy across domains, they mostly assume full automation, failing to represent the collaborative nature of real-world use cases. In this paper, we make two major steps towards the rigorous assessment of human-agent interactions. First, we propose a framework for more efficient human-centric evaluation of agent designs, which comprises collecting user feedback, training an ML model to predict user satisfaction, and computing results by combining human satisfaction ratings with model-generated pseudo-labels. Second, we deploy the framework on a large-scale web platform built around the open-source software agent OpenHands, collecting in-the-wild usage data across over 15k users. We conduct case studies around how three agent design decisions—choice of LLM backbone, planning strategy, and memory mechanisms—impact developer satisfaction rates, yielding practical insights for software agent design. We also show how our framework can lead to more robust conclusions about agent design, reducing confidence intervals by 40% compared to a standard A/B test. Finally, we find substantial discrepancies in-the-wild results with benchmark performance (e.g., the anti-correlation between results comparing `claude-sonnet-4` and `gpt-5`), underscoring the limitations of benchmark-driven evaluation. Our findings provide guidance for evaluations of LLM agents with humans and identify opportunities for better agent designs.

1 INTRODUCTION

Agents are simultaneously one of the most promising emerging technologies empowered by LLMs (QuantumBlack & Technology, 2025), and a perfect storm of complexity and unpredictability for the AI researchers and engineers who are tasked with creating them. There are a plethora of design decisions that any agent developer must face, such as which underlying language model to use (Yue et al., 2025), what tools to provide to the agent (Jin et al., 2025; Soni et al., 2025), how to prompt the agent to use its capabilities effectively (Khattab et al., 2023; Spiess et al., 2025), and how to plan and coordinate across tasks or subworkflows (Fourney et al., 2024). Errors in any of these areas can reduce the agent's effectiveness or lead to performance regressions in deployed systems (Cemri et al., 2025).

Our current best tool for diagnosing and improving agent performance is a rigorous measure of accuracy on agent benchmarks. Fortunately, given the importance and interest in agents, there is now a variety of benchmarks that can be used across areas, such as software engineering (Jimenez et al., 2023a; Yang et al., 2024; Zan et al., 2025), web browsing (Zhou et al., 2023; Koh et al., 2024), and scientific discovery (Chen et al., 2024). On the other hand, these benchmarks are largely based on the premise of *full task automation*, where the agent finishes a well-specified task with no user feedback. Though some have claimed that agents will be eventual replacements for large swaths of human work (Shibu, 2025), in reality, current agentic systems

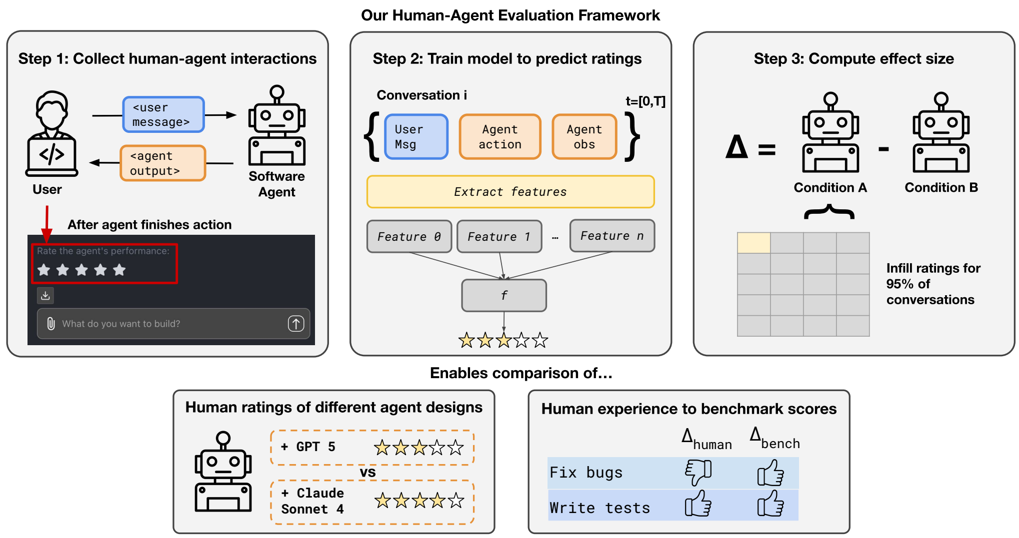

Figure 1: **Our framework for efficient human-centric evaluation of agent designs enables insights into how user experience varies with agent design and comparison to benchmark performance.** We instantiate this framework in a software engineering agent use case and conduct a set of case studies to identify novel insights into designing useful, collaborative agents.

work closely together with human supervisors to *complete tasks collaboratively*. While there has been some attempts to simulate human interaction (Vijayvargiya et al., 2025; Pan et al., 2025), to our knowledge, there has not, to date been a rigorous evaluation protocol proposed or empirical results presented in this setting.

In this paper, we make two major steps towards *rigorous assessment of human-agent interactions*. **First, we propose a novel three-step framework for measuring the effect of a proposed agent change efficiently** (Figure 1, top). The framework begins with setting up the interface and data collection mechanism for user feedback from human-agent interactions. We then train an ML model to predict user satisfaction by extracting important features about the user, agent, and task completion status. Finally, we extend prediction-powered inference (Angelopoulos et al., 2023b) to provide valid confidence intervals about the effect size of a proposed agent change. In our case studies, we find that our framework can reduce confidence interval widths by an average of nearly 40% compared to a standard A/B test.

Second, we deployed this framework in the wild to conduct the first large-scale evaluation of agent designs, in software engineering application (Figure 1, bottom). We use a web-based platform where users perform day-to-day coding tasks with OpenHands (Wang et al., 2024), an open-source, state-of-the-art software engineering agent. Across over 36k sessions and 15k users, we conducted three case studies that varied the choice of LLM backbone and scaffolding changes, like the planning strategy and memory mechanism. Our findings suggest that investing in stronger base models yields large, statistically significant changes in user satisfaction (i.e., Δ = 6-8%). While scaffolding changes had relatively less impact (i.e., Δ <3%), we still observe benefits of showing users the agent's plan and find that changing memory parameters can also lead to cost savings without degradation to user experience. We also compare our results to 7 different code-related benchmarks and find that differences in models across benchmarks do not necessarily translate into human ratings. In particular, while `gpt-5` outperforms `claude-sonnet-4` on 6 out of 7 benchmarks, humans prefer `claude-sonnet-4` over `gpt-5` on 4 out of the 7 task subsets. In summary, our findings highlight the importance of human-in-the-loop evaluation.

Although the focus of this work is on software engineering agents, we believe our methodologies and takeaways apply broadly to diverse domains. We will open-source the framework code, data used in analysis, and our extension to the OpenHands platform to promote reproducibility of results. In Appendix C, we also discuss how our findings motivate better agent designs and how our framework can be readily adapted to other domains to further the study of human-agent interactions.

