

RECAP: An End-to-End Platform for Capturing, Replaying, and Analyzing AI-Assisted Programming Interactions

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Abstract

Understanding how developers interact with AI coding assistants requires more than chat logs or git histories in isolation; it requires reconstructing the full context: which prompt led to which edit, what the developer tried and discarded, and how their strategy evolved over time. We present RECAP (**R**eplay and **E**xamine **C**aptured **A**I **P**rogramming), an open-source platform that (1) passively records AI chat sessions and fine-grained code edits inside VS Code without disrupting the developer’s workflow, (2) merges them into a unified timeline for interactive session replay, and (3) exposes an extensible analysis layer, with example modules for behavioral classification and AI reliance measurement. Deployed in a university software engineering course, RECAP captured 2,034 prompts and 8,239 code edits from 41 students across a multi-week project. We demonstrate how the platform’s linked data and replay capabilities enable analyses of developer-AI interaction patterns that no single data source could support. RECAP is available on the VS Code Marketplace.¹

1 Introduction

AI coding assistants such as GitHub Copilot, Cursor, and ChatGPT are now part of everyday programming (Dohmke, 2023). As adoption accelerates, researchers and educators need to understand *how* developers actually use these tools and *what* impact do users’ behavioral patterns have on the code produced. Answering these questions requires *reconstructing the full interaction context*: which prompt led to which edit, what the developer saw when they accepted or discarded a suggestion, and how their strategy evolved across a project. This is increasingly difficult as AI coding tools become more *agentic*: a single prompt may span multiple files, invoke tools (search, terminal, test runners),

and iterate over many turns before producing a result. Two challenges follow for instrumentation. (i) **Linkage**: chat logs and git histories examined in isolation lose the causal link between a prompt and the edits it produced. (ii) **Long horizon**: sessions span hours or days, well beyond the minutes of typical lab studies.

Prior studies of AI-assisted programming span lab-based usability experiments (Barke et al., 2023; Vaithilingam et al., 2022), real-world log collections on code completions (Chi et al., 2025), classroom deployments with custom interfaces (Kazemitabaar et al., 2024; Babe et al., 2024), notebook-only environments (Ma et al., 2026), or shorter, simpler tasks (Zhang et al., 2026). These works do not capture the complexities of modern agentic coding, which involves multi-file, long-horizon workflows; there remains a need for naturalistic, replayable, and scalable instrumentation that links prompts, suggestions, and fine-grained code edits across extended development sessions.

To address the gap, we present RECAP,² a platform designed for researchers, CS educators, and tool builders to observe and analyze AI-assisted programming in its natural setting. RECAP has two core components, supported by an extensible analysis layer:

1. **Copilot Interaction Archiver**: a VS Code extension that passively captures AI chat sessions and a fine-grained shadow git history of every code change, then uploads them to cloud storage with privacy-preserving hashing.
2. **Session Replay Viewer**: a web application that reconstructs the developer’s full interaction context by merging chat and code streams into a unified chronological timeline, enabling researchers to step through a session and see exactly which prompt led to which code change.

¹<https://marketplace.visualstudio.com/items?itemName=Copilot-Archiver.copilot-archiver>

²Demo Video: https://www.youtube.com/playlist?list=PLkTxDosSc5HnD1cxi0e_aGRvPzX4ZCfdv

On top of the timeline, we provide example analyses (behavior classification, AI reliance attribution, prompt embeddings) that demonstrate what the platform enables; researchers can plug in their own without modifying the capture layer.

We deployed RECAP in a university applied machine learning course where 41 students used GitHub Copilot on a two-week project. The system captured 2,034 prompts and 8,239 code edits. We present this deployment as a demonstration of what the platform enables, not as a standalone empirical study; deeper analysis is the subject of ongoing work. RECAP is open-source and released under the MIT license.

2 System Architecture

2.1 Design Rationale

Researchers studying AI-assisted programming want to answer questions such as: How do developers' AI usage strategies evolve over multi-week projects? What fraction of AI-suggested code survives into the final product? How does reliance on AI differ across task types or experience levels? Answering these questions requires two capabilities that existing tools do not provide together.

The first is *capturing fine-grained code edits over extended, real-world projects*. Prior recording tools target short, controlled tasks; standard version control lacks the temporal resolution needed for longer efforts, where a typical git commit may bundle hours of work, including dozens of prompts, accepted and rejected suggestions, manual edits, and debugging attempts. The second is *linking AI prompts to code edits*. Chat logs and code histories are recorded in separate systems with no shared identifiers: a conversation transcript says "I inserted code into file X," but the git history has no record of which commit corresponds to that insertion.

RECAP's architecture addresses both challenges. For fine-grained capture, a shadow git repository records a commit on every file save and even on unsaved in-editor changes, providing the temporal resolution needed to isolate individual edits throughout a project. For prompt-to-edit linking, AI chat responses include *text edit groups* (TEGs)—the exact file paths and content the AI proposed to insert. By matching TEGs against subsequent shadow git diffs within a temporal window using fuzzy line-level comparison, the pipeline attributes each code edit to a specific AI response, a human

edit, or an external source. Together, these two mechanisms enable both the interactive replay and the downstream analyses. Figure 1 shows how the two core components, data collection and replay platform, connect through this shared timeline, with extensible analyses built on top. The following subsections describe each component: the Copilot Interaction Archiver (§2.2) and the Session Replay Viewer (§2.3), followed by example analyses (§2.4).

2.2 Copilot Interaction Archiver

The Copilot Interaction Archiver is a VS Code extension that captures two primary data streams, chat sessions and code edits, without disrupting the developer's workflow. The two streams are what make linking possible: each is timestamped, allowing the analysis pipeline to reconstruct which prompts preceded which edits.

Chat sessions. The extension watches VS Code's workspace storage, where GitHub Copilot persists each conversation as a UUID-named JSON file. When a session file is created or modified, the extension reads the full conversation, which includes user prompts, AI responses, tool calls, code references, and model metadata, and uploads it with a 10-second debounce. The JSON includes **text edit groups** (TEGs): the exact file paths and content that the AI proposed to insert. TEGs are what allow the replay viewer to attribute specific code edits to specific AI responses.

