

Collaborative Document Editing with Multiple Users and AI Agents

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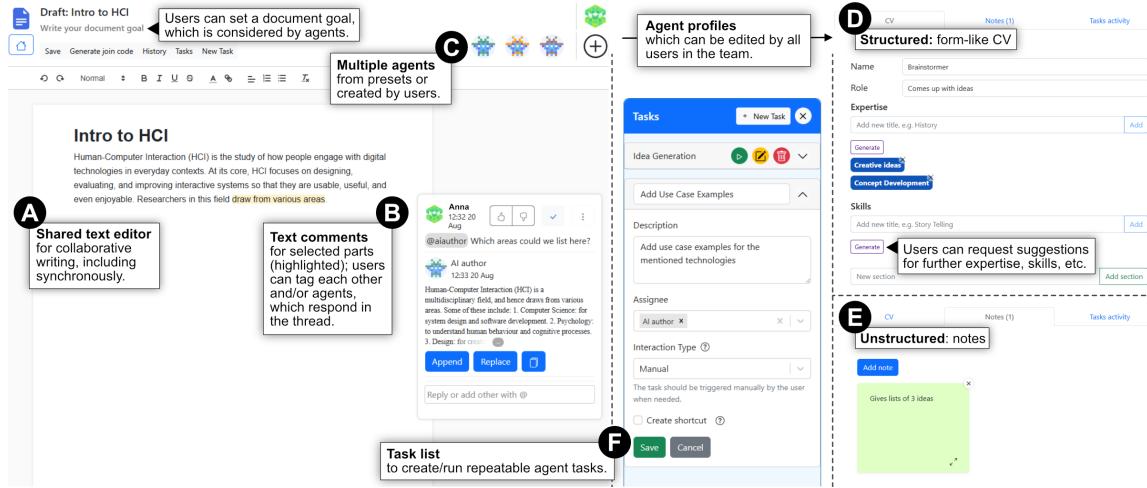


Fig. 1. Overview of our prototype: A shared document editor (A) with comments (B), which co-writers can also use to delegate tasks to AI agents (C). Users create custom agents through profiles, via a structured form-like “CV” (D) and/or unstructured notes (E). Agents can be assigned repeatable tasks in a task list (F). Note: The task list (F) opens as a sidebar that replaces the comments sidebar (B), while (D) and (E) are part of a separate full-screen profile view, shown here in parallel for illustration.

Current AI writing support tools are largely designed for individuals, complicating collaboration when co-writers must leave the shared workspace to use AI and then communicate and reintegrate results. We propose integrating AI agents directly into collaborative writing environments. Our prototype makes AI use transparent and customizable through two new shared objects: agent profiles and tasks. Agent responses appear in the familiar comment feature. In a user study ($N=30$), 14 teams worked on writing projects during one week. Interaction logs and interviews show that teams incorporated agents into existing norms of authorship, control, and coordination, rather than treating them as team members. Agent profiles were viewed as personal territory, while created agents and outputs became shared resources. We discuss implications for team-based AI interaction, highlighting opportunities and boundaries for treating AI as a shared resource in collaborative work.

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1 Introduction

People write *with* people. Teams co-author notes, reports, and academic papers like this one, and even a single-author novel evolves through (written) comments from editors and early readers. Increasingly, teams also write “*with AI*” – or do they?

Today, co-writers can get AI support, such as with recent writing tools and chatbots based on Large Language Models (LLMs) [44]. However, these tools are currently designed for individual use. This narrow focus creates friction and overheads for collaboration: Co-writers must leave the shared workspace to interact with AI and later remember, integrate, and communicate the results with their collaborators.

In this paper, we explore a new design direction: direct integration of customisable, shared AI agents into collaborative documents.

Moving beyond the design focus on a single writer’s use of AI is both timely and important: From a usability perspective, AI should support diverse workflows, including the complex dynamics of collaborative writing. Pragmatically, there is growing industry demand to integrate new AI features into widely used tools that already offer real-time collaboration. Finally, through a human-centred lens, if HCI is to shape AI that augments rather than replaces human collaboration, we need design concepts that enhance teamwork rather than push team members out of their shared context.

Integrating AI into collaborative documents presents a challenging design problem: Enabling teams to use AI together demands addressing multiple aspects at the same time, such as collaborative prompting [29] and task delegation [71], maintaining transparency, and respecting individual and shared needs and preferences [40]. Prompting AI effectively is already difficult for individuals [77] and this challenge is amplified in team contexts, where goals and perspectives must be negotiated [29]. Moreover, no established UI design patterns exist yet for AI in collaborative writing, as reflected in the focus on individual writing found in recent surveys and design theory [11, 45, 59]. As recently concluded by Chen et al. [16], “we have not yet seen AI-assisted writing tools targeting collaborative writing.”

More broadly, existing research has explored collaborative writing among humans [8–10, 40–42], interfaces for individual writing with AI [44], or crowd work contexts [6, 24, 33], where the writer in focus can also involve AI [32]. Related, AI-mediated communication (AIMC) [26, 30, 47] typically involves AI and written messages between people but not teams writing on shared documents. Beyond writing, team use of AI has been explored for group ideation [29, 62, 66] and team organisation [2, 52].

In summary, research has focused on collaborative writing or on writing with AI, but not on the intersection. This motivates our work on these guiding research questions:

- **RQ1:** How do co-writers *create* AI agents in a collaborative setting?
- **RQ2:** How do co-writers *interact with* shared AI agents?

To address these questions, we developed a functional prototype of a collaborative text editor that embeds AI agents (Figure 1). Our design introduces two novel shared objects: (1) *agent profiles*, allowing teams to configure AI personas, and (2) *agent tasks*, which make AI task delegation explicit and visible to all collaborators. AI responses are integrated via collaborative comments, enabling co-writers to engage with AI output within a familiar UI concept.

We deployed this prototype as a design probe, giving it for a week to 30 participants working in 14 groups. Our analysis of interaction logs and interviews revealed how teams incorporate AI into existing norms of authorship, control, and coordination, rather than treating agents as equal team members. Agent profiles were treated as personal territory, while created agents and their outputs became shared resources. Teams also deliberated over the number of agents. Some preferred the efficiency of a single, general-purpose agent, while others saw multiple role-specific agents as an investment into future prompting and diverse perspectives.

In summary, this paper contributes (1) a UI and interaction design concept and prototype for shared AI in collaborative writing, (2) an empirical study of team-AI interaction behaviour and perception, and (3) design insights for integrating AI into collaborative documents. In a broad view, our findings contribute to the literature on team-AI interaction and writing tools by revealing both opportunities and boundaries for treating AI as a shared resource in collaboration.

2 Background and Related Work

We discuss related work on collaborative writing with and without AI, writing tools that involve AI, and group interaction with AI.

2.1 Tools for Writing with AI and Others

First, we review research on writing tools that involve AI and/or other people.

2.1.1 Intelligent interactive writing tools are predominantly designed for a single user. Recently, Lee et al. [44] surveyed 115 intelligent writing tools. None of these designs aims at writing with *multiple users* plus AI. References to “collaborative” writing were limited to (1) paired text suggestions from two language models [17] and (2) human-AI co-writing with a single user (e.g. [3, 7, 14, 45]). Similarly, Ocampo et al. [54] use “collaborative editor” to mean human+AI, not multiple people. We found an exception in SAGA [63], where two people and GPT-3 alternated lines in a story. Recent work continues to focus on single-user co-writing, including another review [59] and work published after the above survey in CSCW [34, 70, 74], an HCI venue traditionally associated with human collaboration. Consequently, the design space covered so far [44] omits multi-user aspects and their integration with AI. This gap motivates our work.

2.1.2 Writing support from the crowd and AI. Some research proposed text editors that involve crowd workers [6, 24, 32, 33, 37], where multiple people (and sometimes AI [32]) contribute text. However, these systems still center on one main writer who requests support rather than team collaboration. For instance, in *Heteroglossia* [33] and *Inspo* [32], the writer highlights a span to solicit suggestions from crowd workers or an LLM, which then appear in a sidebar. That is, the interaction design does not involve multiple writers in jointly managing AI input or evaluating its results. Addressing these gaps motivates our design exploration.

2.2 Group Interaction with AI

Here, we review group interaction with AI, not limited to writing.

2.2.1 Group ideation with AI. Recent HCI work has examined group ideation with AI, such as the CHI'23 workshop by Shin et al. [66]. Han et al. [29] studied synchronous collaboration between two people designing stage sets, where jointly crafting prompts for ChatGPT and Midjourney was both helpful (e.g. finding words, sharing opinions) and costly (e.g. debating prompting strategies). Shaer et al. [62] explored group brainwriting with a canvas UI and access to ChatGPT, but without direct integration. In contrast, we investigate collaborative AI use in a custom text editor with dedicated features (e.g. comments, AI tasks, agent profiles) that integrate prompting and writing for synchronous and asynchronous collaboration.

2.2.2 Group organisation and AI-mediated communication. Another related area explores AI support for team onboarding [65] and coordination, such as facilitating discussions [38] or generating task reminders [52] and meeting recaps [2]. Similar features have recently been added to team software.¹

More broadly, our work differs from AI-mediated communication (AIMC) [30]. While there is conceptual overlap (text, multiple people, AI), AIMC typically concerns text created by one person to communicate with another (e.g. emails [47]), not multiple people co-authoring a shared document with AI. For example, the recent diary study of AIMC tools by Fu et al. [26] did not surface such collaborative use.

2.3 Collaborative Writing and Adding AI

Next, we reflect on insights into collaborative writing (without AI) and how these motivated the features we explore in this work.

2.3.1 Bringing AI into the collaborative home of writing. Larsen-Ledet et al. [42] studied artifact ecologies of collaborative writing, that is, how co-writers use and transition between multiple tools. Based on interviews, they describe the concept of a *collaborative home*, where writing occurs in a synchronized online platform (e.g. Google Docs, our prototype). This pattern implies that all writers see the same content and tools/UI. In this light, our design explores how we might integrate AI features directly into the collaborative home to reduce transition costs between individual AI tools and the shared document.

2.3.2 Integrating AI into tools and text as material for collaboration. Bødker et al. [10] examine how material qualities of tools and text support collaboration. For example, co-writers use *comments* to reference others for planning and task delegation (e.g. “Sue will do this”), linking cooperative activities (e.g. added as a result of a meeting) with coordination (e.g. serves as a reminder to others and Sue herself). Similarly, *written plans* (e.g. outlines, todo lists) “provide a material coupling between the thinking and the material production of text.”