2 METHODS

We overview our evaluation framework to efficiently compare agent designs (Figure 1): (1) feedback data collection, (2) training an ML model to predict user satisfaction, and (3) computing test results and confidence intervals. We use software agent design to instantiate each step, with additional details provided later in Section 3.1.

2.1 FEEDBACK DATA COLLECTION

Collecting user reviews and ratings has been a long-standing practice to understand product quality and guide iterative improvement (McAuley et al., 2012; Fabijan et al., 2015); similarly, to evaluate different agent designs, we ask users for feedback on how they perceived the agent to have performed. However, in the context of human-agent interactions, a natural question is when we should ask for feedback. We want feedback collection to be minimally invasive and align with the agent's own sense of task completion. We propose a design where, in the chat window where users and agents communicate, users are prompted to provide feedback after each *work segment*. A work segment comprises all the events that unfold between when the user sends a command, the agent enters a 'running' state, and returns to 'stopped'. At this point, the chat interface shows users text that says "rate the agent's performance" and asks the user to provide a rating on 5 star scale. We provide examples of the interface in Appendix A.1.

In summary, we define each work segment i as $W_i = \{M_i, T_i, Y_i\}$ where the trajectory $T_i = \{a_{i,1}, o_{i,1}, a_{i,2}, \dots\}$ is a list of actions and observations from the agent and Y_i is the user rating (which may be $\emptyset$ because the user did not choose to give feedback. As such, each session $X_i = \{W_1, \dots, W_j\}$ can consist of one or more work segments. If there are multiple ratings, we take the average across segments $\bar{Y}_i$, which provides us with more granular ratings than the 5 star scale. Across many sessions, we can create a dataset of human-agent interactions and user ratings $\mathcal{D} = \{(X_i, \bar{Y}_i)\} \cup \{(\tilde{X}_i, \emptyset)\}$ where X_i are the sessions where there is at least one rating and $\tilde{X}_i$ are the ones without. For our software agent use case, we collect a dataset of $N = 1747$ labeled user trajectories where the average rating is 4.07. Since ratings are often only provided by a small percentage of users (e.g., about 5%), we have about 20$\times$ more sessions that do not have labels. We next discuss how to train a model to infill these interactions.

2.2 PREDICTING HUMAN SATISFACTION

Given a dataset of labeled trajectories $\mathcal{D} = \{(X_i, \bar{Y}_i)\}$, we train a ML model f to infill user satisfaction $\bar{Y}_i$, when it is $\emptyset$, given human-agent interaction in the session X_i. Unlike prior work on predicting satisfaction in multi-turn dialogue (Hu et al., 2023; Lin et al., 2024), a unique challenge with handling agent trajectories is balancing the number of labeled samples with the dimensionality of agentic trajectories (i.e., each T_i is a complex object that may easily comprise tens or thousands of tokens). We propose a set of features:[1]

- *Features based on the user.* We find user messages $\{M_i\}$ often convey a lot of information that may tell us about how satisfied they are with the agent and include user sentiment as a feature. Additionally, how

[1] In Appendix A.2, we explore how to use LLMs to automatically discover features.

Table 1: **Comparison of methods for predicting user satisfaction.** We evaluate two approaches: traditional ML models trained on labeled trajectories and LLM-as-a-judge (Zheng et al., 2023) across multiple models.

Metric	LogReg	HGB	RF	LLM-as-a-Judge		
				o3	gemini-2.5-pro	claude-4
MSE (↓)	**1.39**$_{\pm 0.01}$	1.44$_{\pm 0.02}$	1.44$_{\pm 0.01}$	2.17$_{\pm 0.01}$	2.52$_{\pm 0.02}$	2.04$_{\pm 0.03}$
MAE (↓)	1.07$_{\pm 0.01}$	1.03$_{\pm 0.01}$	**1.02**$_{\pm 0.01}$	1.87$_{\pm 0.02}$	2.05$_{\pm 0.10}$	1.70$_{\pm 0.04}$
Correlation (↑)	0.24$_{\pm 0.01}$	0.27$_{\pm 0.02}$	**0.29**$_{\pm 0.01}$	0.22$_{\pm 0.03}$	0.14$_{\pm 0.07}$	0.23$_{\pm 0.01}$

many messages that users choose to send $|\{M_i\}|$ can also be indicative. Both features have also been considered in information retrieval and dialogue literature (Sun et al., 2021b; Lin et al., 2024).

- *Features based on the agent.* We also consider features that indicate what kind of task the user is working on (e.g., `implementing new features` or `fixing bugs`), which can be detected through the user messages and agent trajectory, as well as potential failure modes of the agent. We adapt these features to software engineering applications based on task-oriented dialogue (Higashinaka et al., 2015; Siro et al., 2022).
- *Features that show task progression.* In software engineering, task progression is often signaled through git actions (Saidani et al., 2020). For example, if T_i contains actions where the agent pushing code towards the end of a session may be a sign of user satisfaction with the agent's work.

In total, for our software agent use case, we create 15 features which we use to train various ML models ranging from logistic regressions to random forests. We also compare to a baseline of simply providing the full, raw trajectory X_i to an LLM-as-a-judge (Zheng et al., 2023) without the feature post-processing, using models that can handle particularly long contexts (e.g., `o3` and `gemini-2.5-pro`). In Appendix A.2, we provide a full list of features and model parameters. Overall, we find that ML models trained on these features significantly outperform state-of-the-art LLMs across all metrics considered (Table 1). An additional benefit of training a model with interpretable features is that we can use it to understand what aspects of agent behavior lead to more or less user satisfaction. Across models, we find the most important features to be `user sentiment` based on messages and `git push` based on agent actions—the importance of task completion features shows that users care not just about interaction with the agent but about task completion. However, no feature alone is fully predictive of user rating.

2.3 Comparing Agent Designs

With a feedback collection mechanism and labeling model f in hand, we discuss how to efficiently compare agent designs. To compare different agent designs, we adopt an A/B testing framework, a widely used approach in fields such as human-computer interaction and web experimentation to compare different system variants (Siroker & Koomen, 2015). Each test produces datasets indexed by condition, $\mathcal{D}_c = \{(X_i, Y_i)\}$ where c denotes the different versions of the agent being compared.

Naive effect size estimation. We are interested in estimating the true difference in average user satisfaction between conditions:

$$\widehat{\Delta}_{\text{naive}} = \frac{1}{n_{c_1}} \sum_{i \in c_1} Y_i \; - \; \frac{1}{n_{c_2}} \sum_{i \in c_2} Y_i$$

Given $\mathcal{D}_{c_1}$ and $\mathcal{D}_{c_2}$, we compute the empirical difference $\widehat{\Delta}_{\text{naive}}$ and test whether it is statistically significant from 0 (i.e., no difference between c_1 and c_2) using a bootstrap permutation test.