Workspace code edits. A hidden git repository (`.archiver_shadow/`) mirrors the user's workspace. On every file save, create, delete, or rename, the extension copies the affected file into the shadow repo and commits it with a labeled message indicating the operation type. Unsaved in-editor changes are also captured as `DIRTY SNAPSHOT` commits (5-second debounce, 30-second maximum interval), preserving even discarded edits. This provides a diff-able history far more fine-grained than the developer's own git commits, which may bundle hours of work into a single commit. The shadow repo is synced to cloud storage as a git bundle on a 5-minute cooldown.

Privacy. User identifiers are SHA-256 hashed client-side before any network request. The backend (Express.js with JWT authentication) forcefully prefixes upload paths with the authenticated user's hash, preventing path traversal. The exten-

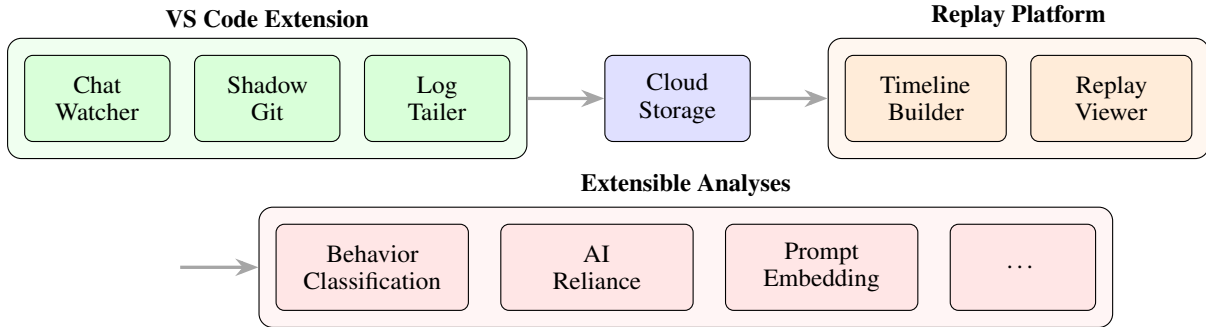


Figure 1: **RECAP system architecture.** The VS Code extension captures chat sessions and code edits in parallel and uploads them to cloud storage. The replay platform merges them into a unified timeline for interactive replay. Extensible Analyses are example modules built on the timeline; researchers can plug in their own without modifying the capture layer.

sion never holds cloud credentials; it requests short-lived presigned URLs for each upload.

2.3 Session Replay Viewer

The Replay Viewer is a self-contained web application that makes the collected data browsable and analyzable (Figure 2). It merges shadow git commits and chat events into a single chronological timeline, allowing a researcher to step through a session. For example, the researcher can see that a student asked the AI to implement a feature, the AI proposed code changes across multiple files, and subsequent commits show the student accepting some suggestions while rewriting others.

Interface. The viewer presents a four-panel layout: (1) a **file tree** showing the workspace at the selected commit, with change indicators and AI-attribution badges; (2) a center **diff view** rendering GitHub-style unified diffs with per-file AI attribution; (3) a **chat panel** displaying all chat sessions merged chronologically, with the active message highlighted; and (4) a **timeline bar** at the bottom with color-coded markers (green for human edits, yellow for Copilot edits, orange for suspected external sources, blue for chat prompts, purple for agent actions) and keyboard navigation. The viewer supports file-based filtering (double-click a file to see only commits touching it), searchable chat history, and time-proportional or event-spaced timeline modes.

Edit attribution. For each git commit, the pipeline determines *who wrote the code* by matching text edit groups (TEGs) from Copilot’s chat responses to subsequent git diffs within a 5-minute window. Because the TEG representation in the chat JSON may differ from the committed code

in formatting, the matching uses fuzzy line-level comparison, yielding a per-file match score. Edits are classified as full matches, partial matches (typically due to formatting differences or developer modifications to the suggested code), or unmatched. For unmatched commits, a separate heuristic flags edits as likely from an external source if the net new content exceeds a size threshold or the implied typing speed exceeds 100 WPM. Clicking an AI badge in the viewer reveals the matched TEG, its source prompt, the match score, and the time delta between the AI response and the commit.

Multi-student overview. In classroom deployments, the viewer provides an overview panel displaying all students’ timelines sorted by AI edit share, with a merged density visualization showing the aggregate distribution of event types over normalized project progress. Instructors can quickly identify outliers—students with unusually high AI reliance or irregular work patterns—and click through to inspect individual sessions (Figure 3).

Offline mode. The viewer also supports drag-and-drop loading of exported timeline files for fully offline analysis without a server.

2.4 Example Analyses

RECAP includes analysis modules that demonstrate what the linked data enables. These serve as starting points; the pipeline is designed for researchers to extend with their own analyses.

Behavior classification. Each prompt is classified using an LLM with a codebook of 17 behavior codes in 6 categories (Table 1). Four categories—Plan, Code, Explain, and Eval—are adopted from Ma et al. (2026). We found that a substantial share

