Screen Reader Users in the Vibe Coding Era: Adaptation, Empowerment, and New Accessibility Landscape

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The rise of generative AI agents has reshaped human-computer interaction and computer-supported cooperative work by shifting users' roles from direct task execution to supervising machine-driven actions, especially in programming (e.g., "*vibe coding*"). However, there is limited understanding of how screen reader users engage with these systems in practice. To address this gap, we conducted a longitudinal study with 16 screen reader users, exploring their experiences with AI code assistants in daily programming scenarios. Participants first completed a tutorial with *GitHub Copilot*, then performed a programming task and provided initial feedback. After two weeks of AI-assisted programming, follow-up studies assessed changes in their practices and perceptions. Our findings demonstrate that advanced code assistants not only enhance their programming capabilities but also bridge accessibility gaps. While the assistant proved beneficial, there remains potential to improve how users convey intent and interpret outputs. They also experienced difficulties managing multiple views and maintaining situational awareness. More broadly, they encountered barriers in learning advanced tools and expressed a need to retain control. Based on these insights, we provide design recommendations for more accessible and inclusive AI-assisted tools.

CCS Concepts: • **Human-centered computing → HCI theory, concepts and models**; **Empirical studies in accessibility**; • **Software and its engineering** → *Software creation and management*; • **Computing methodologies** → *Artificial intelligence*.

Additional Key Words and Phrases: Generative AI, AI Code Assistant, Screen Reader Users, Program Synthesis, Human-AI Interaction and Collaboration, Visual Impairments

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1 Introduction

Recent advances in generative artificial intelligence (AI) have profoundly transformed how individuals interact with digital systems and perform tasks across diverse domains. AI-driven tools now support personalized learning in education [41], enable intuitive data visualization [19], and

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streamline information communication [81]. Among these domains, software development stands out as one of the most promising fields [18, 42].

With the emergence of LLM-based agents [85], modern AI code assistants such as *GitHub Copilot* [30] and *Cursor* [21] are realizing the long-standing vision of intelligent programming support [10]. These tools offer **advanced intelligence and automation** beyond simple code completion. They can retrieve files, edit code, and correct errors based on execution results—capabilities that are further empowered by the introduction of Agent modes [22, 75]. Building upon these advancements, a new interaction paradigm—"*vibe coding*" [59, 83]—has emerged, where developers express goals in natural language queries while AI takes on more programming work. This shift makes coding more accessible and redefines developers' roles from manual coding to guiding and refining AI outputs.

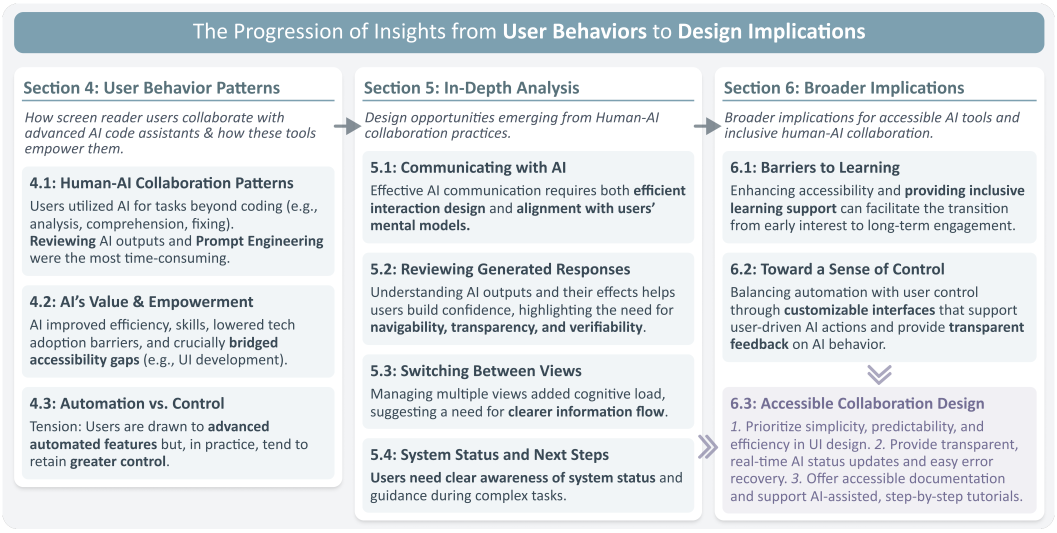
Yet questions remain about whether people with visual impairments can benefit similarly from these **advanced AI code assistants**. These programmers face persistent accessibility and collaboration challenges. They often rely on screen readers to code [4, 44] while many programming tools are designed with graphical user interfaces (GUIs) that are difficult to access [46, 65]. Collaborative tasks—such as interpreting design documents [53] or adapting to sighted programmers' coding styles [54]—can further increase cognitive load [12, 35, 82]. Prior work has examined how generative AI tools affect users with visual impairments [2, 6, 55, 66] and their use of basic code completion or chatbots [29]. However, less is known about how screen reader users work with more advanced AI assistants that enable autonomous, dynamic workflows. To address these gaps, we investigate the following research questions:

- **[RQ1]** *How do screen reader users collaborate with advanced AI code assistants, and how do these tools empower them?*
- **[RQ2]** *What new challenges do screen reader users encounter when using advanced AI code assistants?*

We conducted a two-week, three-phase longitudinal study (see Figure 2) involving 16 screen reader users with diverse experience in programming and AI-assisted coding. In the initial study, participants completed a tutorial and a programming task simulating real-world scenarios, followed by a semi-structured interview. Next, given participants' limited experience with advanced code assistants, we encouraged them to explore these features during two weeks of regular programming tasks, and documented both positive and negative experiences. Finally, we held follow-up interviews to reflect on their real-world usage and the challenges they encountered.

Our findings reveal that advanced code assistants not only enhance screen reader users' programming capabilities (e.g., code writing and comprehension), but also help bridge accessibility gaps in areas such as UI development. Participants favored more advanced and automated features, shifting their roles from directly performing programming tasks to supervising AI-driven actions. However, two critical aspects of this shift—communicating with the AI and reviewing its outputs—remained challenging for participants. Additionally, code assistants introduced new difficulties, including the need to switch between multiple views and to maintain awareness of system status and next steps. Users also experienced learning challenges with advanced tools and emphasized the importance of maintaining control. Based on these findings, we present design recommendations to improve the accessibility of AI-assisted coding and offer broader implications for inclusive human-AI interaction and collaboration. In summary, our work makes several contributions to the field of human-computer interaction (HCI) and computer-supported cooperative work (CSCW) (see Figure 1 for a detailed roadmap):

- We provide an in-depth investigation into how screen reader users engage with advanced AI code assistants, exploring both the value and empowerment AI offers.
- We highlight the need for more accessible communication and review workflows, while also identifying new barriers—managing multiple views and maintaining situational awareness.
- We discuss broader challenges, including difficulties in learning advanced tools and the need to maintain a sense of control, and offer actionable design recommendations to enhance accessibility in human-AI collaboration.


The Progression of Insights from **User Behaviors** to **Design Implications**

Section 4: User Behavior Patterns

How screen reader users collaborate with advanced AI code assistants & how these tools empower them.

4.1: Human-AI Collaboration Patterns
Users utilized AI for tasks beyond coding (e.g., analysis, comprehension, fixing). **Reviewing** AI outputs and **Prompt Engineering** were the most time-consuming.

4.2: AI's Value & Empowerment
AI improved efficiency, skills, lowered tech adoption barriers, and crucially **bridged accessibility gaps** (e.g., UI development).

4.3: Automation vs. Control
Tension: Users are drawn to **advanced automated features** but, in practice, tend to retain **greater control**.

Section 5: In-Depth Analysis

Design opportunities emerging from Human-AI collaboration practices.

5.1: Communicating with AI
Effective AI communication requires both **efficient interaction design** and **alignment with users' mental models.**

5.2: Reviewing Generated Responses
Understanding AI outputs and their effects helps users build confidence, highlighting the need for **navigability, transparency, and verifiability**.

5.3: Switching Between Views
Managing multiple views added cognitive load, suggesting a need for **clearer information flow**.

5.4: System Status and Next Steps
Users need clear awareness of system status and guidance during complex tasks.

Section 6: Broader Implications

Broader implications for accessible AI tools and inclusive human-AI collaboration.

6.1: Barriers to Learning
Enhancing accessibility and **providing inclusive learning support** can facilitate the transition from early interest to long-term engagement.

6.2: Toward a Sense of Control
Balancing automation with user control through **customizable interfaces** that support user-driven AI actions and provide **transparent feedback** on AI behavior.

6.3: Accessible Collaboration Design
1. Prioritize simplicity, predictability, and efficiency in UI design. *2.* Provide transparent, real-time AI status updates and easy error recovery. *3.* Offer accessible documentation and support AI-assisted, step-by-step tutorials.