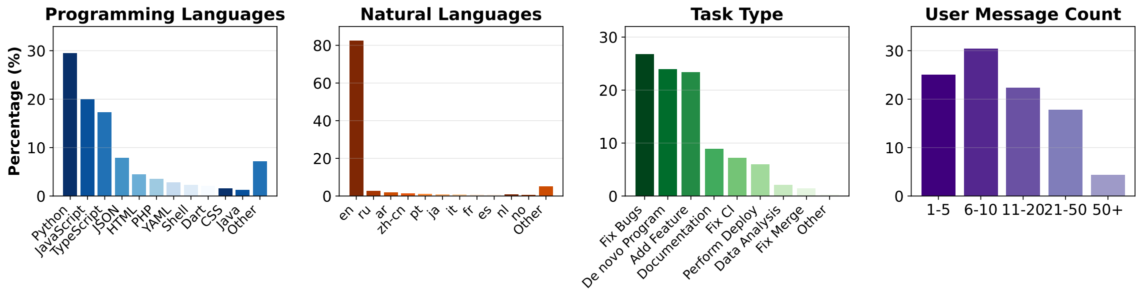

Figure 2: **Overview of statistics of in-the-wild deployment of our human-agent evaluation framework.** Our evaluations spanned over 15k users who were working on a diverse set of problems in terms of programming and natural languages, task category, and interaction style with the agent (as seen through user message count).

Augmenting with unlabeled trajectories. However, since we have f, we can directly extend prediction-powered inference (PPI) (Angelopoulos et al., 2023a;b) to construct an effect size estimator. PPI provides the recipe for the mean estimator of each condition c with tuning parameter $\lambda_c \in \mathbb{R}$ given n_c labeled and N_c unlabeled trajectories:

$$\widehat{\mu}_c(\lambda_c) = \underbrace{\frac{1}{n_c}\sum_i Y_i}_{\text{sample mean of labels}} + \lambda_c \left(\frac{1}{N_c}\sum_j \underbrace{f(\tilde{X}_j)}_{\text{unlabeled traj.}} - \frac{1}{n_c}\sum_i \underbrace{f(X_i)}_{\text{labeled traj.}} \right).$$

The optimal λ_c can be computed using a sample plug-in comprising $\widehat{\mathrm{Cov}}(Y, f(X)|Z = c_i)$ as well as the variance of f. Accordingly, the augmented effect size estimator is the difference

$$\widehat{\Delta}_{\text{augment}} = \widehat{\mu}_{c_1}(\widehat{\lambda}_{c_1}) - \widehat{\mu}_{c_2}(\widehat{\lambda}_{c_2}).$$

Under the regularity conditions in PPI, $\sqrt{n_c}\big(\widehat{\mu}_b(\lambda_c) - \mu_c\big) \xrightarrow{d} \mathcal{N}(0, \sigma_c^2(\lambda_c))$ Because trajectores from each condition (and their unlabeled pools) are independent conditional on assignments, each estimator is asymptotically independent. A Wald confidence interval is therefore

$$\widehat{\Delta}_{\text{augment}} \pm z_{1-\alpha/2}\sqrt{\frac{\widehat{\sigma}^2_{c_1}(\widehat{\lambda}_{c_1})}{n_{c_1}} + \frac{\widehat{\sigma}^2_{c_2}(\widehat{\lambda}_{c_2})}{n_{c_2}}},$$

where each $\widehat{\sigma}^2_b(\widehat{\lambda}_b)$ is the plug-in estimate of $\sigma^2_b(\cdot)$.

3 Experimental Design

3.1 Deployment details

Software agents are the focus of this work, as it is arguably the most commercially impactful use case of current agents. There are many coding agents available, including Devin (Cognition, 2024) and Claude Code (Anthropic, 2025a), but they are largely closed-source. We performed our study using OpenHands, a leading open-source coding agent, as measured by SWE-Bench (Jimenez et al., 2023b) and other benchmarks. All users opted in to collection and analysis of statistical data such as the data gathered in this study.

Randomization for A/B testing was conducted at the conversation level (represented as a trajectory), where each new conversation was assigned a specific agent variant with fixed parameters. This design enables the same user to contribute multiple trajectories under different variants. If a user revisits a given conversation with the agent, the same test parameters would persist.

In total, our study comprised over 36k sessions from 15k different users. Figure 2 overviews the distribution of usage across multiple features: Across these users, they worked on a diverse set of tasks. When we classify a sample of the trajectories, we find that the majority of users were trying to `fix bugs` and `create programs from scratch`. There were multiple programming languages, with Python being the most popular (29.52%) and predominantly English-speaking users (82.61%). Finally, users sent a median of 10 messages to the agent in a session.

3.2 Overview of case studies

Beyond the LLM model powering agents, prior work has discussed the importance of other aspects like planning, memory, and tool use (Weng, 2023; Sumers et al., 2023; Durante et al., 2024). We apply our framework to study three aspects of software agent design.

Case Study 1: LLM Model. The LLM model backbone is arguably one of the most important components of an agent and is the primary independent variable reported when reporting results on benchmarks. We compared 3 different state-of-the-art models in terms of agentic coding performance: `claude-3.7-sonnet`, `claude-4-sonnet`, and `gpt-5 (reasoning effort high)`. We report results of two separate tests, the first, which compared `claude-3.7-sonnet` and `claude-4-sonnet`, and the second, which compared `claude-4-sonnet` and `gpt-5`. All other aspects of the agent design are fixed in these LLM model experiments. These tests were separate because `gpt-5` was not released until after the first test had already concluded.

Case Study 2: Planning. Given a potentially complex user message M_i, the agent typically takes multiple actions A_i before asking for further feedback, thus potentially benefiting from having a plan of attack. In classical AI literature, planning has a long history of formalism and methods (Fikes & Nilsson, 1971; Blum & Furst, 1997; Kautz & Selman, 1992). However, with LLM-powered agents, recent approaches have largely adopted language reasoning as a medium for planning as opposed to symbolic operators and explicit transition models (Yao et al., 2022; Shinn et al., 2023). We investigate how showing agentic planning influences a user's experience. Specifically, the agent calls a `task_tracker` tool at the beginning of the conversation to create a structured task list, which is shown to the user as `TASKS.md` when encountering a complex, or multi-phase development task, to create a structured task list. For simple, atomic tasks, the agent will proceed with direct implementation to avoid tracking overhead. Agent updates task statuses as work progresses, and the frontend display is updated for the user accordingly.

Case Study 3: Memory Management. As the number of work segments increases in a given X_i, after a certain point, the entire history cannot fit into even state-of-the-art LLM context lengths. Additionally, it is no surprise that agents can become especially costly with long contexts (Anthropic, 2025b). There is a growing research community studying how to appropriately manage the context that is used as input to the agent (Jiang et al., 2023; Asai et al., 2024). In our implementation, as the conversation grows beyond a certain threshold, we intelligently summarize older interactions while keeping recent exchanges intact (Smith, 2025). This creates a concise "memory" of what happened earlier without needing to retain every detail. An important parameter in this setup is deciding *when* this thresholding occurs. We decrease `max_step` from 120 to 80, which leads to an expected amortized 0.5 cent savings *per step*, based on simulations on SWE-Bench (Jimenez et al., 2023a).