Building on this, our design integrates AI agents with such materials. In our *comment* feature, users can reference not only each other but also AI agents, which reply in the thread. Users can also create repeatable *plans* as a task list, executable via a button or automatically (e.g. when saving the document).

Further work identified “writing territory” [41] and showed that edits and comments carry social meaning (e.g. edits as criticism) [8, 9, 55]. To respect these dynamics and keep users in control, we designed agents to never edit the text directly. Instead, they add task results as comments, linking the two materials.

2.3.3 Supporting idiosyncratic preferences and common objects, also for AI. Co-writers’ processes often differ. In a co-design study with academic writers, Larsen-Ledet and Borowski [40] found contrasting needs and desires, complicating

¹E.g. AI-generated meeting summaries in [Zoom](#), [MS Teams](#), and [Google Meet](#).

one-size-fits-all solutions. This motivates our exploration of support for defining multiple AI agents, which co-writers can use to tailor agents to different needs. At the same time, all agents remain visible and usable to everyone, making it possible for teams to treat them as *common objects* [42], alongside the text itself.

2.4 Interaction with Multiple Agents

Prior work has explored interactive systems with *multiple* AI agents. Naik et al. [53] interviewed early adopters to identify use cases, and Lee et al. [43] introduced a multi-agent system for resolving group conflicts (e.g. competing requests to a care robot). While not focused on writing, both emphasize transparency and coordination. We address these through a shared agent task list and by integrating AI output into collaborative comments.

Klieger et al. [39] studied collaboration in game development with three predefined agent personas. We extend this by enabling users to create their own agents through a profile UI. Related, Siddiqui et al. [67] provided six fixed personas for prompting AI (“writer’s friends”), while Benharrak et al. [5] allowed users to create many such personas. However, both projects did not consider these as agents and thus did not explore variants of initiative or integration with collaborative features, as in our case here.

Finally, we distinguish our work from text generation systems using multiple LLMs (e.g. [73]), which exclude human writers. More broadly, in this paper we conceptualize “multi-agent systems” from the user’s perspective – as shared, interactive objects in the UI – rather than as (internal) NLP system architectures.

2.5 Summary

In summary, prior research remains divided: It has either focused on collaborative writing among multiple people or on writing with AI, but not on the intersection. Existing AI writing tools are overall designed for individual users and do not explore the collaborative dynamics of writing with AI, as also concluded by Chen et al. [16] recently. To the best of our knowledge, this work is the first to investigate how multiple people work together with multiple shared AI agents within a shared document environment.

3 Concept and System Characteristics

We describe our overarching design goals and the concrete design features that we implemented in our prototype. For each, we include our motivation based on the literature.

3.1 Design Goals

Our design goal is to embed AI writing support directly into a shared document environment. We realise this by introducing AI *agents* into a standard collaborative editor UI. Users configure agents through *profiles* and a *task list*, while agent responses appear in the familiar *comments* interface. To support the goal of enabling teams to use *AI as a shared resource*, all profiles, tasks, and comments are visible and interactable to co-writers.

3.2 Agent Profiles

As one key characteristic, our design explores enabling co-writers to create multiple AI agents as part of their collaborative home [42].

3.2.1 Creating multiple shared agents. Co-writers often take on different roles [48, 56], motivating support for multiple AI agents with distinct roles. Individuals may also have different needs [40]; multiple agents let them tailor support

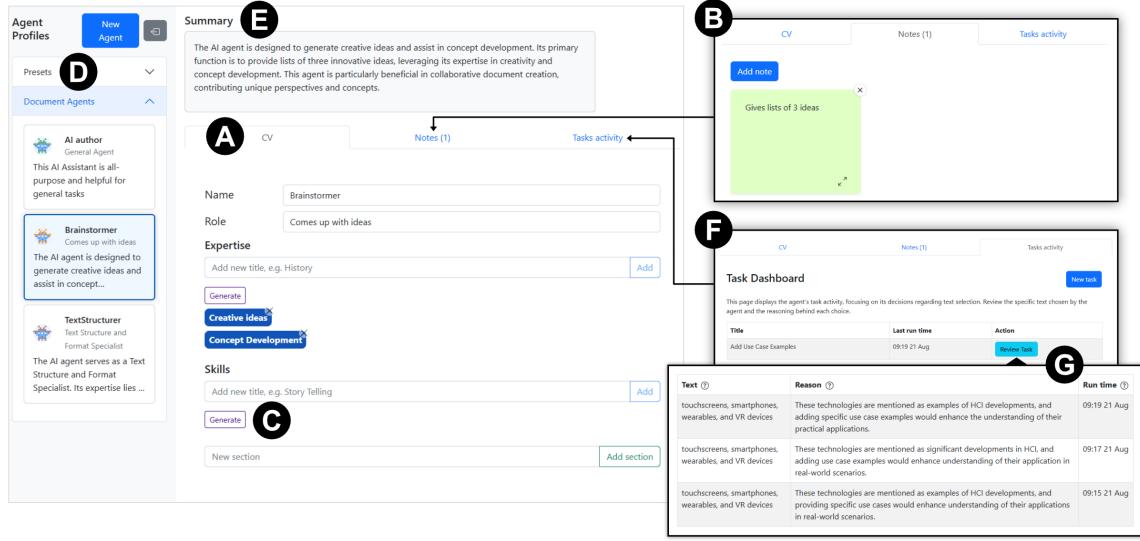


Fig. 2. The UI for agent profiles and creation: Users create agents with descriptive text in two formats. In the structured format (A), they fill out a form-like “CV” with *Name*, *Role*, *Expertise*, and *Skills*, extendable with custom sections. In the unstructured format (B), they add free-form notes. AI suggestions for any section are available via the “Generate” button (C), and fields may be left empty. The UI also shows the list of created agents (D), including a list section with (editable) presets for quick setup. For each selected agent, the UI provides an automatically generated text summary (E) and a history of tasks (F). Clicking “Review Task” (G) reveals logs of all task runs, including the agent’s selected texts, reasonings for commenting, and timestamps.

accordingly. At the same time, our design keeps the agents visible and editable to everyone to support their use as *common objects* [42].

3.2.2 Creating agents in structured and unstructured ways. We designed a dedicated UI for agent creation (Figure 2). Profiles can be built through a structured form (CV-like, Figure 2A), an unstructured canvas with notes (Figure 2B), or a mix of both. The structured form is motivated by work on AI personas for writing feedback [5], which showed that predefined fields (e.g. role, expertise) help users get started. These defaults also reflect findings by Gero et al. [28] on what writers value as individuality of support actors. The unstructured canvas allows users to add any information they find relevant.

3.2.3 Suggestions for agent attributes. To help users define agents with relevant details, the structured profile UI offers to generate suggestions (Figure 2C) based on what has already been entered. This design is motivated by findings that prompting can be challenging, in general [77], in collaborative settings [29], and when describing agents [5].

3.2.4 Agent presets. We provide presets (Figure 2D): *reviewer*, *idea generator*, *structure & formatting*, and *English teacher*. Presets help users get started, addressing challenges of prompting [5, 77] and metacognitive demands [71]. They exemplify roles and tasks that can be delegated to agents. Selecting a preset adds it to the document’s agent list, where it can be edited like any custom agent.

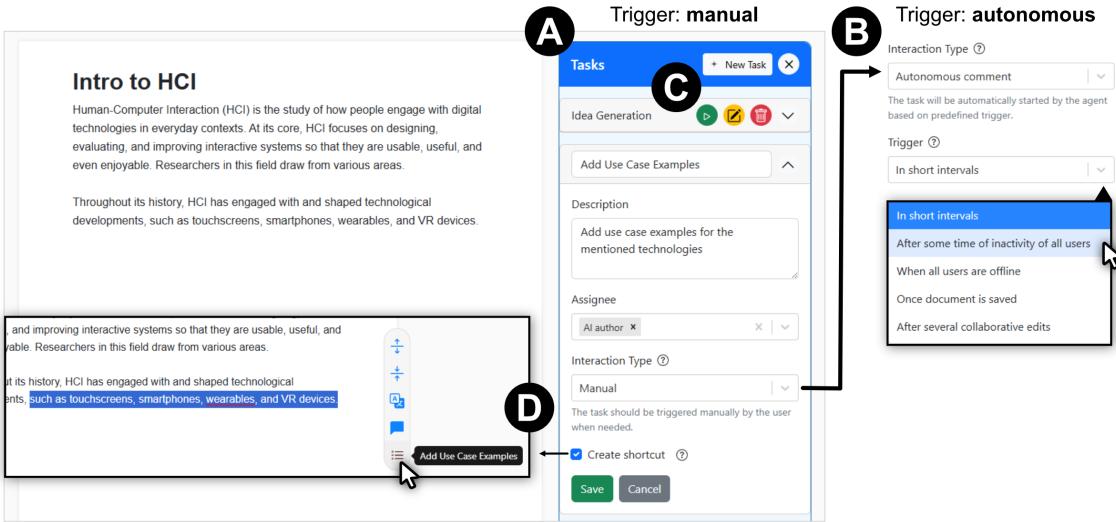


Fig. 3. The UI for task creation and activation: The task list is a fold-out sidebar (A) where users create tasks for agents by entering a title, description (instruction), assigned agent (or default “auto select”), and interaction type (manual or autonomous). For autonomous tasks (B), users choose a trigger from predefined options (elicited via a survey with academic writers, N=16). All tasks can also be run manually via the green “play” button (C). If “Create shortcut” is selected (D), the task additionally appears as a button in the floating toolbar on text selection.

3.2.5 Generated agent summary as an overview. Our design automatically generates a text summary of each agent (Figure 2E). This is in line with the conclusion in related work [16] that AI summaries could help co-writers “sync up” – in our case, keeping an overview and understanding the agents that others have created at a glance.

3.3 Task List for Agents

Task partitioning, coordination, and delegation are central to collaborative writing [4, 23, 64], often supported through materials such as comments and plans (e.g. todo lists) [10]. Users in mixed human-AI teams especially value explicit shared goals [61]. Moreover, Tankelevitch et al. [71] identify task delegation as a key metacognitive demand in working with generative AI, calling for designs to support this. Together, these findings motivate our design of an explicit task list for AI agents.

3.3.1 Creating and editing tasks. Users create tasks in a fold-out sidebar next to the page view (Figure 3A), entering description (instruction/prompt), interaction type, and optionally assigning specific agents. Shortcuts in the top menu (Figure 1, top left) open the task list or add a new task. Existing tasks can be directly triggered, edited, or deleted via buttons (Figure 3C).