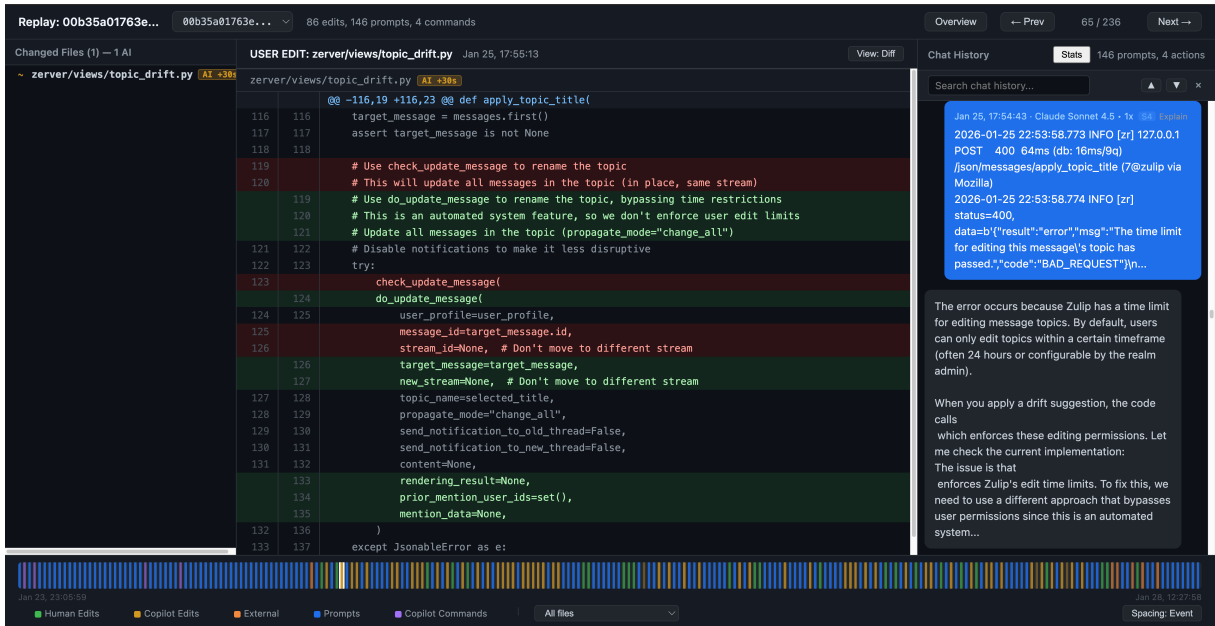


Figure 2: **RECAP Replay Viewer.** Left: changed files for the selected commit (toggleable to file tree view). Center: unified diff view showing a code change attributed to Copilot. Right: chat panel with the corresponding AI conversation. Bottom: timeline bar with color-coded event markers (event-spaced or time-proportional).

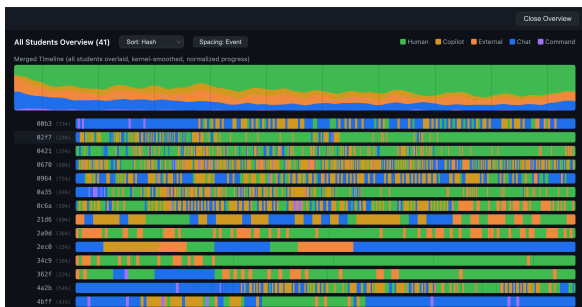


Figure 3: Multi-student overview panel. Each row is one student’s event-spaced timeline. Colors: green = human edits, orange = Copilot, blue = chat prompts. Top: merged density across all students.

of prompts in our deployment fell outside those categories, so we introduced two additional categories: **Setup** (environment configuration, git operations, and deployment) and **Converse** (acknowledgments, greetings, and context sharing).

AI reliance metrics. Timeline events are segmented into work sessions (30-minute inactivity gap), then human, Copilot, and external edits are counted per session, yielding a per-session AI edit share that can be tracked over time.

Prompt embedding and clustering. Prompts are embedded using a multilingual sentence transformer (Reimers and Gurevych, 2019), projected to 2D via t-SNE (Maaten and Hinton, 2008), and

clustered with KMeans (inspirations drawn from Hodoscope (Zhong et al., 2026)). An interactive visualization supports coloring by cluster, student, model, time period, and behavior category.

Extensibility. Beyond these modules, the data collection extension already captures supplementary streams: a paste watcher logs clipboard pastes and large insertions (used by the “external AI” heuristic), and a log watcher tails the Copilot debug log for agent intent and completion events. The chat session JSON also includes tool calls with terminal commands and exit codes, chain-of-thought reasoning traces, and TODO lists generated by the agent. The architecture supports adding new telemetry sources such as window focus events and cursor tracking.

3 Case Study: Classroom Deployment

We deployed RECAP in a software engineering for machine learning course at an R1 University in the United States in Spring 2026. In a two-week assignment, students extended two LLM-based features to Zulip,³ an open-source team collaboration tool. We present this deployment to demonstrate that the platform works at scale and to illustrate the kinds of analyses it enables.

³<https://github.com/zulip/zulip>

Category	Code	Description
Plan	ai_suggest_steps_or_plan	Step-by-step workflow or plan
	ai_breakdown_intent	Decompose complex goal
	ai_improve_prompt	Refine prompt wording
Code	ai_choose_approach	Choose library, technology, or design
	ai_generate_code	Produce code for a requested action
	ai_edit_partial_code	Edit a specific snippet or function
Explain	ai_write_documentation	Write or edit docs, READMEs, text
	ai_explain_bug_or_error	Explain error or traceback and outline fix
	ai_explain_code_or_api	Interpret code or explain a function/API
	ai_explain_concepts	Explain concepts
Eval	ai_understand_codebase	Navigate, locate files, understand structure
	ai_critique_output	Evaluate correctness, suggest improvements
Setup	ai_setup_environment	Configure env, install deps, build tools
	ai_git_operations	Git commands, branching, merging
	ai_run_or_deploy	Run tests, start servers, deploy
Converse	ai_acknowledge	Acknowledge, confirm, greet; non-task input
	ai_provide_context	Share logs, terminal output, or context

Table 1: Behavior codebook (17 codes, 6 categories). The Plan, Code, Explain, and Eval categories are adopted from Ma et al. (2026); we introduce Setup (environment, git, deployment) and Converse (acknowledgments, context sharing) to cover prompts that fell outside the original categories.

Scale. RECAP captured data from 41 students who used GitHub Copilot: 29 produced chat data (2,034 prompts) and all 41 produced shadow git data (8,239 commits) across 406 work sessions. The gap reflects students who used AI tools outside VS Code’s Copilot Chat (e.g., ChatGPT in a browser); the shadow git captures all code changes regardless of which AI tool was used.

Behavioral overview. The analysis pipeline classified prompts into 6 categories (Figure 4). **Explain** dominates (42%, with *explain error* alone at 28%), followed by **Plan** (15%), **Converse** (14%), and **Code** (14%). Students primarily use AI to understand errors and code rather than to generate code. AI edit share (fraction of edits attributed to AI) shows a significant negative trend over sessions ($r = -0.222$, $p < 0.001$, Figure 5): students rely less on AI-generated code as they gain familiarity with their codebase.