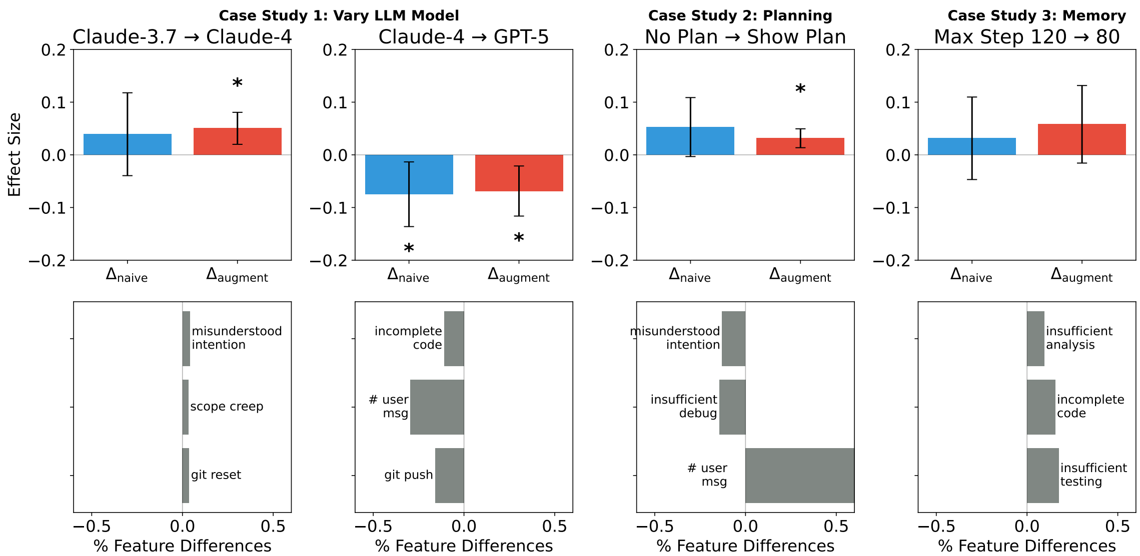

Figure 3: **How do user ratings change based on different software agent designs?** We report average user ratings (on a scale of 1-5) using only human labels and including our framework. For fair comparison of the effect of PPI, we subsample to the same number of data points in human-only (i.e., 150 per condition). We use * to indicate significant results with a cutoff $\alpha = 0.05$). We can see that the LLM model makes the biggest difference (case study 1) compared to scaffold changes (case studies 2 and 3).

3.3 Analysis Procedure

While there was some variance across case studies, we collected at least 150 labels per condition for each case study and ran each comparison for 2-3 weeks. At a rate of about 5% response rate, this means that we collected over 36k unlabeled sessions in addition to the labeled subset. For our analysis next, we use *the same feedback model*, rather than training a specific feedback model per case study. This is because the user population and bulk of the agent scaffold and user interaction process are fixed across case studies. To quantify the effect of agent design change in each case study, we report Δ_{naive} and Δ_{augment} using the best performing f we trained (i.e., random forest model), along with the 95% confidence intervals. Additionally, we also compare conditions using features discussed in Section 2.2 to help interpret the observed effect sizes. In Figure 3 (bottom), we select the top 3 features based on p-value—note these are all trajectories that users rated, not with inferred ratings. We provide full result tables in Appendix B.

4 Results

LLM backbone impacts user satisfaction more than scaffold changes. Figure 3 (top) overviews the observed effect sizes across our case studies. Across both tests in case study 1 that vary the LLM models, users significantly preferred agents powered by `claude-4-sonnet` over the two other LLMs. In the first test, we find a 5.86% difference in user satisfaction between `claude-3.7-sonnet` and `claude-4-sonnet`. In the second test, we find a -7.83% difference in user satisfaction between `claude-4-sonnet` and `gpt-5`. In contrast, for scaffolding changes, we find a small (but significant) 3.1% difference in user satisfaction between planning and no plan variants. Overall, the effect size is smaller

Table 2: **Human ratings do not always correlate with benchmarks.** We compare the difference observed in human ratings (Δ_H) against the differences on 7 benchmarks (Δ_B). We focus human ratings on the relevant subset most similar to the benchmark, ensuring each batch has at least 35 human data points.

Task Type	Claude 3.7 vs Claude 4		Claude 4 vs GPT 5	
	Δ_H	Δ_B	Δ_H	Δ_B
Testing code (Mündler et al., 2024)	24.22%	22.8%	4.01%	21.8%
Fix Continuous Integration (Bogomolov et al., 2024)	20.04%	-4.35%	24.05%	28.87%
Fix Codebase Issues (Jimenez et al., 2023a)	15.68%	12.4%	7.54%	1.80%
Fix underspecified issues (Vijayvargiya et al., 2025)	14.13%	9.74%	-6.07%	15.81%
Deep Research (Mialon et al., 2023)	11.62%	0.00%	-7.84%	14.62%
Administrative tasks (Xu et al., 2024)	4.05%	2.28%	-4.62%	-0.75%
Write code from scratch (Zhao et al., 2024)	0.64%	-5.50%	-17.9%	19.0%
Pearson Correlation Coefficient (Δ_H, Δ_B)	ρ =0.66		ρ =-0.18	

than the first case study where we change the LLM backbone, suggesting that the process is less important to the user (i.e., how the agent gets to a final goal) and rather the quality of the completed work.

Interaction features provide further insight into how user experience changes. Figure 3 (bottom) shows how features described in Section 2.2 across conditions change. We discuss some key observations: Since `gpt-5` was rated significantly lower than `claude-4-sonnet`, user interactions provide some insight into why that might be. Trajectories with `gpt-5` contained 32% fewer user messages on average, suggesting that users often stopped engaging and abandoned prompting earlier. We also observe 16% fewer code pushes when using `gpt-5`, suggesting that users decided it was not worth pushing incremental code edits when progress feels unproductive. In terms of the planning case study, we see that despite a small positive improvement in rating, there are multiple changes in behavioral features that indicate the benefits of showing plans to users. In particular, we see that in the no plan version, the agent is 12.8% more likely to misunderstand the user, which leads to insufficient analysis and debugging (13.0% and 14.4% respectively). The increase in user messages also shows better engagement in what the agent is working on.

Our framework can help provide more conclusive experimental results. When comparing Δ_{naive} and Δ_{augment} across the 4 different experiments, we can see that confidence interval bands decrease on average by 39.5%. In fact, in multiple experiments—`claude-3.7-sonnet` versus `claude-4-sonnet`) and `plan` versus `no plan`, we find that we can draw more conclusive results that are statistically significant using Δ_{augment}. More concretely, the 95% CI for Δ_{naive} in the `claude-3.7-sonnet` versus `claude-4-sonnet` comparison was , while the 95% CI of using augmented labels was [-3.95%, 11.78%], [1.99%, 8.06%]. The variation in CI reduction across case studies is largely due to how well f can explain the specific samples for that particular test.