3.3.2 Task initiative. Our design explores two types of task initiative: autonomous and manual. For the autonomous mode, users specify an event to trigger the task (Figure 3B): short intervals, user inactivity, all users offline, document saved, or after several collaborative edits. We informed these options via a survey with academic writers in our network (N=16). In manual mode, tasks run when a user clicks the green “play” button in the list (Figure 3C) or a saved shortcut (see Section 3.3.3 below). Section 4 provides technical details.

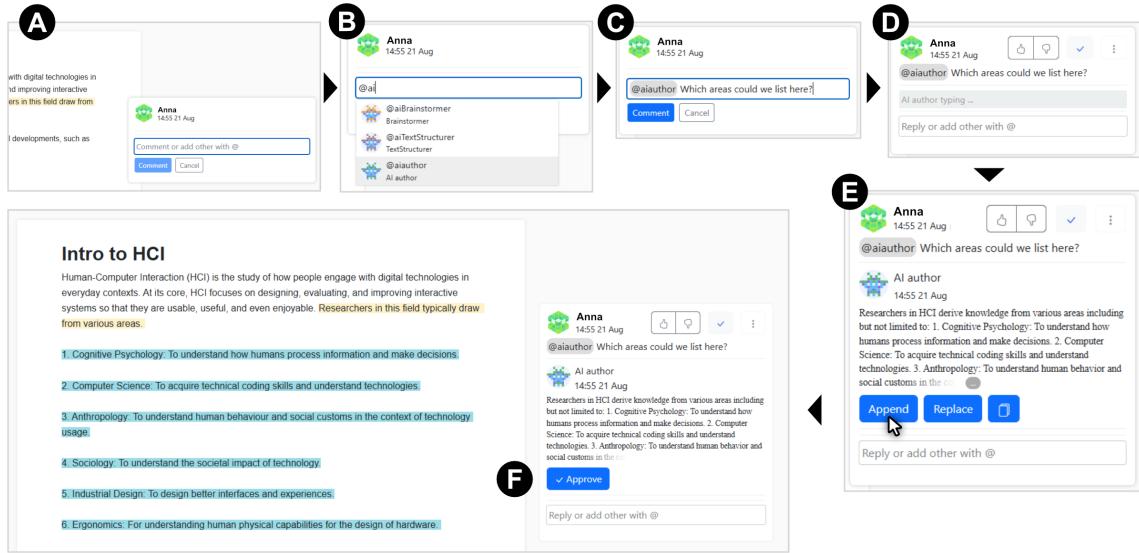


Fig. 4. Example interaction flow when involving an AI agent via the comment UI: The user selects text and clicks the comment button in the floating toolbar (Figure 3D) to open a new comment (A). By typing “@ai”, the user brings up matching agent (or user) names (B); the user selects the default agent (“@aiauthor”) and enters a request (C). An indicator shows the agent is “typing” (D) while the LLM generates a response, which then appears in the thread (E). Clicking “Append” inserts the coloured text on the page (F), which the user edits before clicking “Approve” to finalize the change and close the comment. See Figure 5 for further examples.

3.3.3 Task shortcuts as tools. Tasks can be saved as shortcuts (Figure 3D), displayed as buttons in a floating toolbar whenever text is selected. This enables repeating frequent tasks without opening the task list. More broadly, making prompts repeatable as UI elements is motivated by recent work such as *DirectGPT* [51], *ABscribe* [58], *DynaVis* [72], and the toolbar idea by Dang et al. [22]. As shown in Figure 3D, our toolbar also provides four default tools, available even before creating custom shortcuts (*Extend*, *Summarize*, *Translate*, and adding a comment).

3.3.4 Task history in agent profiles. Whenever an agent executes a task, a task log entry is added to that agent’s profile (Figure 2F, G). This design supports transparency and scrutability in linking agents and tasks, and aligns with Park and Lee [55], who found that co-writers value rationales for edits.

3.4 Collaborative Comments for Users & Agents

Collaboration requires coordination and communication. As early as the 1990s, Sharples et al. [64] highlighted communication as a core issue in collaborative writing software, and Rimmershaw [60] noted the value of “meta-comments” as annotations tied to text, including author attribution. Our comment design builds on these insights and established conventions (e.g. Google Docs, Microsoft Word): Users select text and click the comment button in the floating toolbar (Figure 3D).

3.4.1 Agents respond via comments. Related work [8, 9] shows that edits carry social meaning and recommends presenting revisions as possibilities rather than definitive changes, especially when co-writers do not know each other well. This motivates our choice to have agents respond only through comments, never by editing text directly. Agents select text parts to comment on via a prompt-based procedure (Section 4). Our comment UI (Figure 4) supports this

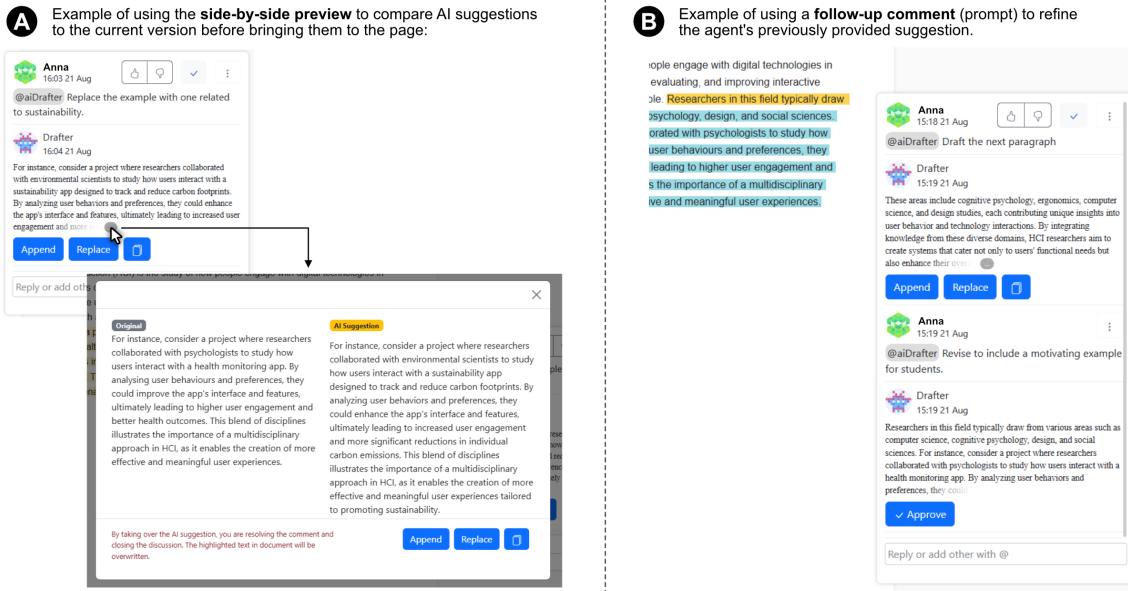


Fig. 5. Two examples of further interactions with agent responses: (A) The user clicks “...” to view the full response in a side-by-side preview, shown next to the selected text that would be replaced if accepted. This lets users read longer AI outputs in full and compare them before committing. In (B), the user asks the agent to draft the next paragraph and follows up in the same comment thread, refining the result (here by requesting a motivating example). The screenshot shows the state after clicking “Append” on the refined (2nd) response, with the new text added to the page in teal colour for review and editing before final approval.

workflow with buttons for users to *append* a suggestion or *replace* selected text, plus a side-by-side view of original and suggested text (Figure 5A). Once an option is chosen, an “*approve*” button finalizes the change and closes the comment.

3.4.2 Referencing others and AI in comments. Users can reference co-writers in comments via “@” + user name, or agents via “@” + agent name. A generic default agent (“@aiAuthor”) is also available, allowing users to seek support without first creating a bespoke agent (Figure 4A-D). The referenced agent replies in the comment thread (Figure 4D, E), which co-writers can continue as usual (Figure 5B). Further agents can also be referenced, enabling them to “converse” with each other.

3.4.3 Ad-hoc tasks in comments. Referencing agents also enables writers to delegate something directly in a comment (Figure 4), bypassing task creation and the task list. This mirrors the common use of comments for delegating tasks to co-writers [10], here extended to AI agents.

4 System Implementation

Our system consists of a backend and frontend application and connects to an LLM provider, as described in this section.

4.1 Frontend Application

Our frontend is based on *React* with *React Bootstrap* for styling and *React Quill* for the text editor. We developed a custom Quill plugin for creating annotations. Real-time collaboration and syncing is implemented with *Yjs*, a high-performance conflict-free replicated data type (CRDT) [19]. We used *RTK Query* for data fetching and local state management.

4.2 Backend Application

Our backend consists of two servers: one responsible for managing data, authentication, and authorization, and another dedicated to performing computationally intensive operations.

The main entry point is a *Python* server built with *FastAPI*, which launches *Yjs* and *Socket.IO* websockets to manage real-time data updates. The second server implements a *Celery* task queue to perform expensive background operations (i.e. agents' document tasks). The servers connect to a *MongoDB* to persist and access data (e.g. documents, texts, comments, agent profiles).

4.3 AI Integration

Both *FastAPI* and *Celery* servers interact with an LLM through API calls. Our prototype in the study used OpenAI's "gpt-4o-mini". This is integrated into the backend via the *openai* and *autogen* libraries. The first is used for simple prompt-based queries, whereas the second handles the multi-turn conversations and agent-based interactions. The LLM is employed in the following cases:

4.3.1 Comment response generation. When users mention agents in a comment, an *autogen* group chat is created. The tagged agents are attached to the conversation and initialized with their profile information. Moreover, document text and goal, selected text, and previous conversation history for the selected text (if present) are added to the chat. The agent initialization prompt is shown in Appendix B.1.

4.3.2 Agent CV suggestions and summary generation. For the suggestion feature on the CV page of the agent profile (Section 3.2.3), *autogen* is queried using a predefined prompt (Appendix B.2). Moreover, each time an agent is saved, its summary is updated via the *autogen* agent, using the prompt in Appendix B.3.

4.3.3 Document task title generation and automatic assignee selection. When a document task is saved, a title is generated based on its description using the *openai* API (prompt in Appendix B.4).

If the user does not specify an assignee, the system queries *openai* (prompt in Appendix B.5) to select the assignee based on the task and agent descriptions. The LLM returns a confidence score; if the confidence is 85% or higher, the recommended agent is assigned. Otherwise, the system assigns the default "AI Author" agent.