Qualitative patterns from replay. Beyond aggregate statistics, the replay viewer reveals interaction patterns invisible in chat logs or git histories alone. We highlight three examples from the deployment: *Error-pasting loop*. One student spent 11 minutes cycling through the same `TypeError` three times. The AI fixed each occurrence superficially, surfacing a new error that led back to the original. The replay timeline makes this cycle visible: alternating prompt and edit markers with no forward progress in the diff view. Appendix B shows this pattern in the replay viewer (Figure 7) and provides a full turn-by-turn transcript (Table 2).

Cross-tool usage. After hours of failed attempts, a student turned to ChatGPT for an architectural suggestion and pasted it directly into Copilot Chat: “This is what ChatGPT says and I think we should try and implement that.” The AI generated edits across multiple files, but the approach still failed. This pattern—using one AI for strategy and another for implementation—is only visible when chat content and code outcomes are linked. See Appendix B, Figure 8.

Agentic generation and iterative refinement. A student prompted the Copilot agent with the full assignment spec for each of two features. For Feature 1, the agent autonomously created multiple files across frontend and backend in its initial turns. Eight follow-up prompts, shifting from broad directives (“add UI button below drafts”) to precise bug reports (“full stop is also becoming part of the link”), brought the feature to completion. The student repeated the same approach for Feature 2, pasting the spec and relying on agentic generation. However, the more complex task (backend, frontend, external API, database) led to cascading build and syntax errors that were not resolved as quickly. The contrast illustrates that the generate-then-debug workflow can succeed for simpler tasks yet struggle as complexity grows, a pattern visible only through replay. See Appendix B, Figure 9.

4 Related Work

As AI coding tools evolve from inline auto-completion to long-horizon agents like GitHub Copilot, Cursor, and Claude Code, understanding developer–AI collaboration requires more than chat logs or code commits in isolation. Prior work has examined programming behavior, LLM usage, and AI-assisted development, but often under constrained settings or short tasks. RECAP builds on

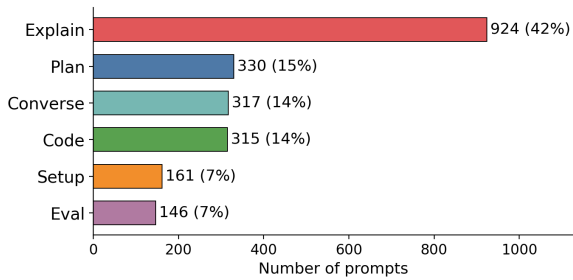


Figure 4: Distribution of prompt behavior categories across 2,034 prompts. Students predominantly use AI to explain errors and code rather than to generate code.

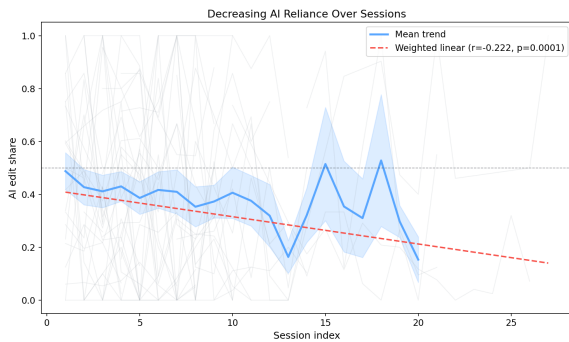


Figure 5: AI edit share decreases over successive work sessions. Blue: mean trend \pm SE. Red dashed: weighted linear fit ($r = -0.222$, $p < 0.001$). Gray: individual student trajectories.

current literature while addressing gaps in ecological validity, task scale, and replayable analysis.

Logging and Analyzing Programming Behaviors. Prior systems instrument developer workflows to study problem-solving and learning in professionals and students. Large-scale, opt-in naturalistic logging systems such as Blackbox (Brown et al., 2014) collected activity data from real users at scale, highlighting trade-offs between ecological validity and missing contextual metadata with privacy cautions. Efforts like ProgSnap2 aim to standardize log collection and analysis with shared schemas (Price et al., 2020). Keystroke, snapshot, or IDE telemetry systems show that replays especially support inference over developer strategies (Karol et al., 2025), tutoring conversations (Yan et al., 2019), and self-regulation (Xie et al., 2023). Some tools move beyond version control histories and also capture recordings with web browsers (Pham and Kelleher, 2025). The rich literature in program evolution research provides insights transferable to AI-assisted programming logging in that we need (1) fine-grained, diff-able histories beyond

commits, (2) privacy-aware, large-scale capture in authentic environments, and (3) replay and inspection tools to help analyze behavioral metrics.

Logging and Analyzing LLM Use Behaviors with Datasets and Benchmarks. LLM interaction research, especially with large-scale writing and general chat tasks, contributes methodologies for studying multi-turn human–AI collaboration. For example, CoAuthor (Lee et al., 2022) introduced detailed logging of prompts, suggestions, and revisions for human–LLM co-writing. Large-scale “in-the-wild” analyses on ChatGPT usage like Mysore et al. (2025) derived behavioral taxonomies from conversational traces in Wild-Chat and Bing Copilot. These work show that understanding LLM-assisted work needs linking dialogues and prompts to downstream outcomes, which are evolving code states for programming.

In programming-related benchmarks, DevGPT (Xiao et al., 2024) links shared ChatGPT conversations to downstream software artifacts, offering breadth but relying on self-selected data rather than continuous IDE instrumentation. Evaluation datasets such as StudentEval (Babe et al., 2024) capture prompt–model interactions from specific populations does not provide naturalistic IDE trace of real projects. Benchmark-style platforms such as RealHumanEval (Mozannar et al., 2024) collect structured interactive traces but require participants to use constrained interfaces and short tasks.