Fig. 1. An overview roadmap of the main insights and implications of this paper. From left to right: users' overarching behavior patterns (section 4), design opportunities emerging from practices, (section 5), and broader implications for future human-AI interaction and collaboration research and design (section 6).

2 Related Work

2.1 Human-AI Collaboration with Code Assistants

In recent years, AI-powered code assistants [20, 21, 30] have emerged, transforming human-machine collaboration by enhancing developer productivity through features like code completion, natural language explanations, code editing, and enabling an interactive and conversational coding experience [3, 24, 59]. These advancements raise important questions about users' successes and challenges when interacting with these tools [13, 26, 36, 62, 63].

Past efforts in this topic have explored diverse aspects of code assistants' influences, including their usability [23, 42], impact on productivity [78, 89], user behavior [9, 48], security implications [7, 56], and educational benefits [38, 58]. These tools have demonstrated potential in various programming tasks, such as explaining code, generating tests, and fixing bugs [80]. Ziegler et al. [89] demonstrated that AI programming tools significantly enhance developer productivity, with novice developers experiencing the most substantial improvements. A recent study [9] examined how developers interact with Copilot to solve different programming tasks and revealed two archetypal patterns: *acceleration* when people know their next steps, and *exploration* when they need to explore what to do next. Another empirical study [72] examined how developers validate and repair AI-generated code to ensure correctness and reliability. While Copilot improves enterprise productivity, Weisz et al. [78] found that adoption barriers include a lack of trust in AI-generated code and a perceived disconnect from its outputs, which hinder its adoption. These trust issues worsen due to buggy outputs and reproducibility problems [23], reducing confidence in the tool's reliability [76]. Liu et al. [43] noted that the abstraction gap between developers and large language models (LLMs) for code generation introduces additional challenges. Addressing these limitations is crucial for improving AI code assistants' robustness and usability.

Researchers are also examining AI code assistants' collaborative impact. Shah et al. [64] studied code assistants in classroom settings, taking the first step toward understanding how senior students utilize GitHub Copilot to navigate and modify large code bases—skills crucial for their future software engineering careers. In open-source software development, GitHub Copilot moderately improves individual productivity and participation but increases coordination costs, with a 41.6% increase in integration time [68]. These findings highlight both the opportunities and challenges in integrating AI code assistants into collaborative workflows.

With the advancement of code assistants, a new interaction paradigm, known as "*vibe coding*" [59, 83] has emerged and gained widespread adoption. In this paradigm, programmers express their intent in natural language while the code assistant autonomously implements the functionality. However, whether screen reader users can experience the same convenience and ease remains largely unexplored. This work aims to address this research gap.

2.2 Programming and Cooperative Challenges for People with Visual Impairments

StackOverflow's annual developer survey [69], one of the most credible surveys of programmers worldwide, reported that approximately 1.7% of respondents identified as having a visual impairment in 2022. This indicates that individuals with visual impairments form a stable and significant group within the programming community. However, despite the support of assistive technologies such as screen readers, screen magnifiers, and braille displays, programmers with visual impairments continue to face unique and persistent challenges [4, 44, 67].

The challenges faced by developers with visual impairments are multifaceted and fall into five areas [47]: navigation, comprehension, editing, debugging, and skimming. While screen readers are essential for enabling non-visual code access, their inherently linear and auditory nature makes these activities more time-consuming and cognitively demanding [5, 57]. The linear output makes it challenging to quickly grasp code structure or locate specific information—tasks which sighted developers easily accomplish through visual cues such as indentation and color-coding [39]. Many developers with visual impairments prefer text editors over integrated development environments (IDEs) because text editors tend to work better with assistive technologies [4]. Though IDEs like *Visual Studio Code* [61] have made efforts to improve accessibility, they and the broader programming ecosystem remain challenging for users with visual impairments due to their heavy reliance on visual interfaces and limited screen reader compatibility [47, 53]. Furthermore, tools and resources beyond IDEs present even greater accessibility challenges [70]. Command line interfaces, for instance, create additional accessibility issues due to their unstructured text nature[60].

Cooperation, a cornerstone of modern software development, presents its own set of barriers for developers with visual impairments. Pandey et al. [53] identified several challenging tasks: pair programming (which depends on shared screens and often lacks assistive technologies on colleagues' machines) and code reviews (which require visual comparison and reasoning about code changes). Furthermore, understanding existing code written by other developers or learning new functionalities and APIs of programming languages can pose significant barriers since most documentation and explanations typically rely on visual reasoning and diagrams [87]. Additionally, since sighted developers and developers with visual impairments access information differently, existing code readability norms—shaped by the preferences of sighted developers—can make it difficult for developers with visual impairments to read code written by their sighted peers [54]. Further, some developers with visual impairments may hesitate to ask for sighted assistance, fearing they might appear less competent or burden their colleagues, as they often face marginalization in mainstream development [37]. These challenges become particularly acute when working with UI frameworks and web development [27, 52].

Our work aims to investigate whether advanced AI code assistants can alleviate the challenges faced by screen reader developers or introduce new barriers. Through our findings, we hope to propose actionable design recommendations that promote more accessible programming experiences for screen reader developers in the future.

2.3 Human-AI Interaction for People with Visual Impairments

In recent years, broader studies have begun to explore how individuals with visual impairments interact and engage with AI tools [8, 33, 55, 73, 86]. Adnin et al. [2] conducted interviews to investigate how blind individuals incorporate mainstream generative AI tools, such as ChatGPT and *Be My AI* [11], into their everyday lives. They found that blind users navigate various accessibility challenges, inaccuracies, hallucinations, and idiosyncrasies associated with GenAI. Perera et al. [55] found that screen reader users faced significant accessibility challenges with GenAI in productivity tools, which diminishes their productivity and independence. Gonzalez et al. [32] found that in scene description tasks, users were sometimes able to infer useful information even from poor or partially correct descriptions; as a result, their satisfaction and trust did not always align with the actual description accuracy. In addition, these tools often lack context awareness and struggle to understand users' intentions accurately, creating additional challenges for users with visual impairments [86]. To address these challenges, blind people develop adaptive strategies, such as comparing outputs from multiple LLMs to achieve optimal results [6].

A recent study of 10 developers with visual impairments examined the impact of AI code assistants [29]. While code assistants streamline repetitive tasks and spark new ideas, they also introduce accessibility barriers through overwhelming suggestions and complex context switching. However, the implications of advanced intelligence and automation features—such as automatic file modifications and iterative error correction—remain unexplored. Furthermore, their findings were based on limited, short-term interactions with IDE-integrated code assistants rather than extended real-world use. Our work addresses these gaps through a two-week, three-phase longitudinal study. We reveal underexplored challenges and opportunities with advanced intelligence and automation features, and propose actionable design recommendations to enhance these tools' accessibility and usability for screen reader developers.

3 Methodology

During participant recruitment, we found that most users had limited familiarity and experience with IDE-integrated AI code assistants. Since a single interview would not provide sufficient insight into their practical use and the challenges they face, we therefore conducted a two-week, three-phase study (see Figure 2). The first phase (subsection 3.3) comprised participants completing a GitHub Copilot tutorial, working on a predefined programming task with Copilot's assistance, and participating in a semi-structured interview to share their initial impressions. In the second phase (subsection 3.4), participants incorporated Copilot into their daily programming work for two weeks, documenting significant experiences (both positive and negative) using a diary template. The final phase (subsection 3.5) consisted of a follow-up study examining participants' real-world experiences with code assistants. This mixed-methods approach captured both in-depth, task-based insights and longitudinal, in-situ usage patterns. This study was approved by our Institutional Review Board (IRB).

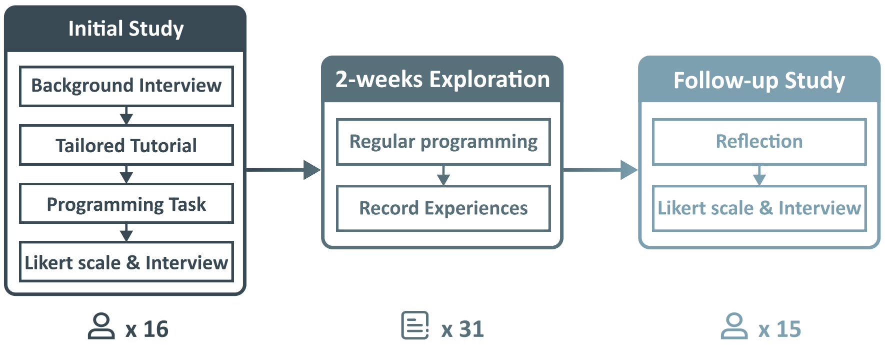


Fig. 2. Overview of the three-phase study design. The study included an initial study with 16 participants, a two-week phase where participants used Copilot in regular programming and record their experiences (in total of 31 recorded cases collected), and a follow-up study.