4.3.4 Task execution across the document. When a task is executed on the entire document, the *Yjs* websocket server sends the task to the *Celery* server. Its response is then applied to the *Yjs* document and stored in the database. These are the steps in detail:

- (1) *Generating selection proposals (Celery)*: The first agent assignee selects relevant text segments. Based on the assignee and task description, the LLM is queried to return the text segments, their length, reasoning, and confidence score (prompt in Appendix B.6).
- (2) *Filtering selection proposals (Celery)*: Segments overlapping with existing text annotations or scoring below 80% confidence rate are discarded. The system notes attempted execution in the existing text annotation comment.
- (3) *Generating responses (Celery)*: For each valid segment, a conversation with the task assignees is initiated using the same process as described in Section 4.3.1. The results are returned to the *Yjs* websocket server.
- (4) *Integrating responses (Yjs websocket)*: New annotations and comments are integrated into the *Yjs* document, while existing annotations are updated. The document is updated in the database.

Table 1. Autonomous task triggers and their implementation.

Trigger condition	Implementation
In short intervals	As soon as someone enters the document socket room, schedule a job to run every 5 minutes. Skip if a job is already scheduled.
After some time of inactivity of all users	Debounce 2 minutes after the last detected user activity (text or comment updates).
When all users are offline	When the last online user disconnects from the document socket room.
Once document is saved	When a user clicks the <i>Save</i> button.
After several collaborative edits	The <i>Yjs</i> document includes a shared array that tracks the users who typed in the document. If the list has more than two users, it indicates a collaborative edit. The array is cleared after the trigger is executed to detect future edits.

4.4 Autonomous tasks

To detect autonomous triggers and execute tasks, the *Yjs* websocket server continuously monitors document activity and evaluates the trigger conditions. Once a condition is met, it requests task execution from the *Celery* server. After receiving the result, it applies the response to the document. Table 1 gives an overview of the triggers with implementation notes.

5 User Study

We conducted an exploratory user study with our prototype as a design probe to investigate how co-writers create AI agents and interact with them through our design features. The study consisted of a collaborative writing task using the prototype, questionnaires, and a semi-structured group interview at the end. Each group had one week to work on the task.

5.1 Participants

We recruited 30 participants (14 female and 16 male) in 14 groups by sharing a study description and registration form in our network across a few universities, where we reached mostly faculty and students. Ten groups signed up as a group directly, three groups signed up individually but knew each other, and one group (7) was formed by us from two individual study registrations.

Participants' age ranged from 22 to 56 years (median 27), and they all had sufficient knowledge of English. Their median frequency of writing documents was daily and the frequency of collaborative writing was weekly. The median use of LLMs was also daily. Their writing domains included academic study, professional work, research, and journalism. Participants were compensated with 25 €.

See Table 3 in the Appendix for further details.

5.2 Study Procedure

The procedure was coordinated via the *StudyAlign* web application [46], which integrated the questionnaires, writing task and application description page, and access to the prototype. Once participants received the study link and provided informed consent, they were free to work with the prototype for a week. We recorded interactions with the prototype. The semi-structured group interviews were conducted using Microsoft Teams and were audio-recorded and transcribed. The study followed our institute's regulations (e.g. information on goals, process, data protection, opt-out and consent form). We next describe each step in more detail.

5.2.1 Introductory meeting (15 minutes). Based on feedback from the first three groups, we concluded that a quick tour of the design features would help the participants get started with the prototype. Thus, we conducted introductory online meetings for the remaining groups, where one researcher demonstrated the features via screen sharing.

5.2.2 Writing with the prototype (7 days). For this main part of the study, our web app guided participants through the following steps:

- (1) **Introduction questionnaire (5 minutes):** It covered demographic information and writing experience.
- (2) **Task briefing (20 minutes):** Participants could choose between two collaborative writing tasks: either working on a real task of their own, or, if none was available, writing an essay about the positive and negative aspects of AI in daily life. The briefing also included a page explaining the prototype's features through text and videos.
- (3) **Writing task (7 days):** Participants used a join code to access their shared document. They could then collaborate on the task. Each group was free to decide how to approach the task and collaborate on the document.
- (4) **Final questionnaire (25 minutes):** Participants rated their experience with the prototype and answered SUS [1] and CSI [13] questionnaires. They also evaluated the individual features, and provided open comments on their negative and positive aspects.

5.2.3 Semi-structured interview (30 minutes). The last step with each group was a video call where we interviewed the group, including questions on likes/dislikes, collaboration, challenges, agents, tasks, and triggers. We chose this group format so that team members could reflect on and discuss their collaborative experience together.

6 Results

6.1 Collaboration and Tool Use

In our initial questionnaire, we asked participants to rate how often they work on texts and how they collaborate (see Table 3 in the Appendix). Further tools that participants use when collaborating on text documents included chat tools like Slack, Mattermost, and Teams (see Figure 10 in the Appendix). Sixteen participants use the chat tools daily, six weekly, four monthly, and four less than monthly.

6.2 Usability Ratings

In the final questionnaire, we assessed the system usability scale (SUS) and the creativity support Index (CSI). Ratings on the SUS score had a mean score of 66.92 ($SD=12.96$, $min=45$, $max=90$), see Figure 7 in the Appendix. This score is slightly below the average benchmark of 68. The CSI score yielded a mean of 67.21 ($SD=15.60$, $min=31$, $max=91$). As shown in Table 4 in the Appendix, the most valued factors of the CSI were "Enjoyment" and "Collaboration".

In addition to these standardised questionnaires, we asked own Likert items on general feedback (Figure 8) and the AI agents (Figure 9). Most users found the interaction with the system natural and felt it helped them complete tasks more efficiently. Around a quarter of participants (23.33%) did not feel in control of the text. The agent features were rated positively overall but participants were divided about if one agent is enough or not.

6.3 Interaction Behaviour

We logged how users interacted with the agent, task, and comment features. One group accidentally accessed the prototype outside of our study setup, such that logs were not recorded. We reconstructed their interactions from database data where possible and note results where this group (G4) is excluded from the analysis.

6.3.1 Metrics on Agent Creation. In total, 39 custom agents were created with an average of 2.79 per group ($SD=1.25$, $min=0$, $max=4$). One group did not create a custom agent. 38.46% of agents were created in the first quartile of each group's normalised editing time, 28.2% were created in the second and third quartiles, and the remaining 33.33% were created in the last quartile. This behaviour reflects initial exploration as well as a demand for agents for drafting and finalising text.

The following results on agent usage exclude G4. Agents could be defined through the "CV" and notes features (Figure 2). A total of 54 CV sections were created (28 skill sections and 26 expertise sections). Participants manually added 71 values (33 skills, 38 expertises). Responding to participants' requests for suggestions, the system suggested 174 values, and participants added 45.4% (79) of them (36 skills, 43 expertises). Notes were added to custom agents in four cases only. Another three notes were added to agents extended from presets. Thus, people mainly used the structured UI ("CV") for defining agents.

Once created, agents were updated in eleven cases; ten such edits happened by the agent's respective creator, and only one edit was by another team member. This indicates that agents were seen as belonging to their creator. The qualitative results shed more light on this (Section 6.4.1).

6.3.2 Metrics on Tasks from the Task List. Participants created a total of 67 tasks via the task list feature (Figure 3), with an average of 5.15 per group ($SD=2.19$, $min=1$, $max=9$). The following results exclude G4. Most such tasks (88.06%) were created by the author of the agent to which the task was assigned. The tasks from the task list were triggered manually 113 times; 84.7% by the task's creator. Task editing occurred 10 times. We also analysed task creation across the normalised editing time of each group. Most tasks were created in the last quartile (41.67%) and in the third quartile (23.33%). The remaining task creations occurred in the first (21.66%) and second (13.33%) quartile.

6.3.3 Metrics on Comments. We counted a total of 468 comments; 376 were added by agents in response to running tasks, while participants added 92 comments. G2, G5 and G12 never used comments for ad-hoc task delegation to AI. The other eleven groups created a mean of 8.36 comments ($SD=7.19$, $min=1$, $max=22$). We analysed specific discussion patterns considering comments and their replies, as shown in Table 2. These reveal that only short discussions happened in comments, for example single turn human-AI discussions. Note that most groups reported to use further communication tools, explaining the small number of human-human discussions in comments in our study.

To accept agents' suggestions in comments, we offered three methods: Appending text at the end of the selected text in the document, replacing the selected text, and copying the suggestion to the clipboard. Excluding G4 again, suggestions were *appended* 76 times; 50 times by the comment's creator and 26 times by others (19 times when the comment was created by a user, 7 times when it was created by AI). The *replace* method was used 60 times; 29 times by

Table 2. Identified discussion patterns from analysing comment and reply events.

Discussion pattern	Description	Count
human-human	comment by user, reply by team members	4
human-AI	comment by user, AI replies; single-turn	57
human-AI negotiation	comment by user, AI replies, human replies; multi-turn	17
human-team-AI	comment by user, AI replies, team members reply; multi-turn	6
AI-human	comment by AI, at least one user replies	7

the comment’s creator and 31 times by others (23 times for user-created comments, 8 times for AI-created ones). The *copy to clipboard* method was used less frequently (16 times): 9 times by the comment’s creator, and 7 times by others (6 times for user-created comments, once for an AI-created comment). This use of the three accept methods shows that agent-initiated suggestions were less often accepted than user-initiated suggestions.

After normalising the editing time of each group, we analysed when participants posted comments. They posted 4.83% of comments in the first quartile, 21.38% in the second, 11.03% in the third, and 62.76% in the last quartile. This behaviour indicates that participants sought support from agents after writing a first draft, particularly in order to complete it.

6.3.4 Final Texts. The final texts had a mean length of 1623 words ($SD=1306.93$, $min=226$, $max=4767$). To assess the readability of texts, we computed the Flesch reading-ease score [25]. We removed four texts for this analysis since they included non-English parts. The mean readability score of 17.71 ($SD=13.71$, $min=2.87$, $max=38.65$) can be interpreted as “very difficult to read” and is described as appearing in “Scientific” and “Academic” reading [25], reflecting the nature of most of the groups’ writing projects.

6.4 Interviews and Open Comments

We transcribed the interviews with Microsoft Teams and analysed them following open and axial coding principles [20], verifying transcripts against audio where needed. One author iteratively grouped, merged, and split codes into categories and subcategories. Another author reviewed and refined the outcome, also going back to the recordings where needed and involving the team for reaching consensus. We coded open comments from the final questionnaire in the same way. Below, we present the main themes we identified.

6.4.1 Territorial functioning: An agent belongs to its creator. Agents and tasks were seen as belonging to their respective creators, with all groups except for two expressing this clearly in the interviews. Their statements reveal different assumptions and expectations that explain this.