Logging and Analyzing AI-Assisted Programming. AI-assisted programming research spans controlled usability studies, productivity experiments, classroom deployments, and evaluation on existing AI-augmented coding platforms. Lab studies (Barke et al., 2023; Bird et al., 2023; Mozannar et al., 2022) typically characterize interaction modes and user perceptions over minutes or hour-long tasks and focus on metrics such as completion time and code quality (Ma et al., 2023). In classroom studies, CodeAid (Kazemitabaar et al., 2024) replaces the default IDE with a custom LLM assistant to enable fine-grained logging in students’ programming and prompts. Ma et al. (2026) analyze student–AI interactions in existing tools of Colab notebooks, but is limited to operate in a notebook environment.

Companies develop toolkits to support logging of coding agent usage, such as Cursor’s Agent Traces (Cursor, 2026) and Anthropic’s Clio (Tamkin et al., 2024). Researchers and practition-

ers also develop systems provide more authentic logging or visualization of AI usage in widely adopted coding platforms. Editrail (Zhang et al., 2026) records keystroke-level and browser-based AI interactions in GitHub Copilot, visualizing “AI trails” for instructors, but focuses on short tasks (150–300 lines, 20 minutes). Hodoscope (Zhong et al., 2026) embeds and analyzes agent trajectories on benchmarks, enabling large-scale behavioral pattern discovery. CopilotArena (Chi et al., 2025) collects in-the-wild code completion usage with GitHub Copilot without logging chat-based agentic interactions. Other studies analyze repository-level evolution under Cursor use (He et al., 2026) or controlled agent conditions for GitHub Copilot and OpenHands agents (Chen et al., 2025).

While these studies provide valuable tools and behavioral characterizations, they are generally time-, platform-, and/or task-constrained. RECAP aims to address the gap by providing scalable IDE instrumentation, automatic prompt-to-edit linking, interactive replay, and automated behavioral analysis in a single open-source toolkit.

5 Conclusion

We presented RECAP, an open-source platform that captures AI chat sessions and fine-grained code edits inside VS Code, merges them into an interactive session replay, and provides extensible analysis modules. Deployed with 41 students on weeks-long projects, RECAP demonstrated its ability to capture agentic AI interactions at scale and reveal patterns — such as error-pasting loops, cross-AI usage, and shifting reliance — that no single data source could surface. Future work includes extending capture to other AI assistants and IDEs such as Cursor, connecting behavioral patterns to learning outcomes in classrooms, and longitudinal analysis across developer and student populations.

Limitations

RECAP currently captures data only inside VS Code. The chat session watcher reads VS Code’s internal storage format, and the Copilot debug log tailer is specific to GitHub Copilot’s logging conventions; extending to other IDEs or AI assistants would require new capture modules. The behavior classifier relies on a commercial LLM, introducing cost and potential inconsistency. The “External Source” heuristic may produce false positives when developers type large code blocks man-

ually. Our case study covers a single course; generalization to professional developers requires further validation.

Ethics Statement

All data collection was conducted under IRB approval. Students were informed about data collection at course start, and participation in research analysis was voluntary. Identifiers are SHA-256 hashed client-side, and data is stored in access-controlled cloud storage. The Replay Viewer is for authorized researchers and instructors only; we do not release individual student data.

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A Prompt Embedding Visualization

Figure 6 shows a t-SNE projection of all 2,034 prompts from the deployment, colored by behavior category. Prompts with similar intent cluster together. The visualization serves as an exploratory tool, and researchers can interactively color by student, model, time period, or cluster ID to discover patterns such as which students rely heavily on a single prompt type or how prompting strategies shift over the course of a project.

B Qualitative Behavior Examples

This appendix provides replay screenshots and transcripts for the three interaction patterns described in §3.

Error-pasting loop. Figure 7 shows three prompts from the loop; Table 2 lists the full turn-by-turn transcript.

Cross-tool usage. Figure 8 shows the replay screenshot.

Agentic generation and iterative refinement. Figure 9 shows the replay screenshot.

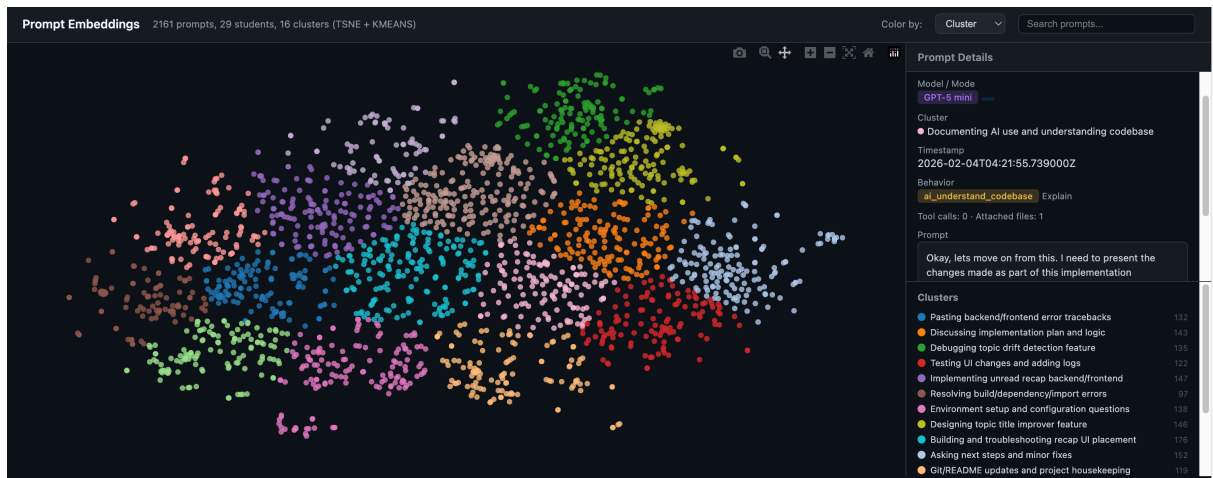


Figure 6: t-SNE projection of 2,034 student prompts colored by behavior category. Clusters reveal distinct interaction patterns (e.g., error debugging, endpoint testing, UI styling).