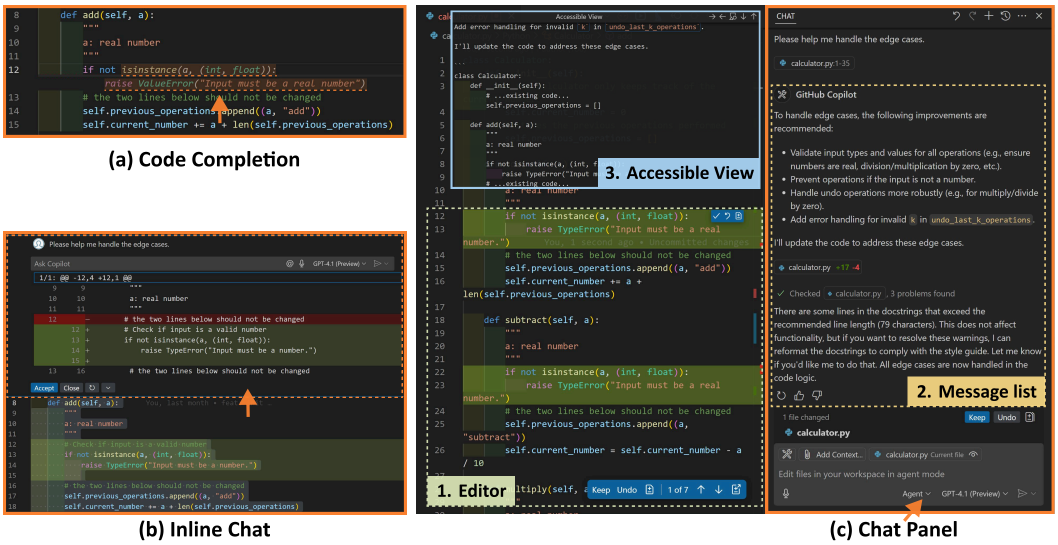
3.1 Copilot-assisted Programming

GitHub Copilot [30], released in 2021, is a widely recognized AI code assistant, with numerous studies examining how humans interact with and are impacted by it [9, 29, 48]. In this study, we selected Copilot within Visual Studio Code (VS Code) because of its widespread adoption, advanced feature set, and strong accessibility support [31]. Copilot's core features include code completion, inline chat, and a dedicated chat panel (see Figure 3). *Code completion* (Figure 3 (a)) provides real-time suggestions as users type. *Inline chat* (Figure 3 (b)) enables direct conversational interactions from the editor or terminal, allowing users to request code explanations or modifications for selected code snippets. The chat panel (Figure 3 (c)) serves as an integrated conversational interface, where users can pose programming questions, request code suggestions, and seek explanations.

The chat panel features three distinct modes: (1) *Ask mode*, for general programming queries and code generation; (2) *Edit mode*, for **automatic application of Copilot-generated changes** to one or more files in the workspace; and (3) *Agent mode*, where Copilot **autonomously plans and executes multi-step tasks**, including searching for relevant files, making code edits, and running terminal commands, iteratively refining its outputs as needed. At the bottom of the chat panel, users can send their requests and attach additional context—such as files, terminal outputs, or other relevant information—and switch between different modes and models to customize their interactions. Users can review and modify Copilot's code changes directly within the editor (Figure 3 (1)) and navigate the message list (Figure 3 (2)). For accessibility, Copilot also offers features such as automatic playback of generated AI responses and an accessible view (Figure 3 (3)), which displays responses in a plain-text format, making it easier for screen reader users to access the information.

3.2 Participants

We recruited 16 screen reader users (2 female, 14 male) who had experience using AI for programming support. All participants used screen readers (such as *NVDA* [51]) as their primary method of accessing development environments. 13 participants were totally blind, while 3 had low vision; of these, P8 and P9 could perceive the screen focus location. Among these participants, 7 had prior experience with Copilot, though most had only used the *code completion* feature and not extensively; only P12 had used the *Ask mode*. P10 and P14 had experience with *Cursor* [21] (both *Ask mode* and *Agent mode*), and P16 had used *Cline* [20] for *code completion*, *Ask mode*, and *Edit mode*. See Table 1 for a summary of participant demographics. Each participant received $70 USD



```
    def add(self, a):
        """
        a: real number
        """
        if not isinstance(a, (int, float)):
            raise ValueError("Input must be a real number")
        # the two lines below should not be changed
        self.previous_operations.append((a, "add"))
        self.current_number += a + len(self.previous_operations)
```

Please help me handle the edge cases.

```
1/1: @@ -12,4 +12,1 @@
 9    9          """
10   10          a: real number
11   11          """
12      -        # the two lines below should not be changed
     12 +        # Check if input is a valid number
     13 +        if not isinstance(a, (int, float)):
     14 +            raise TypeError("Input must be a number.")
     15 +
13   16          # the two lines below should not be changed
```

```
    def add(self, a):           You, last month • feat: init …
        """
        a: real number
        """
        # Check if input is a valid number
        if not isinstance(a, (int, float)):
            raise TypeError("Input must be a number.")

        # the two lines below should not be changed
        self.previous_operations.append((a, "add"))
        self.current_number += a + len(self.previous_operations)
```

```
Add error handling for invalid `k` in `undo_last_k_operations`.

I'll update the code to address these edge cases.

...
class Calculator:
    def __init__(self):
        # ...existing code...
        self.previous_operations = []

    def add(self, a):
        """
        a: real number
        """
        if not isinstance(a, (int, f
            raise TypeError("Input m
        # ...existing code...
```

```
        if not isinstance(a, (int, float)):
            raise TypeError("Input must be a real
number.")      You, 1 second ago • Uncommitted changes
        # the two lines below should not be changed
        self.previous_operations.append((a, "add"))
        self.current_number += a +
len(self.previous_operations)

    def subtract(self, a):
        """
        a: real number
        """
        if not isinstance(a, (int, float)):
            raise TypeError("Input must be a real
number.")
        # the two lines below should not be changed
        self.previous_operations.append((a,
"subtract"))
        self.current_number = self.current_number - a
/ 10
```

Please help me handle the edge cases.

calculator.py:1-35

GitHub Copilot

To handle edge cases, the following improvements are recommended:

- Validate input types and values for all operations (e.g., ensure numbers are real, division/multiplication by zero, etc.).
- Prevent operations if the input is not a number.
- Handle undo operations more robustly (e.g., for multiply/divide by zero).
- Add error handling for invalid `k` in `undo_last_k_operations`.

I'll update the code to address these edge cases.

calculator.py +17 -4

Checked calculator.py, 3 problems found

There are some lines in the docstrings that exceed the recommended line length (79 characters). This does not affect functionality, but if you want to resolve these warnings, I can reformat the docstrings to comply with the style guide. Let me know if you'd like me to do that. All edge cases are now handled in the code logic.

calculator.py

Edit files in your workspace in agent mode

Fig. 3. Overview of GitHub Copilot features. (a) Code Completion provides real-time code suggestions as users type. (b) Inline Chat enables seamless conversational interaction with the AI directly within the editor or terminal. (c) Chat Panel supports multi-turn conversations with three modes (i.e., *Ask mode*, *Edit mode*, and *Agent mode*). Users can review Copilot responses in three ways: (1) directly reviewing and editing generated code in the editor, (2) navigating the message list in the chat panel, and (3) accessing responses in the accessible view.

(or local equivalent) as compensation for their time and effort, or $55 USD if they did not participate in the follow-up, plus an additional $10 USD to cover a one-month GitHub Copilot subscription.

3.3 Initial Study

Each study session was conducted remotely, with participants using their own familiar devices and screen readers. Before the study, participants installed the GitHub Copilot extension and set up a suitable Python or Node.js environment. We provided a step-by-step preparation guide and an accessible Copilot user manual, including feature overview, usage instructions, and keyboard shortcuts. Reviewing these materials was optional. Each session lasted 110-140 minutes, depending on how quickly participants became comfortable with Copilot. With participants' consent, we recorded their shared screen activity and audio for analysis.

The initial user study consisted of four main steps: (1) A **background interview** about participants' programming experience and AI code assistant usage. (2) A **tailored Copilot tutorial** based on prior experience, focusing on the introduction of key features and how to use them with screen readers, was provided. Participants were encouraged to try features they had not previously used, such as inline chat, mode switching, context setting, and different output reviewing methods. After addressing the questions, we proceeded with the coding tasks. (3) A **programming task** randomly chosen from four options (Table 2), with approximately one hour for completion. If unfinished, the task ended with the participant's consent. Participants were asked to enable VS Code's screencast mode to make their keyboard input visible, and were encouraged to think aloud—describing their thoughts, strategies, and decision-making processes while interacting with Copilot. They could use Copilot as usual or ignore it if preferred. The interviewer provided assistance and clarification as needed, particularly for accessibility barriers and Copilot usage challenges. (4) Participants

Table 1. Participants' demographic and study-related information. **Status** denotes the participant's visual status. **Exp.** indicates years of programming experience. **Freq.** denotes coding frequency, categorized as: Daily (multiple times per day), Weekly (multiple times per week), or Monthly (multiple times per month). **Lang.** represents the programming language used during the task. **Res.** indicates the number of completed requirements out of the total for each task.