One rationale is that **everyone knows best what they want from AI support**; as $P_{2,4}$ said “we had two or three different agents, so I had one more which I wanted to focus more on [...] fixing typos or grammar.” And $P_{1,5}$ found that “you cannot really decide how many AI assistants someone would need”. Similarly, $P_{2,2}$ explained: “We have different AI agents and we can set different tools and [...] we can use them for a different purpose.” $P_{1,7}$ valued this for prompting: “I know what to expect. It’s better to use an agent that I made myself, that I know [...] So I also then know how, or I have a better feeling over how, I write the prompts in the comments.” $P_{2,13}$ even envisioned individual visibility: “Something that might be useful for one author might actually be a hindrance to another author, so [...] people could have their own agents that only show up in their version of the document or on their screen.”

Another rationale is **controlled customisation and representing a specific user**. As $P_{1,2}$ said: “AI may not always match individual writing styles or preferences.” Related, $P_{2,7}$ wanted to ensure own agents stay as defined: “I would not like [others to edit it] directly if I’m not seeing this, and then I [...] come to my agent and he’s not, like, the same.” $P_{1,8}$, $P_{2,10}$, $P_{1,11}$, and $P_{1,12}$ expressed similar sentiments and $P_{1,10}$ framed it in terms of identity: “I considered his agents to be him. Kinda. [...] When I used the AI, I was still, like, this is still me.” Even group 14, who stated to see agents as shared, envisioned explicit ownership controls: “Something to consider is that you have some form of rights or access by the owner” ($P_{2,14}$) and their partner $P_{1,14}$ added that “each of us have our own parts in the text and we want to keep our style.” Group 12 also envisioned such controls.

Finally, **workflows** were another reason for creating agents individually. As $P_{2,11}$ said: “I have certain ways of organising myself [...] so therefore I think it would be [better] for my workflow.” Group 12 expressed a similar view, group 4 decided upfront to split the work, group 13 worked sequentially on their task, and group 1 described they explored the new features individually.

In summary, we found that people stayed away from iterating on the profiles of agents not created by themselves.

6.4.2 Emerging roles and norms: Sharing agents is caring. The sense of ownership extended only to the agent profiles and the *creation* of agents/tasks. In contrast, **it was accepted to use others' agents** (e.g. ask them in comments). With three exceptions, all groups explicitly commented on this in the interviews. As $P_{1,9}$ reflected: “I did feel comfortable using all people’s agents, but I did not want to update [them].” And $P_{1,6}$ said: “We tried to use all the agents [...], even if it was created by [another person].” Similarly, $P_{2,4}$ remembered: “The language agent was created by the others and I used that as well. [...] I created two own tasks and just used the ones from the others as well.” Related, $P_{2,3}$ remembered using comments of others’ agents: “When I opened the document, there were [...] suggestions [...]. So I read them and I accepted some of them and integrated [them], and some of them also, I think, I deleted them.”

Moreover, people **created agents and tasks with collaboration in mind**. For example, $P_{1,8}$ was keen to “make sure that the agent in the end is reliable and it’s a good team player for both of us.” And $P_{2,2}$ described it for tasks: “We didn’t split it one task per person. We just kind of mix it.” $P_{2,11}$ saw individually owned agents as an optional team offer: “I’d be happy to use shared ones, but [...] if I don’t like them, then I still want to have my own. [...] I’d be happy to share my stuff and people should only use it if they find a benefit.” And $P_{1,7}$ reflected: “As a team, you could have this agent. Everybody knows what it’s for and you know you use it for this task. So of course, not everyone has to make their own five agents.”

A few people **used agents/tasks as a mediator or “glue” in the team**. For example, $P_{2,4}$ used the all-users-offline task trigger to get recaps: “After logging in again it created the summary which was quite nice. So just to get a recap of what had happened so far.” $P_{2,12}$ reflected on interaction with agents as available alternatives for delegating tasks: “I find it really useful to [use tasks and comments for agents] because I think it’s a natural way when you work together [...] Yeah, you write a task for another co-author [...] and so I think I made no difference if I assign a task to [him] or to an AI agent. I think it was, from the feeling, nearly the same.” Related, $P_{1,7}$ liked how they could use an agent to keep work coherent that they had split across sections with their partner: “I’ve read what he’s done and then I could come back and then ask [the] agent: He wrote something like this. Can you put something related now in my text?”

In summary, once agents and tasks were created, teams thought of them as a shared resource for collaborative use.

6.4.3 One vs multiple agents: A tradeoff between expected functional and perspective values. We observed a specific strategic tradeoff: People weighed the setup effort against the expected benefits of multiple agents. Different views

were discussed within nine of the teams. Overall, 14 participants brought up rationales in favour of one agent, and 20 (also) in favour of multiple ones.

Those who preferred a single agent focused on the AI's functional value. Many considered the functional scope, such as $P_{2,5}$ ("One AI agent is enough, it could make all tasks.") and $P_{2,7}$ ("[The default agent] also understands and will do the task"). $P_{2,1}$ reflected on efficiency: "I don't want to spend my time [...] creating another agent and giving him the background, when I know that the first agent already exists." And $P_{2,3}$ considered creative effort: "I had no idea of which agent I need."

Another rationale was that **differences between agents were not clear enough**. As $P_{1,4}$ said: "As the agents [...] were quite similar in what they were doing, so, one agent would be sufficient for us." Similarly, $P_{1,6}$ found that agents "did not differ from each other that much. [...] The core skills are the same." $P_{2,7}$, $P_{1,10}$, and group 11 made similar statements.

In contrast, **those inclined to use multiple agents focused on perspective value**, such as $P_{1,12}$: "I also really liked using AI agents to incorporate viewpoints that are not my own." Similarly, $P_{1,1}$ said: "You can use the second agent to check the text, like, to play as a professor, as a reviewer." Group 12 also liked agents as personas for feedback. $P_{2,4}$ liked "having different agents for different things", also echoed by $P_{2,13}$ and $P_{2,14}$. $P_{2,8}$ compared it to human teams: "When you are collaborating with others in the same team, you know, some people are more good at this. Some people are more good at that. So for agents it's the same." $P_{2,10}$ reflected on both value and effort: "I can have an external reviewer that reviews from the lens of that community. [...] I'm a bit sceptical [about] having to create and manage and stuff."

A related rationale was that **agent roles support prompting**. For instance, $P_{2,7}$ said that "it could be faster then to refer to specific agents [...] and not explain the only one AI agent [everything]. It's like working in a company. Everybody has its role." Similarly, $P_{1,3}$ considered that defined roles shorten task prompts: "It can be beneficial to have several agents predefined because their answers can be different. Sometimes I want to create a very, very specific description. I don't want to write a very long task for that." $P_{1,7}$ also found that "defining the agent spares you a part of the prompts writing." And $P_{1,13}$ said: "I first thought of the persona pattern [for prompts] and I would try to push the LLMs as much as possible into this role. [...] I thought of tasks I would assign to the agents and design the agents the way I want to implement the tasks."

In summary, participants weighed setup effort against benefits of multiple agents, with their conclusion depending on their focus on functional vs perspective values and future prompting.

6.4.4 Feedback on the design features. Participants shared rich feedback on the design features and ideas for further features. For brevity, here we focus on their key pros and cons.

Participants liked that **direct editor integration saves time and effort for interacting with AI**. For example, $P_{2,1}$ found that "it saves a lot of time that I don't have to switch tabs." $P_{1,2}$ had "a great experience to use it directly in the document, and it saves a lot of time [and] it was surprisingly good." And $P_{1,5}$ said the "assistants were pretty useful [...] Previously, I had to divide my text into several fragments if I wanted to check it in ChatGPT." $P_{2,3}$, $P_{3,4}$, $P_{1,9}$, and $P_{2,12}$ made similar direct comparisons to their usual AI tools.

The **comment integration of agents was valued** here specifically. As $P_{2,8}$ said: "I really like the comments. You can add the agent directly in the comments and that was very convenient, and it feels like you're actually talking to a person or like you're discussing with someone." Similary, $P_{2,3}$ found the comments "very helpful, especially to collaborate with others [...] and very integrated." $P_{1,7}$ wanted to keep using this feature: "What I would include in the

usual editor is the comments with the AI agents.” The comments integrating AI were also highlighted as a valued feature by $P_{1,1}$, $P_{1,3}$, $P_{2,9}$ and everyone in groups 4, 8, 11, 12, and 13.

For some, **using the profile UI was easier than figuring out what information to enter**. As $P_{1,6}$ said, “AI agent creation [is] easy to understand” and $P_{1,11}$ found it “really easy to get your head around, to imagine that you have this little team”, while $P_{2,4}$ “found it a bit confusing to decide whether it now was a skill or just a background.” $P_{1,3}$ reflected explicitly on both sides: “I did not struggle to create agents. Basically, because the interface for agent creation was really easy to understand, but like, some intuition about what kind of agent I want to create. That’s actually kind of [the] problem.” $P_{1,13}$ generalised it: “It’s the typical issue with LLMs. If you’re not really sure what you want to generate, then the answers are typically not so high quality.”

Overall, **participants preferred to give tasks via manual triggers and comments**. One reason was the lack of progress feedback or the inherent invisibility of automated triggers such as leaving the document. For instance, $P_{2,5}$ said: “It works, but I have seen no results, but I have not understood why, but only yesterday, I see it was there.” Another reason was that **calling agents manually in comments constrains their response** to one new comment in the expected location. For example, $P_{1,13}$, $P_{2,4}$, and $P_{1,3}$ highlighted how it was useful to “tag an agent and ask him a question regarding the selected text” ($P_{1,3}$). Related, $P_{2,13}$ liked this for task shortcuts: “I really like the feature where you [...] select the text [...] and just use a task you defined beforehand.”

Some reflected more explicitly on **trust and control** for preferring manual triggers, such as $P_{1,14}$ (“You don’t have much control of what’s going on.”) and $P_{1,7}$: “You’re always afraid that some changes will happen to your documents. [...] So I don’t think people will be doing a lot of really autonomous stuff.” $P_{2,10}$ ’s comment echoes this: “I only did manual because I really hated the idea of it doing stuff when I was not there. [...] I just see it too much as, like, I merge and I control it. I didn’t want it to do anything autonomously.” In contrast to these views, only one person ($P_{1,12}$) envisioned giving a lot *more* initiative to agents, to “feel like the AI is my colleague”.