5 Correlating results with benchmarks

Finally, we present an exploratory analysis of how our findings compare to benchmarks. In particular, we focus on our first case study on varying LLM models because that led to the most drastic changes in human ratings. We consider a variety of 7 benchmarks that test agentic software engineering tasks that range from improving code bases (Jimenez et al., 2023b; Vijayvargiya et al., 2025) to writing tests and fixing continuous integration (Mündler et al., 2024; Bogomolov et al., 2024). We categorize human-agent trajectories into corresponding categories of tasks and compare Δ_H (i.e., the change in human ratings) and Δ_B (i.e., the change in benchmark performance).

Static benchmarks don't tell the whole story. Table 2 shows the comparison between Δ_H and Δ_B on the case study that varies LLM models. We find a moderate positive correlation on the `claude-3.7-sonnet` and `claude-4-sonnet` comparison. However, we observe a weak negative correlation on the `claude-4-sonnet` and `gpt-5` (i.e., $\rho = 0.66$ vs -0.11). This means that we should not always take benchmark improvements at face value as there may be additional deployment challenges when humans are involved. Interestingly, we see the most alignment in tasks like testing (e.g., SWT-Bench (Mündler et al., 2024)) and administrative tasks (e.g., The Agent Company (Xu et al., 2024))—where both Δ_H and Δ_B are the same sign—which are not the standard type of "bug fixing" task that many agentic coding benchmarks are built around. Similarly, we find the largest $|\Delta_H|$ to be from fixing continuous integration issues, rather than simply working on the code base. These results suggest the importance of moving beyond standard SWE-Bench-like evaluations even for benchmarks.

6 Related Work

Coding agent evaluation. Evaluation of existing coding agents is still largely limited to static benchmarks (Jimenez et al., 2023a; Yang et al., 2024; Zan et al., 2025); however, more benchmarks have expanded across a number of software engineering tasks from writing tests to fixing failed continuous integration builds (Mündler et al., 2024; Bogomolov et al., 2024). A few interactive benchmarks simulate human users (Vijayvargiya et al., 2025; Pan et al., 2025). In the context of coding agents with humans in the loop, they are largely focused on comparisons of prior copilot tools to new agentic workflows (Anthropic, 2025c; Chen et al., 2025). However, these studies do not consider evaluations of varying agent designs. Unlike existing user studies, our work considers an agent deployed in the wild with users and studies how to efficiently run experiments in these settings. We also compare to benchmarks on relevant tasks to show which benchmark scores are correlated with human performance.

User satisfaction estimation. Prior works in the speech and dialogue communities have explored user satisfaction in multi-turn chat interactions using signals which include thumbs up/down ratings and a 5 point satisfaction scale (Sun et al., 2021a). Methodologies for predicting user satisfaction range from using text embeddings (Liang et al., 2021) to more recent LLM-powered approaches (Hu et al., 2023; Lin et al., 2024). To our knowledge, our work is the first investigation of modeling user satisfaction with agents, specifically in the software engineering use case. We find that LLM-based approaches struggle given the long context of human-agent interactions, without even the inclusion of few-shot examples, and our predictive methods outperform those baselines.

Efficient estimation of effect size with noisy samples. From clinical trials to public health interventions, there is growing interest in running controlled trials of new treatments more quickly (De Bartolomeis et al., 2025; Poulet et al., 2025; Demirel et al., 2024). One statistical machinery that makes this possible is prediction-powered inference (PPI), which is an approach that reduces the variance of estimators by leveraging predictions from a prediction model f on unlabeled data by constructing a correction term using the labeled data Angelopoulos et al. (2023a;b). Prior work has extended PPI to boost the efficiency of experiments by generating a "digital twin" (i.e., the counterfactual) in randomized control trials (Poulet et al., 2025) or creating synthetic examples that are then labeled using an LLM (Shankar & Fiterau, 2024). Our setting differs from prior work, where there is no obvious choice for f for evaluating human-agent interactions. We discuss how to train such a model for agentic contexts and use this framework in a series of real-world evaluations.

7 Discussion and Conclusion

As humans are increasingly collaborating with agents in real-world use cases, it is important that evaluations of agent designs reflect these settings. In this work, we proposed a framework for more efficiently assessing human-agent interactions and deployed it in practice across multiple case studies on software agent designs. Our findings highlight the importance of human-in-the-loop evaluation and demonstrate that benchmarks are not always able to represent user experience. Based on our findings, we also discuss opportunities for software agent development and evaluations of human-agent interactions (Appendix C).

Limitations. Although our evaluations spanned a diverse set of users and use cases, it is unclear to what extent our results encapsulate all real-world use cases of software engineering. Further, we conduct our case studies on one choice of agent (OpenHands)—we encourage future work to apply our framework to more agents and application domains. Additionally, we focus on user rating as our primary human metric, but this may not fully capture agent work quality and future evaluations of software agents may want to augment these findings with metrics around issue resolution. Finally, due to privacy considerations, we are unable to release code contexts collected in the study. However, we will release code to run our framework, analysis, and extended OpenHands platform.

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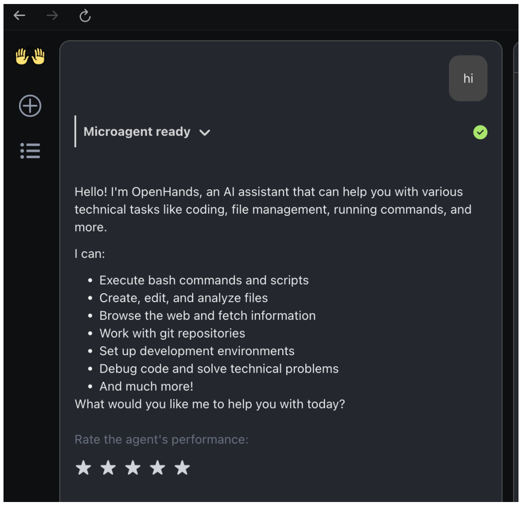
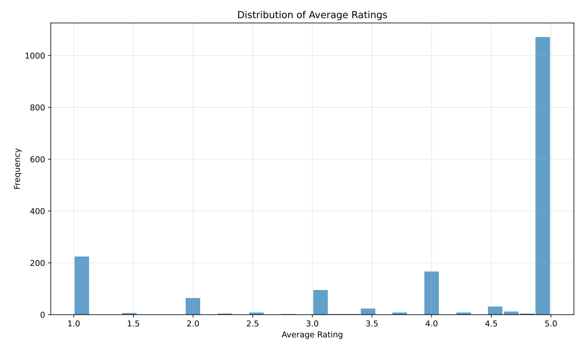
A ADDITIONAL FRAMEWORK DETAILS

A.1 DATA COLLECTION DETAILS

To make feedback minimally intrusive, we prompt users at the end of each work segment to rate the agent's performance on a five-star scale as shown in Figure 4.