ID	Gender	Age	Status	Exp.	Occupation	AI Code Assistant Usage	Freq.	Lang.	Task	Res.
P1	Male	34	Blind	7	Freelancer	Copilot, ChatGPT	Daily	Python	T2	1/2
P2	Male	39	Blind	19	Game Dev.	Copilot, ChatGPT, Gemini, DeepSeek, Doubao	Daily	JavaScript	T4	3/9
P3	Male	29	Blind	2	Masseur	Claude, ChatGPT, Grok, DeepSeek	Daily	Python	T3	1/2
P4	Male	42	Blind	10	Software Eng.	ChatGPT, Doubao	Monthly	Python	T4	9/10
P5	Male	24	Blind	3	Accessibility Testing & Dev.	ChatGPT, Gemini	Daily	JavaScript	T2	1/2
P6	Male	36	Blind	18	Accessibility Testing & Dev.	ChatGPT	Daily	Python	T3	1/2
P7	Female	27	Blind	7	Freelancer	-	Monthly	Python	T4	6/10
P8	Male	41	Low Vision	21	Developer	DeepSeek, Doubao	Monthly	Python	T3	1/2
P9	Female	22	Low Vision	1	Student	ChatGPT, DeepSeek, Copilot	Daily	Python	T2	0/2
P10	Male	28	Blind	9	Accessibility Optimization	ChatGPT, Cursor, Copilot	Daily	Python	T1	2/2
P11	Male	29	Low Vision	5	Accessibility Testing & Dev.	DeepSeek, Doubao	Weekly	JavaScript	T1	0/2
P12	Male	24	Blind	3	Student	ChatGPT, DeepSeek, Copilot	Weekly	Python	T1	0/2
P13	Male	32	Blind	10	Accessibility Testing	Doubao, Gemini, ChatGPT, DeepSeek	Daily	Python	T1	1/2
P14	Male	29	Blind	6	Software Eng.	Cursor, ChatGPT, Gemini, Copilot	Weekly	Python	T4	8/10
P15	Male	35	Blind	10	Accessibility Testing & Dev.	ChatGPT, DeepSeek, Copilot	Daily	Python	T3	1/2
P16	Male	45	Blind	10	Masseur	DeepSeek, CLine	Weekly	Python	T2	0/2

rated their Copilot experience on a 7-point **Likert scale** (Appendix Table C), followed by a semi-structured **interview** about their usage patterns, challenges, and observations (Appendix Table A). Participants with experience using other code assistants shared their comparative perspectives.

3.3.1 Task. We selected four common collaborative programming tasks (see Table 2) representing a broad spectrum of real-world software development activities. These tasks required participants to implement new features based on the existing codebase and requirements *(T1, T2)*, analyze and format data *(T3)*, and debug others' code *(T4)*. In summary, these tasks covered requirements analysis, code comprehension, testing, debugging, and documentation.

Each task was adapted from prior AI code assistant studies[9, 49] and benchmark datasets[88]. However, we found that many published tasks were easily resolved by current LLMs with simple prompts, which may be due to their solutions being available online and used as training data. Therefore, we revised these tasks and validated them with four professional sighted engineers (each with over five years of experience), with each task reviewed by two engineers, to ensure that advanced LLMs could not solve them in a single attempt. With Copilot's assistance, they completed T1 and T2 in approximately 30 minutes each, T3 in around 20 minutes (the simplest), while T4 proved most challenging—they resolved most bugs within 40 minutes. This ensured that participants would interact iteratively with Copilot, allowing us to observe how they reviewed outputs, addressed errors, and engaged in problem-solving throughout the process.

Table 2. Overview of the four programming tasks used in our study. Each task required participants to work with code, documentation, or data originally created by others, simulating realistic collaborative scenarios such as extending existing codebases, writing shareable data reports, or debugging.

ID	Task	Files	Description
T1	Chat Server [9]	3 source files + 1 README	1. Implement server-side logic of a chat application, involving a small state machine. 2. Add a *quit* command involving changes to two files.
T2	Chat Client [9]	3 source files + 1 README	1. Implement networking code for a chat application, using a custom cryptographic API and standard but often unfamiliar socket API. 2. Same as the second point of *T1*.
T3	Data Analysis [88]	1 csv file + 1 report.md	1. Directly manipulate the data in the CSV file and populate the results into the report according to the specified table format. 2. Perform data cleaning, conduct correlation analysis, and insert the processed values back into the report.
T4	Calculator [49]	1 source file	Identify and fix issues in a calculator class, including missing edge case handling and logical errors such as failing to handle invalid operations like division by zero, and incorrect undo logic. The original Python version fails 10 test cases, while the JavaScript version fails 9, as a Python-specific conversion error does not occur in JavaScript syntax.

3.4 Two-Week Exploration Phase

After the initial study, participants spent two weeks using GitHub Copilot in their **regular programming** activities. We provided a structured diary template to **record notable positive and negative experiences**, focusing on participants' intentions, features used, satisfaction, and improvement suggestions. We included two example entries (one positive, one negative) as references.

3.5 Follow-up Study

The follow-up study was conducted approximately two weeks after the exploration phase, lasting about 30 minutes per participant. All except one participant(unavailable due to scheduling) took part and shared their two-week experiences. The follow-up session consisted of two parts: (1) a **reflection**, in which participants elaborated on their documented experiences; and (2) a 7-point **Likert scale** and semi-structured **interview** (Appendix Table B). The Likert scale questions were identical to those in the initial study (subsection 3.3); for any changes in ratings, participants were asked to explain the reasons. The semi-structured interview further explored their current Copilot usage patterns and any new accessibility or usability challenges encountered.

3.6 Data Analysis

We analyzed the recorded videos, transcripts, Copilot's chat logs, and user-shared diary records. To ensure the robustness and richness of our analysis, we triangulated findings across these multiple data sources. Our data analysis methodology was theoretically informed and built upon Activity Theory [25] and Grounded Theory [15], as the full procedure is described below.

To systematically analyze how participants engaged with the AI code assistant during the programming process, we first coded their task processes, extracting both their interaction behaviors with encountered problems. We began by randomly selecting one participant's case from each of the four tasks and annotated these cases with as much thick description as possible [1]. After agreeing on the annotation standards, we annotated the cases for all participants based on these criteria. During annotation, we repeatedly reviewed video recordings to clarify ambiguous steps or behaviors not evident from transcripts alone, focusing particularly on text entries and keyboard shortcuts. We also conducted open coding for interview responses and user diary records, creating written summaries of each participant's initial and follow-up study results.

Two authors independently coded the initial transcripts and observation notes. Group discussions—including a third author who also participated in the interviews—were then held to align codes and resolve discrepancies. Regular meetings were conducted to review and iteratively refine the coding schema and emerging themes, ensuring consistency across all annotations. We conducted thematic analysis and codebook refinement iteratively, with multiple rounds of discussion among coders to finalize the set of themes.

In developing the activity schema, we drew on prior work modeling user interaction behaviors [9, 48] and categorized participants' interaction behaviors into the following activities. We focused on programming-related activities, excluding unrelated interactions (e.g., resolving network problems). Among the observed activities, three represent the most fundamental procedures in resolving a programming task, which we collectively refer to as **Coding**:

- **Analysis**: Analyzing task requirements to determine necessary code edits.
- **Comprehension**: Understanding the structure, logic, and purpose of existing code.
- **Writing**: Implementing code based on requirements, which includes adding new functionalities, writing analysis results to files, debugging existing bugs, and installing dependencies.

Other activities emerged specifically from AI assistant interactions:

- **Prompt Engineering**: Converting intentions into natural language queries and configuring appropriate settings (e.g., mode, model, and context) for the AI assistant.
- **Reviewing**: Navigating and examining the code or responses to evaluate the *suggestions*.
- **Validation**: Verifying that *code suggestions* meet requirements through executable actions, such as running the code or writing test cases.
- **Fixing**: Resolving errors identified in the *code suggestions*.

4 Results Overview: Overarching User Behavior Patterns

Figure 1 presents an overview roadmap of our main results and insights, which are discussed in the following sections. In this section, we focus on the overall interaction and collaboration behaviors observed from users' usage patterns and feedback. A summary of users' self-reported ratings on various aspects of their experience is shown in Appendix Figure A.