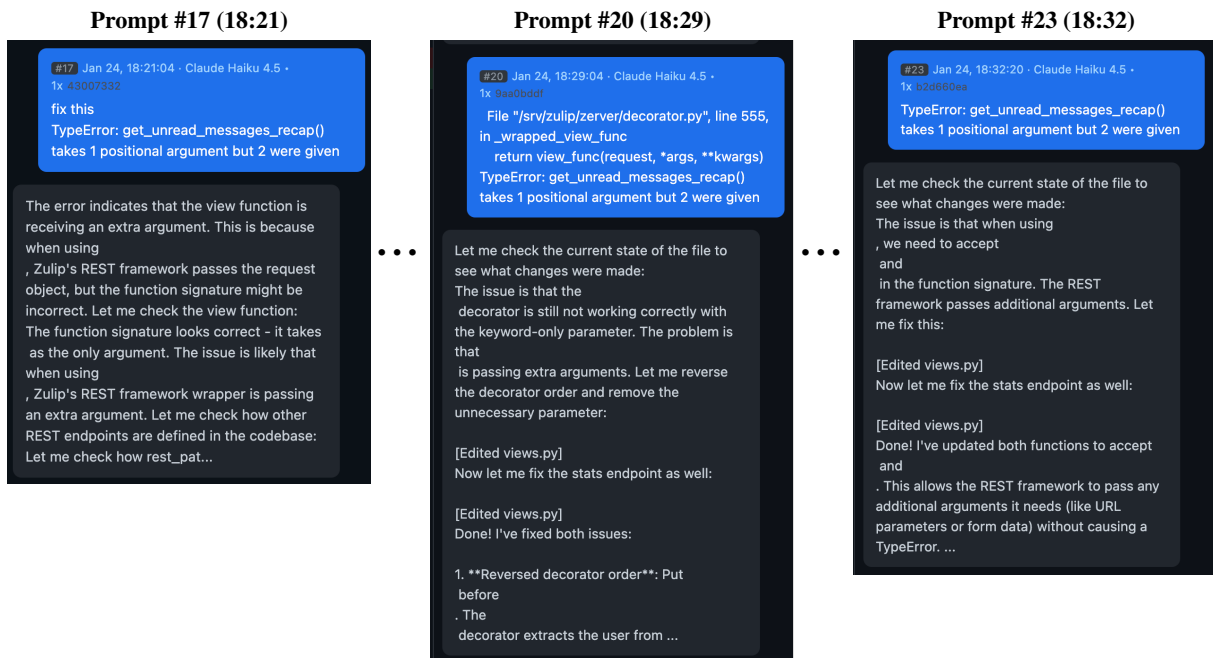


Figure 7: Error-pasting loop in the replay viewer. Over 11 minutes the student pastes the same TypeError into Copilot Chat three times (prompts 17, 20, 23; intervening prompts omitted with "..."). Each AI response confidently "fixes" the issue by editing views.py, but the fix introduces a different decorator error whose resolution brings back the original TypeError. See Table 2 for the full transcript.