(a) Toy example showing the 5-star feedback interface.



(b) Distribution of ratings.

Figure 4: Illustration of the feedback setup: (a) the 5-star feedback interface, and (b) the distribution of ratings collected.

A.2 PREDICTING USER SATISFACTION

Feature list. We identified 15 features used to train ML model to predict user satisfaction ratings.

1. User sentiment: positive, negative, neutral
2. Number of user messages
3. Task Category: we identified 8 common tasks that developers use software agents for.
4. Misunderstood Intention: Agent misunderstood the user's goal or intent.
5. Did not follow instruction: Agent ignored or failed to comply with explicit
6. Insufficient Analysis: Didn't explore existing materials sufficiently (prior code/docs/examples) before acting.
7. Insufficient testing: Skipped reasonable verification/tests for non-trivial or risky changes (note: trivial edits may be acceptable).
8. Insufficient Debugging: Did not investigate or reduce failing behavior when needed to make progress.
9. Incomplete Implementation: Delivered unfinished or non-functioning work.

10. Scope Creep: Implemented unrequested features without approval.
11. `git_commit`
12. `git_push`
13. `git_pull`
14. `git_reset`
15. `git_rebase`

We use LLM as a judge to detect features 1,3,4,5,6,7,8,9,10. We analyze the event stream to detect features 2,11,12,13,14,15. Below we include the prompt used with `gpt-5-mini`.

Prompt for labeling features

```
Analyze the following user messages from a coding assistant session:

{combined_messages}

Please provide the following analysis:
1. One sentence describing what the user is trying to accomplish
2. Classify the overall sentiment of the user's messages into one of
    these categories: [Positive, Negative, Neutral] and explain why
3. Classify the type of task into exactly one of these categories (
    choose only one that best fits): [Fix Bugs, Implement Features,
    Create Programs from Scratch, Fix Failing Continuous Integration,
    Fix Merge Conflicts, Write Documentation, Perform Deployments,
    Perform Data Analysis]
4. Classify the development cluster into up to two of these categories
    (choose only the ones that are the best fits):
     - Write code from scratch
     - Fix python issues
     - Fix underspecified issues
     - Fix Java issues
     - Testing code
     - Web browsing and research
     - Administrative tasks
     - Fix continuous integration issues
     - None of the above
5. Provide 1-2 brief example messages from the conversation that
    support your sentiment classification (truncate if too long)

Format your response as JSON with these fields:
{{
   "task_description": "one sentence",
   "sentiment": {{
       "classification": "Positive/Negative/Neutral",
       "explanation": "brief explanation",
       "example_messages": ["message 1", "message 2"]
   }},
   "task_type": "one of the categories",
   "development_cluster": ["cluster 1", "cluster 2" (if applicable)]
}}
```

```
Analyze the following user messages from a coding assistant session:

{combined_messages}

For each issue item below, answer YES or NO based on whether there is
    evidence in the user messages that this issue occurred. Provide a
    brief explanation for each:

    [item 1] misunderstood_intention: Agent misunderstood the user's
       goal/intent.
    - Examples: User asked for a summary and agent produced a rewrite;
       user wanted high-level bullets but agent delivered full code.

    [item 2] did_not_follow_instruction: Agent ignored or failed to
       comply with explicit instructions/system constraints.
    - Examples: User: "Do NOT push to main." Agent pushes to main;
       System says not to create pull request unless user asks for it
       and user didn't ask for it, agent creates pull request; user
       asked for bullet points only, agent gives long prose.

    [item 3] insufficient_analysis: Didn't explore existing materials
       sufficiently (prior code/docs/examples) before acting.
    - Examples: User points to an existing function/file that is
       relevant OR already solves it; agent reinvents it.

    [item 4] insufficient_testing: Skipped reasonable verification/tests
        for non-trivial or risky changes (note: trivial edits may be
       acceptable).
    - Examples: No run/validation for a new parser; no check that a
       migration applies cleanly; no sanity check of output.

    [item 5] insufficient_debugging: Did not investigate or reduce
       failing behavior when needed to make progress.
    - Examples: Ignores stack trace; no isolation of failure; proceeds
       while errors persist.

    [item 6] incomplete_implementation: Delivered unfinished or non-
       functioning work.
    - Examples: TODO/FIXME left; stub methods; code that cannot run.

    [item 7] scope_creep: Implemented unrequested features without
       approval.
    - Examples: Adds a dashboard or endpoint not asked for.

Format your response as JSON with these fields:
```

Exploring Automatic Discovery of Features. We create a script that takes as input a user-agent interaction trajectory and queries one or more LLMs to propose 10 general, reusable features that predict user satisfaction, using each conversation as contextual examples. The script calls models asynchronously and creates a JSONL of per-conversation/per-model outputs plus an aggregated per-model summary of recurring features. The authors of the paper then aggregate features generated by each model and compare them to the ones used in our study. Table 3 shows the results across 5 models.

Table 3: With a simple prompting scheme, we find that multiple models, including claude-opus-4.5 and claude-4-sonnet can re-identify a majority of our features.

Model	Feat about user	Feat about agent	Feat about task progression	Overall (↑)
o3	2/2	5/8	0/5	7/15
gpt-4o	2/2	4/8	2/5	8/15
gpt-5.1	2/2	7/8	0/5	9/15
claude-opus-4.5	2/2	7/8	2/5	12/15
claude-4-sonnet	2/2	6/8	3/5	12/15

Prompt for identifying features

```
You are an expert product analyst. Using the following conversation
    ONLY as an example of the kinds of signals available (user/agent
    messages, visible errors, git actions, etc.), propose 10 general,
    reusable features that would predict user satisfaction or
    dissatisfaction across coding-assistant conversations.

Do NOT evaluate this particular conversation. Define features that
    apply broadly. Each feature should be clearly computable from
    typical traces like this one.

EXAMPLE CONVERSATION CONTEXT (for reference only)
---
{conversation}
---

Return ONLY valid JSON with this schema:
{{
  "features": [
    {{
      "name": "short, canonical feature name",
      "definition": "what the feature measures in general terms",
      "why_predictive": "why the feature correlates with satisfaction/
          dissatisfaction",
      "how_to_compute": "signals/heuristics to extract it from
          conversation logs",
      "value_type": "one of: binary | ordinal | count | ratio |
          continuous",
      "polarity": "satisfaction | dissatisfaction | mixed",
      "example_indicators": ["short, concrete examples of signals"]
    }},
  ],
  "overall_guidance": "one sentence on how to use this feature set"
}}

Constraints:
- Provide exactly 10 features
- Do not include per-conversation judgments or values
- Keep definitions concise and implementation-oriented
- Respond with JSON only (no prose outside JSON)
```

ML Model set-up and parameters: We consider the following model families

- Ordinal logistic "regressor" (Pipeline: DictVectorizer → to_dense → StandardScaler(with_mean=True) → OrdinalLogitRegressor(C=2.0, class_weight='balanced'))
- Random forest regressor (Pipeline: DictVectorizer → to_dense → RandomForestRegressor(n_estimators=400))
- HistGradientBoostingRegressor (Pipeline: DictVectorizer → to_dense → HistGradientBoostingRegressor())

We perform k-fold cross-validation with 5 splits with a fixed random seed (42). For each fold, we fit the model on train indices, predict on test indices, collect out-of-fold predictions, then finally computes metrics on all out-of-fold predictions combined.