4.1 Human-AI Collaboration Patterns in Programming Tasks

Figure 4 illustrates how four representative participants collaborated with the code assistant to complete their programming tasks and where they encountered challenges. These cases show that the code assistant not only helped participants in writing code, but also **provided valuable support** in requirements analysis, code comprehension, validation, and fixing. On average, participants spent 61.14 minutes on programming tasks—with 43.88 minutes on programming-related activities, of which 38.29 minutes were human efforts. Figure 5 shows the average time spent on each activity.

Among all activities, **Reviewing** was the most time-consuming, with users spending an average of 11.73 minutes examining the code assistant's responses. Participants reviewed suggestions using

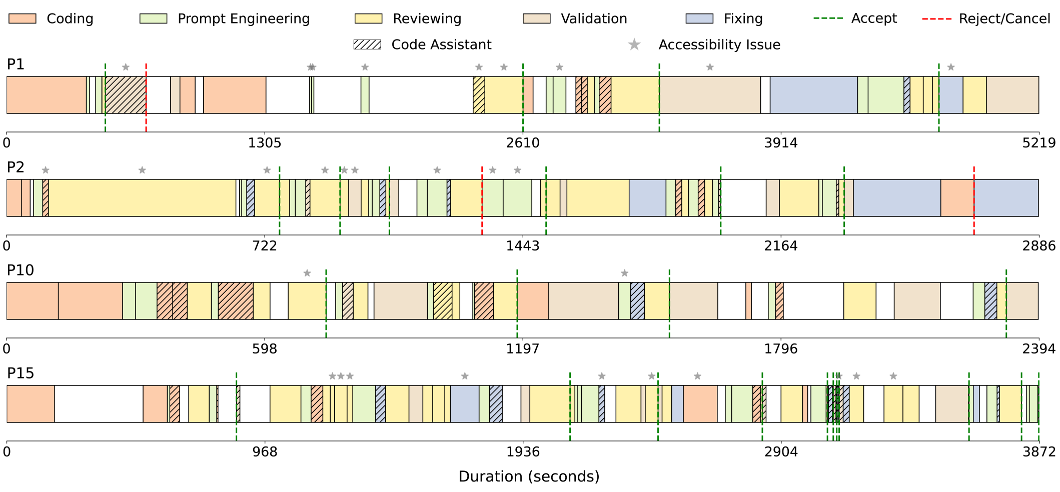


Fig. 4. Four users' timelines—P1 (task: T2), P2 (task: T4), P10 (task: T1), and P15 (task: T3)—during their programming task. Code Assistant indicates when the assistant generated a response or performed an action after receiving a user's prompt or acceptance. Accessibility Issues denote points where users encountered difficulties that hindered smooth operation during the activity.

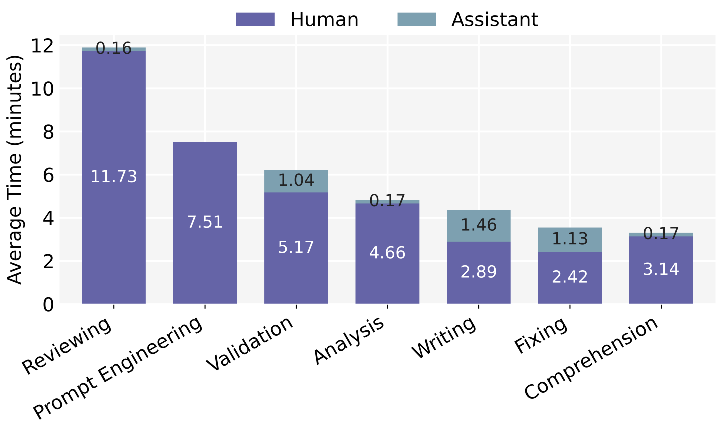


Fig. 5. Average time spent by participants on different activity types during programming tasks, categorized by human and assistant contributions.

various methods: the code editor (2.06 times, 2.61 minutes before accepting; 2.56 times, 2.47 minutes after accepting), the message list (2.50 times, 2.14 minutes), and the accessible view (3.44 times, 3.18 minutes). They also reviewed responses via automatic playback and the diff view in the inline chat. Participants switched between these methods based on the complexity of the suggestions and their personal preferences. To reduce the burden of manual review, some participants (6 out of 16) sought assistance from the code assistant. For example, P5, P10, and P14 asked the assistant to evaluate the completeness of the generated code in meeting specific requirements (e.g., "*please check the coverage of my unit tests*"), while P1 and P12 inquired about the functionality of the generated code (e.g., "*Does this code handle incoming messages from the client?*"). Additionally, P6 requested a credibility assessment of the output to ensure its reliability. See more details and challenges about reviewing in subsection 5.2.

The second most time-consuming activity was **Prompt Engineering**, averaging 7.51 minutes per user with 8.38 prompts sent. During this time, users spent 5.92 minutes crafting and refining prompts, plus 1.59 minutes on preparation—opening the chat panel, switching modes, selecting models, and configuring context. Participants communicated their intentions to the code assistant through prompt engineering, seeking assistance across a range of tasks. These included traditional programming activities such as writing (3.69 prompts), requirements analysis (0.50 prompts), and code comprehension (0.44 prompts). They also leveraged the assistant for validation (1.50 prompts) by executing code or writing test cases, and for fixing (1.50 prompts) to address defects in the AI output. An additional 0.25 prompts addressed miscellaneous needs outside our predefined categories, such as verifying the code assistant's access to specific files. In subsection 5.1, we discuss in detail how participants communicated with the code assistant and the challenges they encountered.

4.2 User Experiences: AI's Value and Empowerment

Participants collectively shared 31 real-world use cases with us, 16 reported as satisfactory, and 15 as unsatisfactory. Overall, participants agreed that the code assistant improved their efficiency, enhanced their programming skills, and lowered the barrier to adopting new technologies. As P13 noted, "*With a code assistant like this, it's much easier to get started with programming. In everyday life, we have all kinds of needs, and being able to program more easily helps us better meet personalized and customized requirements.*"

These collected cases illustrate how the code assistant supported participants in diverse programming scenarios. Some participants used AI code assistants for **learning** purposes, such as exploring new programming languages or identifying suitable technical frameworks and libraries. Others leveraged the assistants in **development tasks**, including adding features to open-source projects, processing subtitle files for audio-described videos, inspecting and optimizing legacy codebases, and drafting software documentation. Additionally, several cases highlighted how code assistants **bridged accessibility gaps** by allowing users to perform tasks that would otherwise be challenging or impossible, such as developing user interfaces (UI), recognizing pin diagrams of electronic components, and converting code screenshots from blogs into editable code.

UI development [52, 53] was mentioned as particularly challenging due to its visual nature, yet emerged as the most common scenario among participants. The following two cases illustrate both the opportunities and limitations that Copilot presented in this context:

- **Case from P10:** "*I primarily worked on backend development in the past, as my visual impairment made it difficult for me to handle UI tasks effectively. [...] I turned UI-related user feedback into prompts for Copilot to make changes, then asked it to check its generated code and sent interface screenshots for further inspection. I also double-checked the code myself. Once I was confident, I asked a sighted colleague to verify the interface and made further adjustments based on their suggestions. [...] It can generate a usable interface, even if the visual design may be basic. Still, this has made my workflow much easier. Before, when I wrote UIs, I focused solely on preventing element overlap—a task that required significant mental energy to determine proper component placement. Now, with Copilot, I no longer have to handle this challenging process alone.*"
- **Case from P11:** "*I wanted to provide Copilot with an image and have it help me implement a UI. However, when I asked Copilot if it could assist with images, it responded 'no.' I tried switching models several times, but the answer was always the same, so I had to give up.*"

4.3 Feature Preferences: Automation vs. Control

As shown in Figure 6(a), the most advanced and automated *Agent mode* was used most frequently during programming tasks, followed by the *Edit mode* and *Ask mode*. Many participants were eager to try and use the highly automated *Agent mode* to complete their tasks. As P1 commented, "*I find Agent mode to be the most powerful, as it includes all the features of Edit mode. I feel that just using this mode is sufficient for my needs.*" In the follow-up study (Figure 6(b)), however, usage patterns shifted: 12 out of 15 participants reported frequently using *Ask mode*, 10 used *Agent mode*, and 5 used *Edit mode*. This shift reflected participants' growing desire for control.

Most participants viewed *Ask mode* as a **safer** choice because it required explicit confirmation before modifying files. As P11 explained, "*I like to discuss my plan or ask for explanations in Ask mode first, before letting Copilot touch my files.*" This approach allowed them to use *Ask mode* for brainstorming, learning, or clarifying requirements before switching to Edit or Agent mode for actual code changes.