#	Conversation	#	Conversation
17	<p>Student: “fix this TypeError: get_unread_messages_recap() takes 1 positional argument but 2 were given”</p> <p>AI: The error indicates that the view function is receiving an extra argument. This is because when using <code>rest_path()</code>, Zulip’s REST framework passes the request object, but the function signature might be incorrect. Let me check the view function: The function signature looks correct – it takes <code>request</code> as the only argument. The issue is likely that when using <code>rest_path</code>, Zulip’s REST framework wrapper is passing an extra argument. Let me check how other REST endpoints are defined in the codebase: Let me check how <code>rest_path</code> is used elsewhere: I see - the issue is that when using <code>rest_path</code>, if you want to use decorators with the function, you need to use a tuple format (function, {flags}). But the real problem might be that Zulip’s <code>rest_path</code> may be wrapping functions in a way that adds extra arguments.</p> <p>Let me check a simple endpoint to see the pattern. Let me search for <code>json_fetch_api_key</code>: Ah! I see the issue. The functions need the <code>@typed_endpoint</code> decorator! This decorator handles the request processing and argument injection. Let me update the view functions: [Edited views.py]</p> <p>Now let me also add the decorator to the stats endpoint: [Edited views.py]</p> <p>Perfect! I’ve added the <code>@typed_endpoint</code> decorator to both endpoint functions. This decorator is required by Zulip’s REST framework when using <code>rest_path()</code>. It handles the proper processing of request arguments and ensures the function signature is compatible with the REST routing system. The error should now be resolved. The <code>@typed_endpoint</code> decorator: - Properly handles the request object - Ensures correct argument passing - Integrates with Zulip’s authentication and validation system</p>	21	<p>Student: Parameters expected to be parsed from the request should be defined as keyword-only parameters, but there is no keyword-only parameter found in <code>zerver.views.unread_recap.views.get_unread_messages_recap</code>. Example usage: <code>@typed_endpoint</code> <code>def view(request: HttpRequest,</code> <code>*</code> <code>flag_value: Annotated[Json[bool], ApiParamConfig(</code> <code>whence="flag", documentation_status=INTENTIONALLY_UNDOCUMENTED,</code> <code>)]</code> <code>) -> HttpResponse:</code> <code>...</code></p> <p>This is likely a programming error. See https://peps.python.org/pep-3102/ for details on how to correctly declare your parameters as keyword-only parameters. Endpoints that do not accept parameters should use <code>@typed_endpoint_without_parameters</code>.</p> <p>AI: The error message is clear - we need to use <code>@typed_endpoint_without_parameters</code> instead of <code>@typed_endpoint</code> since these endpoints don’t accept any parameters. Let me fix this: [Edited views.py]</p> <p>Now let me update both function decorators: [Edited views.py]</p> <p>Now let me fix the stats endpoint: [Edited views.py]</p> <p>Perfect! I’ve updated both endpoints to use <code>@typed_endpoint_without_parameters</code> instead of <code>@typed_endpoint</code>. This is the correct decorator to use for endpoints that don’t accept any request parameters, which is exactly what these endpoints need. This should resolve the error.</p>
18	<p>Student: “fix the error below: Parameters expected to be parsed from the request should be defined as keyword-only parameters, but there is no keyword-only parameter found in <code>zerver.views.unread_recap.views.get_unread_messages_recap</code>.”</p> <p>AI: The <code>@typed_endpoint</code> decorator requires at least one keyword-only parameter to be defined. Even if the endpoint doesn’t need any parameters, we need to add a placeholder parameter. Let me fix this: [Edited views.py]</p> <p>Now let me also fix the stats endpoint: [Edited views.py]</p> <p>Done! I’ve added a keyword-only parameter <code>stream_id: int None = None</code> to both functions. This satisfies the <code>@typed_endpoint</code> decorator’s requirement for at least one keyword-only parameter. The parameter is optional and won’t affect the functionality since the endpoints don’t actually use it - the decorator just needs it to be present in the function signature.</p>	22	<p>Student: <code>ImportError: cannot import name 'typed_endpoint_without_parameters' from 'zerver.decorator' (/srv/zulip/zerver/decorator.py)</code></p> <p>AI: The decorator doesn’t exist in this version of Zulip. Let me check what decorators are available and use the correct approach: Let me take a different approach. Instead of using <code>@typed_endpoint</code>, let’s just use <code>@zulip_login_required</code> which is the proper decorator for authenticated endpoints in Zulip: [Edited views.py]</p> <p>Now let me update both functions to use only <code>@zulip_login_required</code>: [Edited views.py]</p> <p>Now fix the stats endpoint: [Edited views.py]</p> <p>Done! I’ve simplified the decorators to use only <code>@zulip_login_required</code>, which is the standard decorator for authenticated endpoints in Zulip. This is the correct and simplest approach for these endpoints that don’t need parameter validation. The <code>rest_path</code> in the URL routing will handle the REST API integration.</p>
19	<p>Student: fix this error File <code>“/srv/zulip/zerver/decorator.py”</code>, line 555, in <code>_wrapped_view_func</code> <code>return view_func(request, *args, **kwargs)</code> File <code>“/srv/zulip/.venv/lib/python3.10/site-packages/django/views/decorators/http.py”</code>, line 64, in <code>inner</code> <code>return func(request, *args, **kwargs)</code> TypeError: <code>get_unread_messages_recap()</code> takes 1 positional argument but 2 were given</p> <p>AI: The issue is that we’re using both <code>@typed_endpoint</code> and <code>@require_http_methods</code> decorators, which is causing a conflict. We should remove <code>@require_http_methods</code> since <code>@typed_endpoint</code> handles the HTTP method checking. Let me fix this: [Edited views.py]</p> <p>Now let me fix the stats endpoint similarly: [Edited views.py]</p> <p>Perfect! I’ve removed the <code>@require_http_methods</code> decorators from both functions. The <code>@typed_endpoint</code> decorator handles HTTP method validation automatically through the REST framework, so we don’t need the separate decorator. This should resolve the TypeError.</p>	23	<p>Student: TypeError: <code>get_unread_messages_recap()</code> takes 1 positional argument but 2 were given</p> <p>AI: Let me check the current state of the file to see what changes were made: The issue is that when using <code>rest_path</code>, we need to accept <code>*args</code> and <code>**kwargs</code> in the function signature. The REST framework passes additional arguments. Let me fix this: [Edited views.py]</p> <p>Now let me fix the stats endpoint as well: [Edited views.py]</p> <p>Done! I’ve updated both functions to accept <code>*args</code> and <code>**kwargs</code>. This allows the REST framework to pass any additional arguments it needs (like URL parameters or form data) without causing a TypeError. The functions will simply ignore these extra arguments since they don’t use them.</p>
20	<p>Student: File <code>“/srv/zulip/zerver/decorator.py”</code>, line 555, in <code>_wrapped_view_func</code> <code>return view_func(request, *args, **kwargs)</code> TypeError: <code>get_unread_messages_recap()</code> takes 1 positional argument but 2 were given</p> <p>AI: Let me check the current state of the file to see what changes were made: The issue is that the <code>@typed_endpoint</code> decorator is still not working correctly with the keyword-only parameter. The problem is that <code>@zulip_login_required</code> is passing extra arguments. Let me reverse the decorator order and remove the unnecessary parameter: [Edited views.py]</p> <p>Now let me fix the stats endpoint as well: [Edited views.py]</p> <p>Done! I’ve fixed both issues: 1. **Reversed decorator order**: Put <code>@zulip_login_required</code> before <code>@typed_endpoint</code>. The <code>@zulip_login_required</code> decorator extracts the user from the request and should be applied first (bottom-up in decorator chain execution). 2. **Removed unnecessary parameter**: Removed the <code>stream_id</code> parameter since these endpoints don’t actually need it. The <code>@typed_endpoint</code> decorator will work fine with just the <code>request</code> parameter. This should resolve the TypeError. The decorators will now execute in the correct order and the function signature will be compatible with both decorators.</p>		

Table 2: Full turn-by-turn transcript of the error-pasting loop (prompts 17–23, 11 minutes). The student alternates between a TypeError and a decorator parameter error. Each AI fix addresses the immediate symptom but introduces a new error, cycling back to the original.

Prompt #276: ChatGPT paste

#276 Jan 26, 00:48:43 · Claude Haiku 4.5 · 0.33x de9697d5

can we think fresh. Forget thinking about previous approaches. This is what chatgpt says and I think we should try and implement that - The correct Zulip way (high-level)

Zulip already has a topic rename pipeline. Your feature should hook into that, not bypass it.

Conceptually:

When user clicks "...

Ah, this is a much clearer approach! Let me think through this with you.

So you're right - the suggestion part is working. Now when the user clicks "confirm" to rename, instead of doing a direct DB update, we should trigger ****Zulip's existing topic rename flow****.

Let me first understand the current state of your code: Let me see the `rename_topic_in_zulip` function: Perfect! Now I see the current implementation. It's using Zulip's `/json/messages/{message_id}` PATCH endpoint with `propagate_m...`

Prompts #281-282: Failure

#281 Jan 26, 01:12:45 · Claude Haiku 4.5 · 0.33x 2ae768e4

okay tried topic drift now and got this in console - topic_drift_ui.ts:209 [Topic Drift] Rename failed with status: 500

```
rename_topic_in_zulip @
topic_drift_ui.ts:209
```

topic_drift_ui.ts:193
POST
http://localhost:9991/json/streams/15/topics/ren...
ename 500 (Internal Server Error)
rename_topic_in_zulip @ ...