Prompt for LLM-as-a-judge baseline

```
Please analyze the following conversation between a user and an AI
    coding assistant to determine user satisfaction.

CONVERSATION:
{conversation}

Please provide your analysis in the following JSON format:
{{
    "binary_satisfied": true/false,
    "likert_score": 1-5,
    "explanation": "detailed explanation of your reasoning"
}}

EVALUATION CRITERIA:
- Binary satisfaction: Was the user satisfied with the agent's help by
    the end of the conversation? (true/false)
- Likert scale (1-5): 1=Very Dissatisfied, 2=Dissatisfied, 3=Neutral,
    4=Satisfied, 5=Very Satisfied
- Consider factors like:
  - Whether the user's problem was solved
  - Quality of the agent's responses
  - User's tone and feedback throughout the conversation
  - Whether the user expressed gratitude or frustration
  - If the conversation ended on a positive or negative note

Respond ONLY with the JSON format above, no additional text.
```

A.3 Selecting Memory Management Parameters

To select the appropriate `max_step` parameters for case study 3 we ran OpenHands on a randomly-selected subset of 50 problems from the Verified subset of SWE-Bench while varying `max_step` from 20 to 160 in increments of 20. OpenHands was configured to run at most 200 steps, but trajectory lengths varied based on the problem instance. For each value of `max_step` we averaged the API cost per-step across all problem instances and applied locally-weighted scatterplot smoothing with a bandwidth of 0.1 to better illustrate the amortized cost behavior. The results are given in Figure 5.

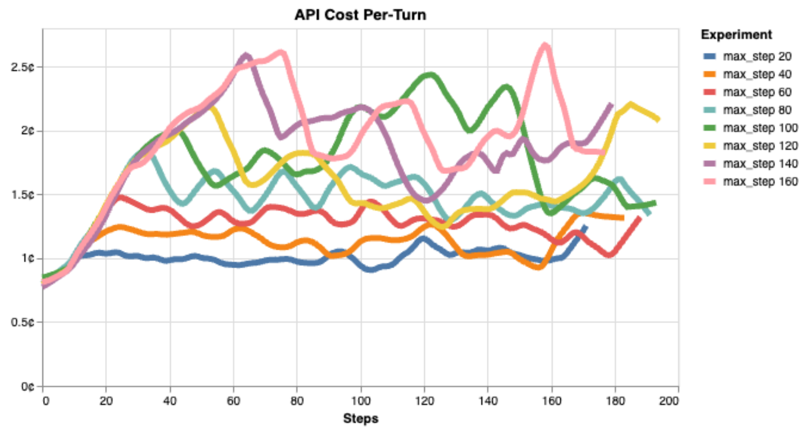


Figure 5: Average API cost per-step with varying `max_step` values.

To ensure that changing `max_step` did not meaningfully impact agent performance we evaluated the trajectories associated with the selected values (80 and 120) using the SWE-bench evaluation framework. The framework was able to evaluate trajectories for 22 of the 50 problem instances: with `max_step` set to 80, OpenHands resolved 16 problems, and with `max_step` set to 120 OpenHands resolved 15 problems.

B Full Results

A full table of effect sizes across all experiments is provided in Table 4. We provide full feature comparison for each case study: Claude 4 vs. GPT-5 (Table 5), Claude 3.7 vs. Claude 4 (Table 6), Condenser 120 vs. 80 (Table 7), and Planning vs. No-planning (Table 8). We also present average costs per model in Table 9. Finally, we also show the relative reduction in confidence intervals using other model families in Table 10.

Table 4: Effect sizes (Δ) with 95% confidence intervals. An asterik (*) indicates the CI does not include 0.

Comparison	**Condition**	**Effect**	**CI Lower**	**CI Upper**	**Sig.**
Claude-3.7 → Claude-4	Δ_{naive}	0.039	-0.040	0.118	
	Δ_{augment}	0.050	0.020	0.081	*
Claude-4 → GPT-5	Δ_{naive}	-0.075	-0.136	-0.013	*
	Δ_{augment}	-0.069	-0.116	-0.021	*
No Plan → Show Plan	Δ_{naive}	0.053	-0.003	0.109	
	Δ_{augment}	0.031	0.014	0.049	*
Memory max step	Δ_{naive}	0.032	-0.047	0.110	
	Δ_{augment}	0.058	-0.016	0.132	

C Opportunities for Agent Design

Our case studies show that user satisfaction is more sensitive to the choice of LLM backbone than to scaffolding changes, with `claude-4-sonnet` consistently outperforming alternatives. Interaction features

Table 5: Claude-4 → GPT-5 Feature Comparison.

Feature	Var A	Var B	Mean A	Mean B	Diff (B-A)	p-val
Misunderstood intention	control	gpt5	0.2771	0.1805	-0.097	0.039
Did not follow instruction	control	gpt5	0.3463	0.2857	-0.061	0.235
Insufficient analysis	control	gpt5	0.3723	0.2857	-0.087	0.094
Insufficient testing	control	gpt5	0.3550	0.3008	-0.054	0.292
Insufficient debugging	control	gpt5	0.3723	0.2932	-0.079	0.127
Incomplete implementation	control	gpt5	0.4589	0.3459	-0.113	0.036
Scope creep	control	gpt5	0.1212	0.0902	-0.031	0.364
User message count	control	gpt5	19.17	13.52	-5.65	0.028
Git commit	control	gpt5	0.6580	0.6241	-0.034	0.515
Git push	control	gpt5	0.6104	0.4511	-0.159	0.003
Git pull	control	gpt5	0.0866	0.0827	-0.004	0.900
Git reset	control	gpt5	0.0909	0.0526	-0.038	0.188
Git rebase	control	gpt5	0.0173	0.0150	-0.002	0.871