Not everyone shared the same level of comfort with the more autonomous modes. P2, P10, and P12 preferred *Edit mode* but rarely used *Agent mode*. P12 worried about **losing control**, stating, "*I worry that Agent mode will make too many changes.*" P13, despite frequently used *Agent mode*, noted, "*I only use Agent mode to generate code, not to execute commands automatically. Letting it execute feels* ***unreliable*** *and doesn't fit my habit of using external terminal tools; running code myself feels more familiar and gives me more confidence.*" For P10, it was a matter of efficiency: "*Agent mode takes too long and doesn't search files the way I want. It does a lot of unnecessary things and wastes my usage quota. I know exactly which files I need, so Edit mode is sufficient for me.*" For others, even *Edit mode* felt risky. P6 and P7 rarely used either *Edit mode* or *Agent mode*, expressing a strong sense of **discomfort** with the assistant making direct changes to their files. As P6 described, "*Agent mode is hard to manage. It edits my files directly, but it's not easy for me to review, and I'm never sure if I've checked everything, especially when multiple blocks are modified. The status notifications also confuse me, and I don't know what step it's on.*"

Inline chat, by contrast, earned praise from P1 and P6 for offering **precise control**. P6 noted, "*With inline chat, I can select specific code and make small changes. The diff view opens automatically, making it easy to review code differences and giving me a greater sense of control.*" P1 agreed but pointed out a trade-off: "*I felt that inline chat was* ***less stable*** *because of how the window floats. A fixed window feels more stable.*"

Code completion was less popular among our participants. While some initially felt overwhelmed or distracted [29], many eventually adapted and found the auditory cues less disruptive. Others encountered practical issues, such as the `Tab` key conflicting with indentation, uncertainty about when suggestions would appear, and less manual coding resulted in fewer code completions.

5 In-Depth Analysis: On Accessible Human-AI Interaction and Collaboration

In this section, we further investigate user interaction patterns, especially in communicating with AI (subsection 5.1), reviewing AI-generated responses (subsection 5.2), switching between views (subsection 5.3), and maintaining awareness of system status and next steps (subsection 5.4). These findings highlight the real-world opportunities and challenges of accessible human-AI interaction and collaboration for screen reader users.

5.1 Communicating with AI Code Assistant

To ensure accurate interpretation of their intent, participants typically began by configuring the session through the selection of mode, model, and context. After setup, they composed prompts in natural language and submitted them to the assistant. While this process appears straightforward,

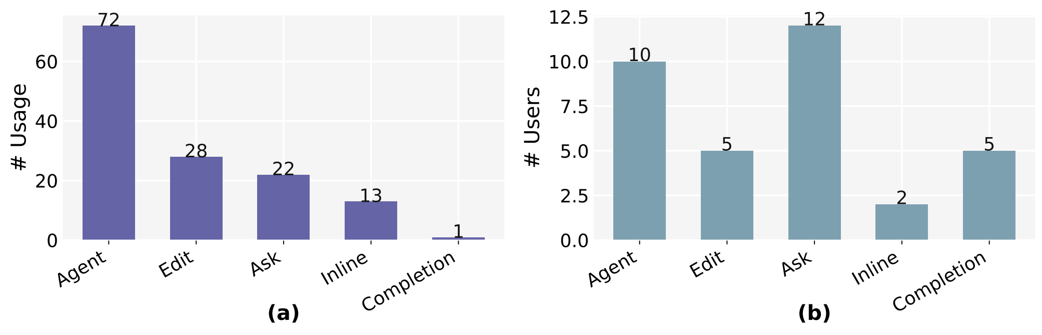


Fig. 6. Usage and user preference for different Copilot features. (a) Initial study: Number of times each feature was used during programming tasks. (b) Follow-up study: Number of participants reporting frequent use of each feature.

participants encountered challenges both in basic interaction and in higher-level decisions, such as prompt formulation and model selection for specific needs.

5.1.1 Interaction Experience. Copilot's **rich set of keyboard shortcuts** significantly improved participants' efficiency, convenience, and sense of control in their workflow. As P3 put it, "*I honestly rely on keyboard shortcuts a lot. Without them, I'd probably get lost in the interface. They really help me stay focused and in control.*" The thoughtful shortcut design was especially appreciated. P14 noted, "*I can use the same shortcut to open and close the chat panel, which is very convenient.*" These shortcuts not only improved efficiency but also gave users a greater sense of control and confidence when working with the assistant.

For screen reader users, keyboard shortcuts are a double-edged sword. Many participants expressed frustration when shortcuts **conflicted with their established keyboard habits**, leading to unexpected behaviors or workflow disruptions. Nearly all participants struggled with the up and down arrow keys in the input box—rather than moving between lines in a multi-line prompt, these keys cycled through previous commands, often without users realizing it. As P13 put it, "*It makes editing multi-line prompts cumbersome.*" Some users, like P5, worked around this by composing complex prompts in their clipboard editor to avoid accidental shortcut triggers and enable multi-line editing. **Context-dependent shortcut behavior** created additional confusion. For example, P4 found that pressing `Ctrl+I` once opened inline chat, but pressing it again unexpectedly opened the command panel, resulting in accidental command input. Similarly, P2 reported that (`Ctrl+Enter`) in the chat panel would accept a code change, but in the editor, it opened the code completion suggestions panel and shifted the focus to a new window. As P2 expressed, "*Where am I? How do I close this?*" These contextual inconsistencies in shortcut behavior disrupted workflows and increased cognitive load, highlighting the need for more consistent and predictable shortcut design.

Participants sometimes struggled to **obtain timely feedback about current session settings**, such as selected mode, model, or context. To check their selected mode or model, they had to open the selector rather than accessing this information directly when focusing on the selector. As P11 described, "*After writing some code and returning to the chat panel, I forget which mode I selected before. Now it takes several steps to find out my previous choice, which is a bit troublesome.*" A similar issue occurred with configured context. By default, Copilot uses the open file or selected lines as context, but several participants found it difficult to determine exactly what content was included. As P9 explained, "*I selected several lines in the editor, but only the file name was announced. I couldn't* *tell what was actually being used as context by Copilot.*" These challenges highlight the need for more accessible and immediate feedback on session settings for screen reader users.

Implications

- **Designing consistent and predictable keyboard shortcuts** can help users efficiently access key functions and reduce unnecessary navigation within the interface.
- **Providing accessible and timely access to session settings** enables screen reader users to maintain awareness and control with less cognitive effort.

5.1.2 Prompt and Model Selection. Beyond interaction, participants also faced challenges in translating intent into effective prompts, particularly in deciding **how much detail to include**. When prompts were too concise, Copilot sometimes made incorrect assumptions. For example, P4's brief prompt like "*please check if there are errors in the code*" led Copilot to suggest changes to calculation rules that were already documented as unchangeable. P9 shared, "*There was a time when the model made an implicit choice, like importing data row-wise or column-wise, without asking me or clarifying what it was doing. The code was executable, but I only noticed the data processing error when I carefully reviewed the code afterwards.*" In response, some participants (e.g., P7) provided highly detailed prompts and revised them frequently to avoid misunderstandings and minimize corrections, resulting in increased time spent on prompt crafting and refinement.

This behavior stemmed from **uncertainty about the code assistant's capabilities**. As P14 put it, "*Although there are many models to choose from, I don't know which models are reliable for which tasks, nor when they might make mistakes.*" Similarly, after using Copilot for software documentation, P10 expressed a desire for more specialized models: "*It would be better if there were a dedicated model for writing documentation. Right now, it's hard to decide which model is best for documentation. If I could clearly know which model performs best for which task, I would be more confident in my choice.*"

Over time, participants **developed their own strategies** for crafting prompts to communicate more effectively. For example, P8 shared, "*I now list requirements one by one, and specify the expected outcome. I try to communicate all my needs as clearly as possible, because otherwise, the process of checking the assistant's reply and then revising the prompt for another response can be quite slow.*" P10 emphasized the importance of actively guiding the assistant, "*It should be **you use AI, not AI uses you**. At first, I would just let the model do its thing. But over time, I realized that doesn't work, the model can easily go off track if you don't guide it. Now, when I have a complex task, I first ask it to clarify and confirm my needs, and only then do I let it modify the code or I make the changes myself. I find I need to give explicit instructions to keep things under control. I'll say things like 'do not modify the code yet' or 'make changes step by step' to make sure it doesn't rush ahead and change things based on its own assumptions instead of mine.*"

Implications

- As users become more familiar with the assistant's capabilities, code assistants should also **actively help reduce misunderstandings** by prompting users to clarify their intent or provide more details when requests are ambiguous, thereby supporting human-AI co-evolution for better communication.
- Providing users with **clearer guidance for model selection or automatically recommending** suitable models based on user prompts to support more confident collaboration.