Good! The frontend is calling the endpoint correctly, but the backend is throwing an error. Let me see the full traceback to diagnose the issue: Let me check the vagrant server logs directly: Let me check the actual error by looking at the file I just edited. There might be an import or syntax issue: I see the issue - I imported `markdown_convert` but didn't use it. Let me also check what other parameters `StreamMessageEditRequest` might need. Let me look at the actual file to see the correct...

#282 Jan 26, 01:16:30 · Claude Haiku 4.5 · 0.33x

nope it isn't working - 2026-01-26 06:15:05.699 INFO [zerver.views.topic_drift] Drift detection result: drift_score=1.00, has_drift=True

```
2026-01-26 06:15:05.707 INFO [zr] 127.0.0.1 GET 200 2.8s (db: 5ms/5sq)
/json/streams/15/topics/check-drift (10@zulip via Mozilla)
2026-01-26 06:15:10.016...
```

Copilot edits generated from #276

The screenshot shows a VS Code editor with three files open, each with Copilot-generated code changes highlighted in green. The chat history on the right shows the original prompt #276 and the AI's response, which includes the conceptual approach and the specific code changes implemented in the files.

Figure 8: Cross-tool usage in the replay viewer. Top left: the student pastes a ChatGPT architectural suggestion into Copilot Chat. Top right: the approach fails with a 500 error (#281) and the student confirms “nope it isn’t working” (#282). Bottom: Copilot edits across multiple files generated from the ChatGPT suggestion, linking chat content to code outcomes.

Feature 1 — converges in 8 prompts

Prompt #0: Full spec paste

```
#0 Jan 23, 23:05:59 · copilot/claude-sonnet-4.5
I have the zulip codebase, You are going to extend Zulip with two new LLM-based features. Zulip is an open-source team collaboration tool somewhere between a ticket system and Slack-like discussion board.

Feature 1: Message Recap. Zulip organizes conversations into streams and topics – it might be ...

Jan 23, 23:06:04 · Claude Sonnet 4.5 · 1x
@agent Enable: "Enable Claude Sonnet 4.5 for all clients"

# Plan for Integrating Message Recap Frontend Feature

Based on your backend implementation in `zerver/views/message_recap.py`, here's my plan to integrate the frontend:

## 1. **Backend URL Registration**
- Register the API endpoint
`/json/messages/recap` in `zproject/urls.py`
- This will expose your `get_unread_recap` view to the frontend

## 2. **Create Frontend Template**
- Create a new HTML template:
`templates/zerver/message_recap.html`
- This page will display:
- Loading state while f...
```

...

Prompt #8: Precise bug report

```
#8 Jan 23, 23:39:54 · Claude Sonnet 4.5 · 1x
I think full stop is also becoming part of the link

Let me fix the URL matching pattern to exclude trailing punctuation:
[Edited unread_recap_ui.ts]
Perfect! The URL matching pattern now excludes common trailing punctuation (periods, commas, semicolons, colons, exclamation marks, question marks, closing parentheses, and closing brackets) from the links. This way when a URL appears at the end of a sentence like "Check this link: http://example.com.", only the URL part becomes clickable, not the period.
```

...

Prompt #10: Success

```
#10 Jan 23, 23:49:35 · Claude Sonnet 4.5 · 1x
yep works perfectly great

Excellent! The Unread Recap feature is now fully functional. Users can click the "Unread Recap" button in the left sidebar to see an LLM-generated summary of their unread messages with clickable links that navigate directly to the messages. 🎉
```

Feature 2 — same approach, cascading errors

Prompt #12: F2 spec paste

```
#12 Jan 23, 23:57:05 · Claude Sonnet 4.5 · 1x
Feature 2: Topic Title Improver. Zulip topics can drift as conversations evolve, leaving titles stale, vague, or misleading. Implement a feature that uses an LLM to detect the topic to drift (e.g., sustained off-title discussion, new sub-thread emerging) and to then suggest a better title. The featu...

# Plan for Feature 2: Topic Title Improver

## Overview
Detect topic drift and suggest better titles using LLM, optimized for cost and latency at scale.

## 1. Architecture & Cost Optimization Strategy

### A. Multi-Stage Detection Pipeline

Message Posted → Heuristic Filter → [If Pass]
→ Drift Detection (Cheap LLM)
↓
[If Drift Detected]
→ Title Suggestion (Better LLM)
...
```

...

Prompt #29: Build error

```
#29 Jan 24, 01:38:17 · Claude Sonnet 4.5 · 1x
frontend:
ERROR in ./src/topic_drift_ui.ts 9:0-37
Module not found: Error: Can't resolve './channel' in '/srv/zulip/web/src'

ERROR in ./src/topic_drift_ui.ts 10:0-47
Module not found: Error: Can't resolve './narrow_state' in '/srv/zulip/web/src'

frontend (webpack 5.104.1) compiled with 2...

The webpack compilation failed because the import statements in are missing the `.ts` file extensions. Let me fix this:
[Edited topic_drift_ui.ts]
The imports now have `.ts` extensions to match Zulip's TypeScript module resolution. The webpack compilation should succeed now. Try refreshing the development server - it should automatically rebuild.
```

...

Prompt #34: SyntaxError

```
#34 Jan 24, 01:49:32 · Claude Sonnet 4.5 · 1x
File "zerver/views/topic_drift.py", line 125
"""
^
SyntaxError: unterminated triple-quoted string literal (detected at line 146)

I see the problem! The first function's docstring is corrupted - it's missing the closing `"""` and has mangled code mixed in. Let me fix it:
[Edited topic_drift.py]
Now the file should have correct syntax. The issue was that the docstring closing `"""` was missing and the code got scrambled. Try running the server again!
```

Figure 9: Agentic generation and iterative refinement. Same student, same agentic approach applied to two features. Top: Feature 1 converges from a broad directive (“add UI button below drafts”) through precise bug reports (“full stop is also becoming part of the link”) to success in 8 prompts. Bottom: Feature 2 uses the same pattern but spirals into cascading import and syntax errors, illustrating that the generate-then-debug workflow scales poorly with task complexity.