Finally, the main point of critique concerned the LLM’s output. Group ten was the most critical; it did not meet the bar for them, as they perceived it as worse than ChatGPT. All other groups found it useful overall but voiced the specific concern that **AI output was too verbose**, in three flavours: First, AI agents added **too many comments**, when not tagged in a specific place via a comment but rather given a task via the task list. As $P_{1,3}$ concluded “it’s left, like, comments over all [the] document and I would not want to use these autonomous tasks too often.” Second, some **AI comments were longer than desired**, which made $P_{1,4}$, for example, suggest to “shorten the comments quite a bit”. Third, AI responses included **unwanted conversational parts** (e.g. “Sure, here’s a draft: ...”), such as in the case of $P_{1,6}$: “[agents] reply in conversational messages, [which would be] added to the text, regardless of whether you choose to append or replace.”

In summary, participants valued the integrated, collaborative AI features, while pointing to challenges in agent definition and control, as well as tuning the volume of AI contributions.

6.5 Further Text Analyses

We further analysed the texts entered in the agent profiles, task descriptions, and the comments that delegated ad-hoc tasks to agents. We deductively coded *co-creative roles* for the agent profiles, and the user’s *primary intent* and intended *writing stage* for task descriptions and delegations in comments. Possible codes were the typical writing stages (outlining, drafting, revising), aligned with the literature [44]. Similarly, we defined co-creative roles based on related work [48, 56], as well as the primary intents [21, 27, 76] (see below for concrete codes). Three researchers coded the data logged from

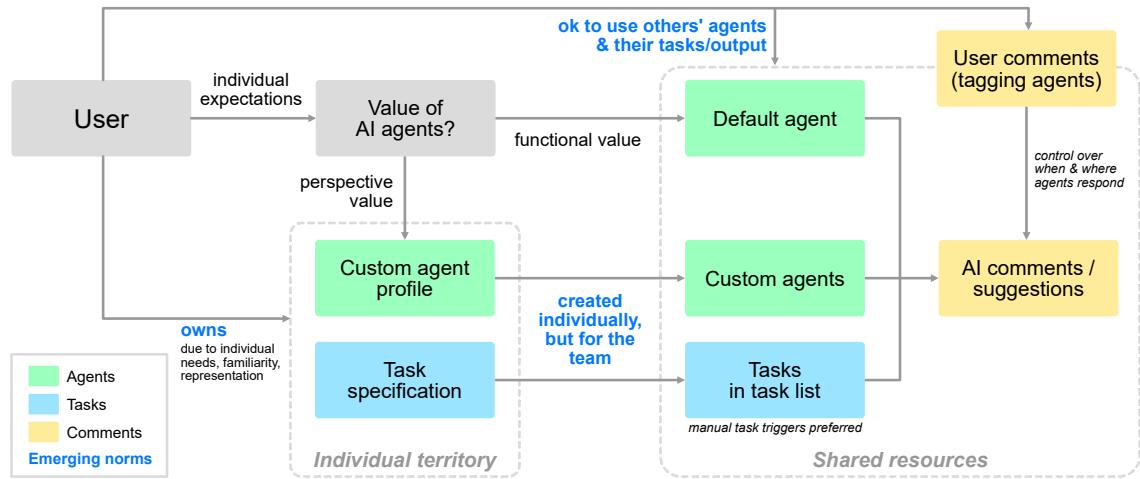


Fig. 6. High-level overview of our findings on how teams create and interact with AI agents, tasks, and comments. From left to right: Individual users expect agents to provide value. For those focused on functional value (e.g. speed, efficiency), a single agent is sufficient (e.g. any agent can check grammar). Others value multiple agents for distinct perspectives (e.g. role play, feedback, cf. [5]) and/or view creating specific profiles as an investment that eases future prompting. Agents and tasks are created individually but with sharing in mind: While seen as belonging to their creator, it is accepted to use them as shared resources. Users' preferred ways of using agents are those that provide control over their behaviour; either tagging an agent in a user comment on selected text (controlling where & when it responds) or triggering tasks from the task list manually (controlling when it responds).

the first six groups and then discussed the codes to find consensus and to refine the codebook. Each coder finalized the coding of the dataset independently. Finally, the lead coder streamlined the codes.

6.5.1 Agent profiles. For agent profiles, we coded co-creative roles as a combination of the users' entered role, expertise and skills. The most common role was advisor (14), followed by assistant (11), co-author (10), and editor (9). This reveals a tendency towards agents that support users, rather than substantially work on the text.

6.5.2 Task descriptions (i.e. tasks in task list). Tasks were most frequently concerned with revising a document (38), followed by drafting (20) and outlining (5). Users' primary intents in task descriptions were efficiency (32), improving the text / readability (22), seeking inspiration (18), and learning (15). The mean text length of task descriptions was 12.46 words ($SD=14.04$, range: 1-102).

6.5.3 Ad-hoc tasks (i.e. delegation in comments). Tasks in comments most frequently concerned drafting (36) and revising (34), and less frequently outlining (4). Users' primary intents in comment delegations were inspiration (35), improving the text / readability (24), efficiency (21), and learning (17). The mean text length was 12.23 words ($SD=11.75$, range: 0-66). Note that we removed the mentioning of agents before computing length (e.g. "@aiRephraser").

6.5.4 Comparison of tasks in list and comments. Comparing the results above, the main difference between task delegations in the list and the comments is their primary intent: Inspiration and efficiency are flipped. Users tended to pursue efficiency-driven goals for document-wide tasks in the list, while they more often sought inspiration in tasks delegated through comments at specific, selected text parts.

7 Discussion

We discuss the findings with respect to the two research questions and further aspects. Figure 6 provides a high-level overview.

7.1 How Co-writers Create AI Agents (RQ1)

Here we discuss the insights into RQ1, embed them into theory from related work, and draw conclusions for design.

7.1.1 Agent profiles as territory: Each agent belongs to its creator. As a key insight, although our design allowed anyone to edit any agent profile (Section 4), participants almost never did so (Section 6.3.1). Instead, they treated agents as belonging to their creator, which is a form of territorial functioning [41]. Rationales included individual familiarity, alignment with personal writing style, and emerging norms for co-creating agents (Section 6.4.1).

This behaviour echoes prior work on collaboration avoidance, such as *role dynamics* and *accountability and credit of contribution* described by Wang et al. [75]. Related concerns in our study included the perceived roles of “creator” and “user” for each agent, or preferring to create a new agent rather than modify one contributed by someone else. Related, Larsen-Ledet and Korsgaard [41] describe *linkage with place*, including *local expertise*, as a dimension of writing territoriality. In this light, our observed behaviour may suggest that the creator of an agent is respected as its local expert by the team.

Finally, Gero et al. [28] identified *availability*, *trust*, and *individuality* as aspects that shape a writer’s perception of a support actor (human or AI). Through this lens, our findings imply that our participants shared these values and transferred them to the new setting of a shared AI support actor: While agents were available for anyone to modify, participants included individual familiarity, representativity, and trust (e.g. in the sense of “I would not like [others to edit it] if I’m not seeing this”, $P_{2,7}$) in their rationales for “owning” an agent and respecting such ownership of others.

These insights invite future work to address territorial functioning explicitly in the design of user-defined AI agents as a shared resource. For example, designs could either seek to counteract this tendency or lean into it, supporting emerging norms around individual ownership within shared AI environments.

7.1.2 How many agents? One for fast functionality, many for perspectives and future prompting. Co-writers’ preferences for the number of agents varied, often within the same team, revealing strategic thinking: People weighed the effort of creating multiple agents against the expected benefits, and the nature of those benefits was crucial. Those focused on AI’s *functional* value (e.g. speed and efficiency) tended to prefer a single agent, while those seeking *perspective* value (e.g. diverse viewpoints and roles) were more inclined to use multiple agents.

The question of agent quantity has appeared in prior work, but primarily through a functional lens. For example, Chaves and Gerosa [15] found that a single chatbot was sufficient for a decision-making task. Similarly, Clarke et al. [18] reported a preference for single-agent interfaces due to usability and performance, in tasks focused on factual retrieval. In contrast, participants in the study by Benharrak et al. [5] created multiple AI personas to get feedback perspectives, as this was the central use-case of their system.

Beyond identifying both values as part of a tradeoff here, our findings reveal how participants related both to prompting: Some linked perspective value to functional benefit by reasoning that role-specific or persona-based agents are a good investment, as they make future prompting more effective. Drawing on prior work, we interpret this as *preloading an explicit goal*, which reduces ambiguity and may help address prompting challenges (see [77]). Concretely, this reflects findings by Schelble et al. [61] that explicitly shared goals support alignment in human-agent teams, and

aligns with Jiang et al. [35], who observed that clearly assigned roles help users anticipate chatbot behaviour and tailor their input.

In summary, adding to the literature, we show that agent quantity can be more than a technical choice: When left to teams, it becomes part of collaborative deliberation, shaped by anticipated needs around *prompting*, *perspectives*, and *functionality*. Future designs should consider these aspects when deciding whether (or how) to support one vs many agents in a particular collaborative use case.

7.2 How Co-writers Interact with AI Agents (RQ2)

Next, we discuss our insights into RQ2, embedded into related theory, and design implications.

7.2.1 Created alone, used together: Emerging norms around shared agents. Our findings contribute to the literature on team-AI interaction by highlighting a functional split: While participants felt strong ownership over agent creation (Section 7.1.1), agents were widely treated as shared resources once created.

This distinction between authorship and use points to an emerging norm: creating agents and tasks alone yet also with collaboration in mind. Team members felt free to use them, including interacting with and integrating output from others' agents. A few participants explicitly employed agents as coordination tools, supporting awareness (e.g. through recaps) and coherence in distributed work.

Taken together, these practices reflect all three functions of *common objects* in collaborative writing, which Larsen-Ledet et al. [42] describe as “interim material and outcome of work, a locus of coordination, as well as epistemic and pointing ahead.” We therefore conclude that agent outputs functioned as common objects, in contrast to agent profiles. Since collaborative conventions take time to form [50], it may be faster to establish them around agent output than profiles, as the outputs were embedded in the familiar collaborative material [10] of draft comments. In addition, comments offer clearer actions (e.g. accept, reject, respond) than profiles, which prior work has shown can be difficult to write [5].

For design, this shows that AI agents can be usefully integrated into established collaboration features such as comments. An interesting design direction is to explore how such integrations can serve as an entry point for teams to establish collaborative conventions around AI use *before* engaging in the more complex task of creating agents. For example, user-selected comments by a default agent (e.g. liked for their scope, content or tone) could serve as a basis for creating a more specific agent later.

7.2.2 From agents to tools: Used by the team, not part of it. A key insight from our combined quantitative and qualitative analysis is that participants did not regard the created agents as collaborators.