5.2 Reviewing Generated Responses

Reviewing the outputs from code assistants—both textual explanations and code snippets—is critical for users to understand and evaluate the assistant's suggestions. However, participants reported several challenges in this process. For example, P16 shared, "*reviewing responses in CLine wasn't smooth because of its poor accessibility. So I often just accepted suggestions automatically, then read the files and tested the code, but that made it harder for me to notice what had actually changed.*" Similarly, P14 noted, "*In Cursor, it's not easy to browse the assistant's responses efficiently. If there were an easier way to navigate the message list, I would feel more confident about the changes.*"

GitHub Copilot provides four primary ways for users to review generated responses: (1) displaying code changes directly in the **code editor**; (2) structured presentation of messages and code changes in a **message list**; (3) presenting responses in a plain-text **accessible view**; and (4) **automatic playback** of responses via screen reader upon generation. Despite these options, participants highlighted the need for more accessible and efficient ways to review and verify assistant-generated content, particularly in tracking code modifications or navigating through multiple responses.

5.2.1 *Code Editor.*

After code edits are applied, users typically return to the editor to review file modifications in detail (Figure 3 (1)). VS Code uses earcons [61] (sound cues) to help screen reader users perceive these changes and provide keyboard shortcuts for navigation between modifications.

For programmers, reviewing code directly in the editor is intuitive. **Meaningful comments in generated code** help users understand the logic and reduce the need to switch between views. As P3 shared in the follow-up study, "*I usually check the modified code directly in the editor first. It's more straightforward, and with comments, I can generally understand the changes. If I can't, then I'll look at the textual explanation.*"

Participants also **valued sound cues** for code modifications. P13 commented, "*The accessible experience isn't just about adding labels or shortcuts. Having more types of cues, like sound effects, really helps me understand changes better. If there are too many text prompts mixed in, it might actually interfere with my understanding of the code.*" Meanwhile, some participants found them **confusing or difficult to distinguish**, which occasionally hindered their ability to interpret code changes accurately. P7 shared, "*It's easy to mix up the sound effects and forget what they mean.*" P5 added in the follow-up study, "*I wish there were more direct explanations.*" P13, who praised sound cues, also mentioned, "*At first, I couldn't tell the different sound effects apart, but since I'm familiar with the code, I could roughly guess whether it was an addition, deletion, or modification. Over time, I gradually got used to them and came to appreciate the benefits of sound cues.*"

Participants also expressed a need to **clearly understand and track changes**. P3 explained, "*When browsing code differences in the diff view, the mixing of unchanged, deleted, and added code makes it hard to follow the changes. Since I can't scan visually, I have to remember what I just heard. If I could switch between old and new code with a shortcut, it would help me understand the changes better.*" Another challenge was **tracking the number, location, and status of changed code blocks**. P11 said, "*If there are many code block changes, I get confused and don't know how many I have not reviewed. If it could tell me how many items there are and which one I'm on, I'd be clearer.*" P3 also mentioned, "*Automatically jumping to the next change after I accept a code change confuses me and makes me lose track of where I am. I wish I could control whether to jump, and if it would automatically read the code line after jumping, that would be more convenient.*"

Implications

- **Support accessible change tracking with sound cues or textual prompts**. While sound cues are efficient, some users may have difficulty distinguishing them. Providing concise textual descriptions as an optional feature can help these users understand changes or assist them as they adapt.
- **Group related information together to reduce navigation effort and cognitive load.** For example, including comments in the generated code, or presenting entire changed or unchanged code blocks for each module separately.

5.2.2 Message List. The message list presents each user message and the corresponding assistant response as individual blocks (Figure 3 (2)), allowing users to efficiently navigate between them.

Participants appreciated the **structured format of the message list**, as it clearly organizes user messages and assistant responses. P10 commented, "*Compared to the unstructured layout in Cursor, Copilot puts all user messages and responses in a single list, so it's much easier for me to navigate.*" P1 shared that his preference shifted from the accessible view to the message list, stating, "*The message list has stronger presentation capabilities. VS Code is much like a website. I prefer switching the screen reader to browse mode*[1]*, where I can use familiar shortcuts to jump between headings with* `H`*, buttons with* `B`*, and code blocks with* `E`*, and use the arrow keys to read text*"

Navigation within the message list also posed challenges. While some users enjoyed switching between browse and focus modes[2], others found it **unfamiliar or uncomfortable**. P5 said, "*After opening a complex application like VS Code, I don't switch the screen reader mode anymore. When I navigate to a block in the message list, the information is linear and hard to understand.*" P9 noted, "*Replies are sometimes too long, making it inconvenient to browse with arrow keys. If there were a table of contents, it would be much easier.*" P5 mentioned during the tutorial, "*The code block in the message list is an editable input box. Once I enter it, pressing Tab edits inside, and it's hard to exit.*"

In addition, users pointed out that when using *Agent mode* for multi-turn automatic iteration, all results and changes were presented in a single response block, which was **not well structured** and made it difficult to locate information. P15 remarked, "*It would be easier to find the latest changes if automatic iterative fixes were broken down into sections or had headings. Right now, the replies are too long and not well segmented, so it's hard to quickly locate what's new.*"

In addition, participants had **higher expectations for the content of responses**. Due to concerns about model hallucinations, users often cross-checked generated code with existing code to verify whether referenced methods or properties actually existed. As P12 described, "*If it could verify whether a referenced function from a non-Python standard library actually exists, and accurately tell me which class and function it's in, I'd trust its suggestions more. Now, I suspect it's making things up, which increases my verification time.*" Other users found that, especially with complex tasks, the model sometimes only partially completed the requirements without making this explicit. For example, P6 submitted an entire report file and expected Copilot to complete all tasks, but only after being notified did the user realize that only the first subtask was completed. P6 said, "*If it hasn't read everything, it should tell me.*" P2 also noted, "*It sometimes skips difficult parts and only responds after being prompted again. I can understand this, but if it could indicate what has and hasn't been completed, I'd be more aware of the situation.*"

[1]Browse mode: A screen reader mode that enables users to navigate content using virtual cursors and structural shortcuts (e.g., headings, buttons) without directly interacting with the application.
[2]Focus mode: A screen reader mode where keystrokes are passed directly to the application, allowing users to interact with interface elements and input text in real time.

Implications

- **Present messages in a structured and navigable way.** Group related messages, add headings, or provide a table of contents to help users quickly locate relevant content and reduce cognitive load.
- **Ensure transparency and verifiability of response content.** Reducing model hallucinations and providing more references as evidence can help users quickly verify information and increase trust in the assistant's suggestions.

5.2.3 *Accessible View.*

The accessible view (Figure 3 (3)) in Copilot is designed to alleviate navigation difficulties in the message list. It presents information in a single, plain-text window, allowing users to browse all details using only basic arrow key navigation.

Many participants expressed a preference for the accessible view, citing its **ease of learning and simplicity of operation**. For example, P1 shared, "*Using the accessible view reduces view switching. After composing my input in the text box, I can keep my focus unchanged. Once the response is generated, I open the accessible view directly from the input box, and after exiting, my focus remains in the input box.*" P1 further noted, "*When I open the accessible view, I can be sure my focus is at the top.*" P3 also stated in the follow-up study, "*Compared to the message list, I use the accessible view more often. Navigating the message list requires too many key operations.*" However, this convenience comes at **the cost of reduced expressiveness**. For example, P6 noted that "*the accessible view sometimes includes markup language or presents formatted information like tables in ways that are difficult to interpret.*"

There are also **shortcomings related to information completeness**, as the accessible view sometimes displays less information than the message list. For instance, P5 found that the accessible view only showed the changed code, without indicating which files were affected. Additionally, both P2 and P7 suggested that automatic updates to the accessible view would improve usability, as it currently requires manual refreshing to display newly generated content.

Implications

- **Less is more.** Interfaces with fewer UI elements are often easier for screen reader users to control, allowing them to access more information. **Providing such a streamlined option can make the tool more approachable and user-friendly.** However, it is important to ensure that this simplicity does not come at the expense of information completeness.

5.2.4 *Automatic Playback.*

Automatic playback of responses after they are generated is another accessibility feature provided by Copilot to support accessible review. participants praised the **convenience** brought by automatic playback. As P4 noted, "*Automatic reading is convenient; I can hear the generated result without any extra operation.*" P6 also mentioned, "*For simple replies, listening is sufficient for me to understand the content, so I do not need to check it again. This is very convenient.*" However, some users found it could be **disruptive**. P1 said, "*After the result is generated, I don't want it to be read automatically. Just a sound cue is enough. Even if it is read, it is often a long segment. Since the reading is purely linear, it can be difficult to understand.*"

Implications

- Accessibility features can be a **double-edged sword**: while they provide convenience, they may also disrupt some users. Like the accessible view, making such features optional allows users to choose what best fits their needs and can better accommodate individual preferences.

5.3 Switching Between Views

Interacting with code assistants within an IDE requires users to switch between more views (e.g., editor, message list) to complete tasks. As noted by Flores et al. [29], we also observed that users frequently encountered difficulties when switching between different views, a challenge that was particularly evident in the highly automated *Agent mode*.