Table 6: Claude-3.7 → Claude-4 Feature Comparison

Feature	Var A	Var B	Mean A	Mean B	Diff (B-A)	p-val
Misunderstood intention	Claude 4	Claude 3.7	0.2900	0.2491	-0.041	0.105
Did not follow instruction	Claude 4	Claude 3.7	0.3940	0.3764	-0.018	0.524
Insufficient analysis	Claude 4	Claude 3.7	0.4309	0.4244	-0.007	0.815
Insufficient testing	Claude 4	Claude 3.7	0.4104	0.3911	-0.019	0.489
Insufficient debugging	Claude 4	Claude 3.7	0.4186	0.4336	0.015	0.593
Incomplete implementation	Claude 4	Claude 3.7	0.4952	0.4797	-0.016	0.584
Scope creep	Claude 4	Claude 3.7	0.1231	0.0904	-0.033	0.064
User message count	Claude 4	Claude 3.7	16.41	15.77	-0.64	0.641
Git commit	Claude 4	Claude 3.7	0.5335	0.5277	-0.006	0.837
Git push	Claude 4	Claude 3.7	0.4829	0.5018	0.019	0.504
Git pull	Claude 4	Claude 3.7	0.0602	0.0849	0.025	0.090
Git reset	Claude 4	Claude 3.7	0.0848	0.0480	-0.037	0.010
Git rebase	Claude 4	Claude 3.7	0.0205	0.0111	-0.009	0.191

also provide additional context, revealing patterns such as early disengagement and reduced code pushes with `gpt-5`, and improved engagement when plans are surfaced to users. We identify two directions for future work and show how our framework can be adapted to other domains in Table 11:

More Interactive LLM Backbones. Since our results suggest that improvements in backbone quality remain the primary driver of user satisfaction, it also highlights an opportunity to train backbones that are tuned for interactivity. Rather than optimizing solely for benchmark accuracy, future models could emphasize capabilities that users find desirable in collaborative contexts. For example, this might include maintaining a consistent multi-turn state, dynamically clarifying ambiguous user intent, and proactively getting feedback. Such properties would support more sustained engagement and reduce failure modes like misunderstandings or abandoned sessions, as we observed in our study.

Better Modeling of User Satisfaction and Engagement. Our findings also underscore the value of modeling user satisfaction. We find signals like early disengagement, frequency of corrective messages, or code

Table 7: Memory max step treatment (120) and Control (80) Feature Comparison

Feature	Var A	Var B	Mean A	Mean B	Diff (B-A)	p-val
Misunderstood intention	Treatment	Control	0.2308	0.2329	0.002	0.981
Did not follow instruction	Treatment	Control	0.3846	0.3014	-0.083	0.335
Insufficient analysis	Treatment	Control	0.4231	0.3288	-0.094	0.284
Insufficient testing	Treatment	Control	0.4615	0.2877	-0.174	0.047
Insufficient debugging	Treatment	Control	0.4615	0.3699	-0.092	0.307
Incomplete implementation	Treatment	Control	0.5385	0.3836	-0.155	0.088
Scope creep	Treatment	Control	0.0769	0.0411	-0.036	0.396
User message count	Treatment	Control	19.08	18.03	-1.05	0.307
Git commit	Treatment	Control	0.5577	0.5479	-0.010	0.917
Git push	Treatment	Control	0.5192	0.4932	-0.026	0.777
Git pull	Treatment	Control	0.0769	0.0685	-0.008	0.862
Git reset	Treatment	Control	0.0577	0.0548	-0.003	0.950
Git rebase	Treatment	Control	0.0000	0.0274	0.027	0.235

Table 8: No Plan $\rightarrow$ Show Plan Feature Comparison.

Feature	Var A	Var B	Mean A	Mean B	Diff (B-A)	p-val
Misunderstood intention	Planning	Control	0.2222	0.2771	0.055	0.168
Did not follow instruction	Planning	Control	0.3128	0.3463	0.034	0.438
Insufficient analysis	Planning	Control	0.3004	0.3723	0.072	0.098
Insufficient testing	Planning	Control	0.2963	0.3550	0.059	0.173
Insufficient debugging	Planning	Control	0.2922	0.3723	0.080	0.064
Incomplete implementation	Planning	Control	0.3868	0.4589	0.072	0.113
Scope creep	Planning	Control	0.0988	0.1212	0.022	0.435
User message count	Planning	Control	13.16	19.17	6.01	0.070
Git commit	Planning	Control	0.6461	0.6580	0.012	0.786
Git push	Planning	Control	0.5514	0.6104	0.059	0.194
Git pull	Planning	Control	0.0947	0.0866	-0.008	0.761
Git reset	Planning	Control	0.0782	0.0909	0.013	0.619
Git rebase	Planning	Control	0.0165	0.0173	0.001	0.944

Table 9: Cost comparison across LLMs.

Model	Avg Cost and Std Dev Per Conversation
Claude-3.7-Sonnet vs Claude-4-Sonnet	
Claude-3.7-Sonnet	\$2.62 ± \$3.80
Claude-4-Sonnet	\$2.63 ± \$4.22
Claude-4-Sonnet vs GPT-5	
Claude-4-Sonnet	\$3.05 ± \$5.90
GPT-5	\$2.97 ± \$6.50

push behavior can serve as early indicators of dissatisfaction, which can complement sparse, explicit rating data. We encourage future work to explore how these behavioral features in human-agent interactions can

Table 10: Percent CI Reduction (higher is better)

	LogReg (*Corr = 0.24*)	**HGB** (*Corr = 0.27*)	**RF** (*Corr = 0.29*)
Claude-3.7 vs Claude-4	3.57	17.55	61.5
Claude-4-Sonnet vs GPT-5	5.5	6.61	26
Planning vs no planning	4.23	50.93	65
Memory Max Step	2.8	0.96	5.5

be studied in more detail to see if they can be used to learn adaptive or more personalized interventions in real time.

Table 11: Overview of how future work can apply our three-step framework to varying domains to evaluate human-agent interaction: shopping with web agent, conducting experiments and literature search with research agent, and planning trip with travel agent.

	Shopping Agent	**Research Agent**	**Trip Planning Agent**
Step 1:	Create an interface that periodically collects 5-star ratings as the agent is adding items to the cart.	Create an interface that periodically collects 5-star ratings as the agent is collecting literature and running experiments.	Create an interface that periodically collects 5-star ratings as the agent builds a travel itinerary.
Step 2:	Train ML model using user features (number of messages and sentiment), agent features (shopping site, item category), and task progression (whether a purchase was made).	Train ML model using user features (number of messages and sentiment), agent features (research topic), and task progression (success of experiments).	Train ML model using user features (number of messages and sentiment), agent features (travel type), and task progression (whether a hotel was reserved).
Step 3:	Apply directly: the methodology to compare $\widehat{\Delta}_{\text{naive}}$ and $\widehat{\Delta}_{\text{augment}}$ is entirely agnostic to the software engineering use case.	Apply directly: the methodology to compare $\widehat{\Delta}_{\text{naive}}$ and $\widehat{\Delta}_{\text{augment}}$ is entirely agnostic to the software engineering use case.	Apply directly: the methodology to compare $\widehat{\Delta}_{\text{naive}}$ and $\widehat{\Delta}_{\text{augment}}$ is entirely agnostic to the software engineering use case.

D DISCLOSURE

The authors used ChatGPT for minor copyediting tasks.