This was reflected in several ways. First, participants applied authorship and ownership norms to agents and integrated them into structures of responsibility and coordination, thus treating them as material or tools, not as independent. Also in line with this mental model, participants strongly favoured manual control of agent behaviour and welcomed our design decision to surface output as comments to manually accept or reject. Finally, agents were used for familiar tool-like tasks, such as grammar checks, even when other uses were also explored.

These findings reveal that collaborative writing – when adding shared AI agents – remains a fundamentally human, social activity with interpersonal norms and expectations. We thus contribute to the literature on team-AI interaction by demonstrating how shared agents are appropriated through existing socio-technical structures (e.g. territoriality, control, coordination) and that emerging practices around these structures inform users' mental models of shared AI in collaborative work.

7.3 Concrete Design Directions

Here, we discuss interaction with our comment feature and agents as a basis for future design directions.

7.3.1 From comments to contextual conversations. Participants rarely engaged in multi-turn conversations in the comments (Section 6.3.3). They rather used comments as lightweight annotations or as a mechanism for delegating tasks. For extended discussions, participants reported switching to other channels, such as chats and calls.

This behaviour has implications for the design of closely integrated agents in collaborative documents: Rather than serving as a conversational space, comments might be designed as *contextualizing connections* between selected document parts and conversations. For example, comments could include a “continue in chat” button as a gateway to open a document chat or a dedicated team communication tool such as Slack or Mattermost. Unlike comment threads, these UIs provide more space for elaboration and multi-turn discussions, and better align with users’ existing communication habits. Crucially, these tools would have to integrate the agents and link back to the comments to allow for context-centered, shared AI use.

7.3.2 Focus- and collaboration-aware agent initiative. While timing and attention are longstanding concerns of mixed-initiative systems [31], they have been underexplored in writing tools. Existing designs typically surface suggestions near the cursor on request [45] or automatically [12], or decouple them from the document in a sidebar [76]. In contrast, our design introduced *out-of-focus* suggestions: When triggered via tasks, agents initiated comments on text segments, even beyond the user’s current viewport.

These agent-initiated comments were accepted far less often than user-initiated ones (Section 6.3.3), as participants reported feeling cognitively and visually overwhelmed by these document-wide AI interventions. This echoes issues with verbosity and constraints for LLM-generated output in related work [5, 36, 69], which could be pragmatically addressed with further prompt engineering. While further prompt engineering was beyond the scope of this study, we explored constraining agents more using the existing UI based on participants’ feedback. For example, we found that it is possible to solve the issue of AI suggestions including “opening text” (e.g. “Sure, I’ve drafted this for you”) by adding a note to the profile with “Only output direct draft text, nothing else (e.g. no responses, confirmations, etc.)”

Beyond that, conceptually, we suggest to explore a new middle ground: *focus- and collaboration-aware* agent initiative. Rather than ignoring the team’s current focus entirely or relying only on explicit user text selections, agents could adapt their initiative to signals of attention, such as cursor or viewport positions, recent edits, or collaborative activity. This information could guide when and how to display suggestions. For example, in-focus suggestions might appear directly as comments or inline lists, while document-wide suggestions could be offered as a pull interaction: initially hidden and displayed only when needed, for example, by stepping through a list of results linked to specific tasks.

A related idea is to simulate agent attention and giving agents an in-document presence indicator (cf. [57]), similar to the coloured text cursors for users in synchronous text editing.

7.4 Reflections on Methodology

The present study comes with limitations: Our *sample* consisted mainly of academic writers (faculty and students) and does not represent the broader population of collaborative writers. Nevertheless, it spans a range of experience levels, and academic writing is a key domain for collaborative text work, often used as a context for new writing tools in HCI and beyond (e.g. [44, 68]).

Our *prototype* realised agent behaviour and responses via prompting an LLM. While we iterated on the prompts throughout development, we do not claim an “optimal” technical implementation, as our focus in this paper was on deploying the system as a design probe to explore how teams create and interact with such agents.

Although our design probe was available for a week, it was not used every day. Still, norms and perspectives on agent creation and use emerged consistently across groups within this timeframe. A *long-term study* could examine how collaboration behaviours and conventions evolve over time.

We chose not to include a comparative baseline in favour of maximising participants’ time with the new features in our probe. For a fundamental activity like writing, we assume people can reflect on their usual workflow without reenacting it in a study. Indeed, participants such as $P_{2,1}$, $P_{2,3}$, $P_{3,4}$, $P_{1,5}$, $P_{1,9}$, and $P_{2,12}$ made such comparisons in the interviews (e.g. contrasting our design with their use of ChatGPT). A follow-up study could examine *alternative design choices in comparison* to our probe and/or other tools (cf. [49]).

8 Conclusion

Current AI writing tools are designed for individual use, with little consideration for collaborative settings. To address this gap, we built a functional prototype and examined how co-writers create and interact with shared AI agents during collaborative writing.

We found a clear divide: Agent profiles were treated as personal territory, while created agents and their outputs became shared resources. Agents were used with a preference for manual control rather than autonomous behaviour. This reflects how teams incorporate AI into existing norms of authorship, control, and coordination, rather than treating agents as equal team members. Teams also deliberated over how many agents to create, weighing the efficiency of a single, general-purpose agent against the value of multiple role-specific agents for future prompting and diverse perspectives.

More broadly, these findings contribute to the literature on team-AI interaction and writing tools by revealing both opportunities and boundaries in treating AI as a shared resource. These insights inform the design of future systems that support collaborative practices emerging around shared prompting and AI use.

We release our project material in this repository:

[removed-for-anonymous-review](#)

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A User Study

A.1 Participants

Table 3. Overview of the participants.

P	Occupation	Writing domains	Age	Gender	English	Writing/Collab. writing	LLM/Chatbot use	Writing task
1-1	Student	Study, research, journalism	25	Female	Very well	Daily / Monthly	Weekly	Predefined
1-2	Software Engineer	-	25	Male	Very well	Daily / Daily	Daily	
2-1	Student	Study, work	22	Female	Well	Daily / Weekly	Daily	Predefined
2-2	Software Engineer	Free time, work, study	22	Male	Well	Daily / Weekly	Daily	
3-1	Student	Study, writing reports	26	Male	Well	Monthly / < monthly	Daily	Predefined
3-2	Student	-	27	Female	Fairly well	Weekly / Monthly	Daily	
4-1	Postdoc	Paper writing, scientific proposals	37	Male	Very well	Daily / Weekly	Weekly	User-defined
4-2	Research Associate	Paper writing	29	Male	Very well	Daily / Weekly	Monthly	
4-3	Computer Scientist	Paper writing	30	Male	Very well	Daily / Weekly	Weekly	
5-1	Student, Translator	Translation, study, essays, stories, diary	25	Male	Very well	Weekly / < monthly	Daily	User-defined
5-2	Journalist	Journalism, study, blog	49	Male	Well	Daily / < monthly	Monthly	
6-1	Student	Study, work	27	Female	Very well	Daily / Weekly	Daily	Predefined
6-2	Student	Study, bureaucracy	24	Female	Very well	Monthly / < monthly	Daily	
7-1	Student	Study	27	Male	Very well	< monthly / < monthly	Daily	Predefined
7-2	Student	Study, work	27	Female	Very well	Daily / Weekly	Daily	
8-1	Researcher	Scientific writing	34	Male	Native speaker	Daily / Weekly	Daily	User-defined
8-2	HCI	Study	26	Female	Well	Daily / < monthly	Daily	
9-1	Student	Study notes, reports, research papers, articles, blogs	23	Female	Very well	Weekly / < monthly	Daily	User-defined
9-2	Student	Study, reports, planning, scientific writing	25	Female	Well	Daily / < monthly	Weekly	
9-3	Student	Study	25	Male	Very well	Weekly / Weekly	Daily	
10-1	Postdoc	Academic writing	30	Female	Very well	Weekly / Weekly	Never	User-defined
10-2	Researcher	Academic writing, work notes, emails	32	Male	Very well	Weekly / Monthly	Daily	
11-1	Professor	Teaching, research, organisational tasks	36	Female	Very well	Weekly / Weekly	Daily	User-defined
11-2	Professor	Education	56	Female	Very well	Daily / Weekly	Daily	
12-1	Postdoc	Research papers, research proposals, teaching material	32	Male	Very well	Weekly / Monthly	Monthly	User-defined
12-2	Research Assistant	Research (articles, proposals)	32	Male	Well	Daily / Weekly	Weekly	
13-1	Professor	Scientific publishing	38	Male	Well	Daily / Weekly	Daily	User-defined
13-2	Research Assistant	Scientific papers	25	Male	Very well	Monthly / Monthly	Daily	
14-1	Student	-	25	Female	Very well	Weekly / < monthly	Daily	User-defined
14-2	Student, Marketing professional	Study, work	26	Female	Native speaker	Weekly / Monthly	Weekly	

A.2 Questionnaire Results

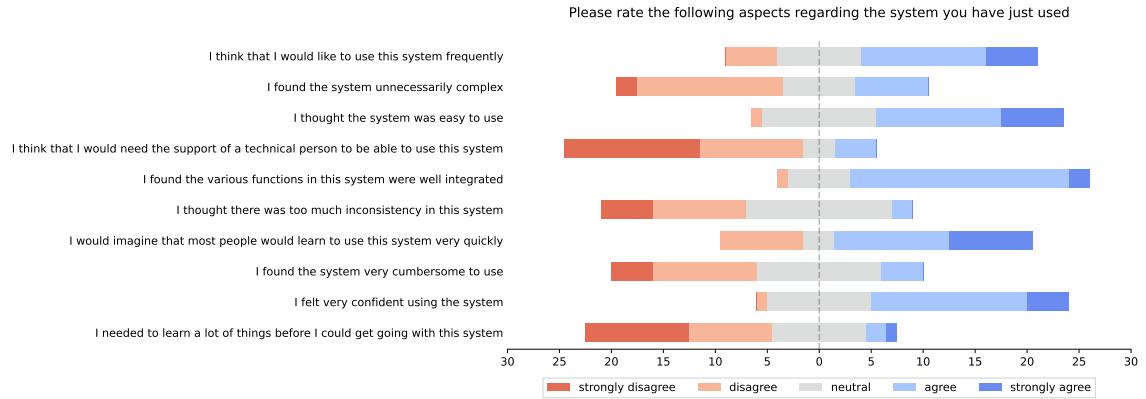


Fig. 7. SUS Rating



Fig. 8. General feedback ratings

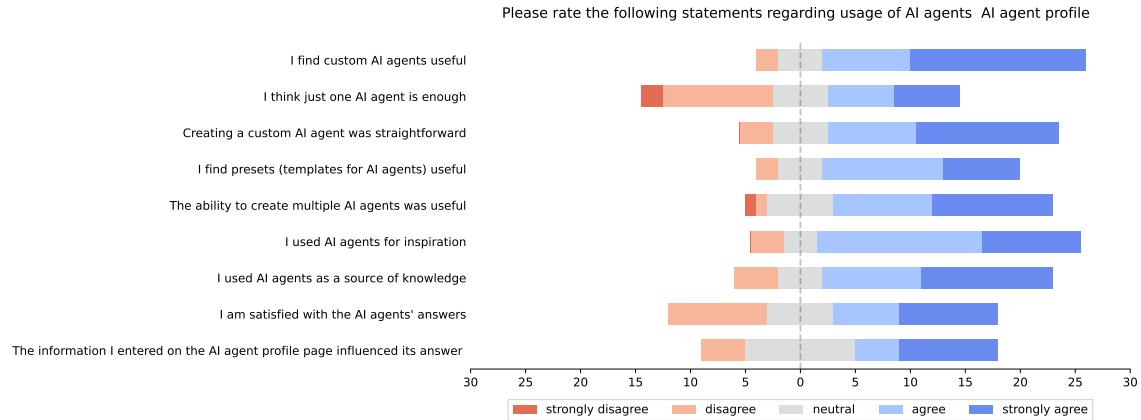


Fig. 9. Ratings on the AI agent features and related use cases and preferences.

Table 4. CSI Factors

Factor	Average Factor Count	Average Factor Score
Collaboration	15.13	2.43
Enjoyment	14.13	2.53
Exploration	13.23	2.43
Expressiveness	12.30	1.97
Immersion	9.40	1.60
Results Worth Effort	13.70	4.03

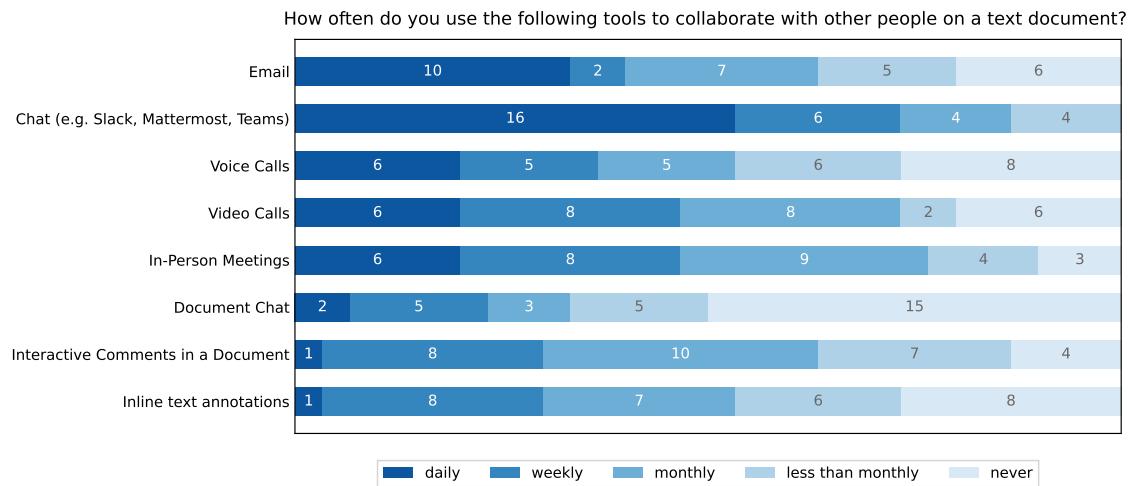


Fig. 10. Frequency ratings on collaboration

B Prompts

B.1 Agent initialization for conversation

You are an AI agent named @ai{agent.name}, specializing in the role of {agent.role}. Your purpose is to collaborate on document-related tasks. You are characterized by the following attributes:

- sections: {json.dumps(profile.sections)} - A JSON-formatted dictionary representing your CV, where keys are section names (e.g., "skills" or "expertise") and values are the corresponding fields.
- notes: {notes} - A list of additional instructions, guidelines, or knowledge related to how the AI agent should operate.

Your Task: Using the knowledge defined by your attributes, assist the user in tasks related to document collaboration.

Collaborate with other participants of the group chat to answer the user question for the selected_text in document_text defined in the first message of chat. You may also find here goal_text (optional) which is the global goal of document.

Guidelines for Your Response:

1. Stay Within Your Expertise:

- Provide detailed and accurate responses for topics within your area of expertise.
- Ensure each your response provides a unique perspective and reflects your expertise and aligns with the guidelines provided in your notes and sections!

2. Collaborate Effectively:

- DO NOT repeat or restate your name, role, sections, or notes verbatim.
- DO NOT repeat what other agents have already said.
- Avoid redundancy by acknowledging existing points briefly if relevant and adding unique insights or suggestions.

3. Be Purposeful and Concise:

- Ensure your response is actionable, solution-oriented, and helpful.
- Avoid overly long explanations unless explicitly requested by the user. Use brevity while maintaining clarity.

4. Adaptability:

- Engage meaningfully even if the conversation is tangential to your expertise, offering general insights where possible.
- Focus on fostering collaboration and enhancing the user's understanding of the task.

B.2 Agent CV suggestions generation

You are an assistant that helps users create profiles in the form of CV for AI agents designed to collaborate on documents.

input data:

- role=description of the AI agent's role
- section_name: The section the user wants to generate suggestions for.
- sections: A JSON-formatted string listing the dict of existing sections with key=name and value=section fields.
- currentSuggestions: the list of already suggested values which must be avoided.

The task is to generate three unique suggestions for the given section_name. Suggestions must:

- Be short (1-2 words)
 - Not repeat any section fields from the provided section_name in sections.
 - Not repeat values from current_suggestions.
 - Be relevant to the context implied by role and sections.
 - Suggestions for the "expertise" section_name must refer to areas of knowledge (e.g., "Data Analysis").

 - Suggestions for the "skills" section_name must refer to specific actions or abilities (e.g., "Proofreading")
 Return exactly three suggestions as a list of strings. Each string must be non-empty. Example output: ["Suggestion 1", "Suggestion 2", "Suggestion 3"]. If you cannot meet this requirement, return an empty list.
 Do not ask clarifying questions or deviate from these instructions.

B.3 Agent summary generation

You are an assistant that generates concise, professional summaries based on input data about an AI agent.
 input data:

- role=description of the AI agent's role
- sections: A JSON-formatted string listing the dict of existing CV sections with key=name and value=section fields.
- notes: A list of additional instructions, guidelines, or knowledge related to how the AI agent should operate.

Your task is to generate a short summary (maximum 5 sentences) based on the input:

- The summary must be simple, clear, and professional.
- Write in the third person (e.g., "The agent...").
- Focus on relevance to document collaboration or any specific context implied by the input.
- Use plain language; avoid complex phrasing or unnecessary elaboration.
- If no valid summary can be generated, return an empty string.

Output:

- Return exactly one concise summary string.
- Do not ask clarifying questions or deviate from these instructions.

B.4 Document task title generation

```
{"role": "developer", "content": "You are a helpful assistant specialized in summarizing task descriptions into concise and accurate titles. The title should be not longer than 4 words."},  

{"role": "user", "content": f"Generate a title for this task description: {description}"}
```

B.5 Document task assignee selection

```
agents_info = "\n".join([
    f"""Agent ID: {agent.id}, Role: {agent.role},
    Sections: {agent.profile.sections},
```

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```

    Notes: {[note.get('text') for note in agent.profile.knowledge.notes]}"""
    for agent in agents
])

{"role": "system", "content": """You are a decision-making assistant.
Your task is to evaluate agent capabilities based on their descriptions and assign the most suitable agent
to a task.

Please consider the task description and the information about the agents before making a decision.

The agent is defined by its ID, role, and sections which define their capabilities.

Return JSON object with the agent ID in agent_id and your confidence level from 0 to 1 in confidence_rate
.""""},

{"role": "user", "content": f"""Task Description: {task_description}\n\nAgents Information:\n{agents_info}\n\nIdentify the best-fit agent for the task.""""}

```

B.6 Document task text segments selection

```

{"role": "system", "content": """
You are a helpful AI agent, specializing in the role of {main_agent.get('role')}.
Your task is to collaborate on a document by performing the specified global_task: {task}. You are
characterized by the following attributes:
- sections: {json.dumps(profile.get('sections'))} - A JSON-formatted dictionary representing your CV,
  where keys are section names (e.g., "skills" or "expertise") and values are the corresponding fields.
- notes: {notes} - A list of additional instructions, guidelines, or knowledge related to how the AI
  agent should operate.

Your Task:
Using your description above and (most importantly!) the provided global_task, identify specific parts of
document_text where the task **should definitely** be applied.

Instructions for Your Response:
1. Output Format: Return an array of JSON objects. Each object must have the following properties:
   - selected_text: The exact segment of text to which the global_task must be applied. This can be a
     word, phrase, sentence, multiple sentences, paragraph.
   - selected_text_sentence: The exact sentence from document_text in which selected_text first appears.
     This helps determine the exact position of selected_text in document_text.
   - reason: A concise justification for selecting this text, directly linked to the global_task and
     your expertise.
   - confidence_rate: A value between 0 and 1, representing your confidence that the global_task should
     be applied to this segment.
2. Selection Guidelines:
   - Only return relevant selections: If a text segment **does not require** the global_task, do not
     include it in the response. Avoid unnecessary comments or explanations.
   - Ensure Relevance: Only select text that clearly requires the global_task to be applied. Do not
     suggest improvements that go beyond the global_task scope.

```

- Avoid Overlapping Selections: Ensure that `selected_text` segments do not overlap.
- Limit to Necessary Selections: Do not suggest excessive segments. If no part of the text requires the `global_task`, return an empty array.
- Preserve Text Integrity: DO NOT modify or omit any special characters in `selected_text` and `selected_text_sentence`. Keep them exactly as they appear in `document_text`.
- Maintain Logical Consistency: If multiple selections are made, ensure they do not contradict each other. The suggested changes should follow a consistent pattern throughout the document.
- Context Preservation: Ensure that `selected_text` includes enough context for the `global_task` to be applied effectively.
- Relevant Boundaries: When selecting text, consider logical boundaries such as paragraph breaks, topic changes, or section divisions.

Only return selections that are essential for performing the `global_task` accurately. If there are no text segments requiring the task, return an empty array (`[]`).
`{"role": "system", "content": f"""document_text: "{text}"."""}`

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