Participants reported that **managing focus across multiple views** was challenging and sometimes led to confusion or errors. For example, P7 shared, "*Sometimes I don't know where my focus is.*" During the programming task, P7 accidentally triggered a shortcut that moved the focus from the chat input box to the editor, resulting in text entered into an open file instead. Similarly, P4 described frequent focus jumps between the chat window and the editor while navigating in the inline chat, stating, "*How can I get back to the previous window?*"

This complexity was evident when participants needed to **gather information from multiple views** to understand the assistant's feedback. The introduction of *Agent mode*, which allows automatic code modifications and execution, further exacerbated these challenges. While *Agent mode* uses the built-in terminal, users had to **manage an additional but unfamiliar view**. Most participants reported a preference for using external terminals rather than the built-in terminal, as they were concerned about focus traps or found switching between views cumbersome. For instance, after automatic execution, P15 had to switch between the editor and the message list to review code changes and explanations. Although the message list indicated a successful result, the terminal showed an error. Only after being noticed by the interviewer did P15 check the terminal and discover the failure. P14 also said, "*I found that terminal output isn't clearly announced, so I can't always tell if a command has run or what happened. Even though I can run code in the chat panel, I still need to switch to the terminal to check the results, which adds extra burden.*"

Additionally, participants found it difficult to **verify results across multiple views**. For example, after printing data analysis results in the terminal, P3 and P8 tried to use the terminal output as context for Copilot, hoping it would insert the results into their reports. However, the assistant inserted hallucinated data instead of the actual output. After being reminded, users spent significant time understanding the error and had to frequently switch between different views to compare the data. P8 remarked, "*How can we verify it? It can lie.*" P3 added, "*If it could write the correct result directly into the file, it would save me a lot of steps. But if I still have to check like this, I'd rather copy and paste it myself.*"

Implications

- **All in One.** Centralizing key information and actions within a single panel can help users complete tasks more efficiently and with less cognitive effort. For example, if the assistant can execute commands and display correct results directly in the chat panel, users do not need to switch between the chat, editor, and terminal to verify outcomes.
- **Supporting self-verification mechanisms** and providing reliable feedback can reduce the need for users to manually cross-check results. For example, the assistant could automatically compare outputs, such as checking whether the generated text matches the source content.

5.4 System Status and Next Steps

After submitting a request to the code assistant, users must wait for a response to be generated. **Timely status notifications** are essential for helping users understand the current system state and alleviating uncertainty during the waiting period. As P10 described, "*Cursor does not provide status notifications well. I keep checking to see if the response is finished. Copilot, on the other hand, plays a continuous sound while generating a response, so I can work on other tasks in parallel and return when I hear it is done.*"

However, in *Agent mode*, where there are many possible states, **status notifications are not clear enough**. Participants frequently asked, "*What happened? What should I do next?*" During response generation, the system continuously announces "*Working*" and "*Progress*" accompanied by sound effects to indicate ongoing processing. When *Agent mode* generates terminal commands and waits for user confirmation before executing them, the system announces "*Action required: Run command in terminal,*" but then continues to say "*Progress,*" making it unclear that the assistant is waiting for the user to take action. For example, after hearing such notifications, P4 asked, "*Do I need to execute the command now? What exactly is the command?*" P7 noted, "*Status notifications are brief. If I miss them, I don't know what happened.*" To keep the study moving forward, the interviewer would relay status information to the participant whenever they asked. In response, P3 remarked, "*You are my accessibility feature.*"

Beyond clearer instructions, some participants **wanted greater transparency** in the process, enabling them to judge earlier whether the assistant's actions aligned with their expectations. P8 commented, "*I can hear it is processing, but I don't know what it is doing. Visually, I can vaguely see text being generated, but there is no timely notification of the content. Only after the generation is complete do I hear everything.*" P4 also felt, "*The notifications during execution are not specific enough. Now it just says 'Progress,' but often does not indicate what is actually happening. Whether it is executing code or starting to make fixes?*"

Conversely, some users found **continuous status notifications distracting**. P14 said, "*While the response is being generated, I want to check the content that's already returned. When I switch to browse mode in the message list to review, the 'progress' notification interrupts what I'm listening to, so I have to go back and listen to the same sentence again.*" P5 shared, "*When using Agent mode, sometimes the response is slow, so I switch to other software to work on other tasks in parallel. In these cases, the notifications interrupt my thinking, and I try to ignore Copilot's sound effects. I hope it only notifies me when my action is required.*"

Implications

- Status notifications should be **clear** so users can easily distinguish between actions performed by the AI and those requiring user intervention. AI assistants should also provide **transparency** by indicating what the assistant is currently doing, which helps reduce uncertainty.
- Users should be able to **check the assistant's current status on demand** in case they missed previous notifications. For example, a convenient shortcut could allow users to easily find out what the assistant is doing and what actions are required.
- A **"Do not disturb" mode** could be provided, so that the assistant only notifies users when their input is required, reducing unnecessary interruptions.

6 Discussion

Our findings reveal the unique needs, challenges, and design considerations of screen reader users. Many interaction patterns, interface complexities, and accessibility barriers observed also apply to other AI tools such as Microsoft Copilot [45], Google Gemini in Workspace [34], and Notion AI [50], which feature complex UI workspaces and conversation-based interactions [14, 16]. As these interaction paradigms become widespread, ensuring accessibility is critical—driving innovations that improve usability for everyone. Building on prior design principles for generative AI [71, 77], we offer implications for designing accessible AI tools and inclusive human-AI collaboration.

6.1 Barriers to Learning for Screen Reader Users

While code assistants are widely adopted in the developer community, many screen reader developers have limited exposure to or expertise with these tools. However, once introduced, participants expressed strong interest and willingness to use code assistants, recognizing their benefits across development tasks, consistent with prior findings [29]. This gap between interest and adoption highlights several critical barriers to learning and onboarding for screen reader users.

A key barrier to effective learning is **the inaccessibility of code assistant tools**, a long-standing issue in the accessibility of programming tools. [47, 53]. Participants who had used Cursor and Cline reported significant challenges with these tools. P14 described, "*Some UI elements on the Cursor, like code blocks and chat input fields, lack clear labels or distinction in their types. For example, both appear as 'Input' components, making it difficult for me to tell them apart. To address this, I write custom NVDA plugins to process these elements and add more meaningful labels. Additionally, when the code assistant makes changes to my files, it's often hard to understand what modifications were made. I rely on git diff to see the changes, which is not always the most intuitive solution.*"

The complexity of elements in interfaces also increases cognitive load and anxiety when exploring tool functionalities with a screen reader. P5 noted, "*For such complex software, I don't attempt to navigate through all the elements—there are too many. I worry about getting stuck in an element and being unable to exit.*" P1 described the challenge of regaining their location after an unintended action, a difficulty that is compounded by the compatibility and accessibility issues of using a screen reader, IDE, and operating system together: "*It's challenging to return to my previous location if I accidentally trigger a new window.*" For example, although Copilot includes an undo function to revert code changes, it was not introduced during the tutorial. Many participants were unaware of its existence and later inquired about whether such a feature was available. When informed about the presence of an undo button within the message block, P5 responded, "*That feature is hard to find. I rarely go back to my own messages. If it had been placed in the assistant's response block, I might have noticed it.*" Instead, he demonstrated an alternative interaction strategy: "*I just asked Copilot to undo using natural language, and it seemed to work.*"

The lack of accessible learning resources often leads to screen reader users spending considerably more time learning new tools. Key gaps include screen reader-specific documentation—particularly for new features—and community-based technical sharing. Similar challenges have also been observed in the context of productivity applications [55]. As P14 recalled, "*When Cursor became popular, none of the recommendations mentioned how to operate it with a screen reader. I had to rely on general tutorials and my own experience to figure things out.*" P13 further elaborated, "*I usually start by looking for official documentation, but that depends on whether the developer provides it. After that, I browse technical blogs, whether text or video. However, most of these are aimed at sighted users, so I typically need to convert them into an accessible format myself. For example, if it says 'click here,' I try to figure out where that is based on the context. If the software design follows familiar patterns, it's easier to understand, but if not, it can be pretty challenging.*"

6.2 Toward a Sense of Control

As discussed in subsection 4.3, although automation can improve efficiency and reduce effort for screen reader users, maintaining control over both the interface and AI collaboration is equally vital. Specifically, users emphasized the need for transparency and predictability in anticipating their own actions and AI's behavior. Uncertainty regarding the current focus or ambiguity about what the AI has done or is doing, often creates discomfort and impairs their interaction experience.

Customization: Less or More. To meet diverse user needs, software tools have introduced increasingly rich features. However, for screen reader users, more features don't always mean better usability. In subsection 5.2, users showed varying preferences between the structured message list (*more*) and the plain-text accessible view (*less*). While the message list enhances readability and efficient key navigation, users unfamiliar with shortcuts found it challenging and frustrating. The simpler accessible view, though limited to line-by-line navigation with arrow keys, offered greater clarity and control. This trade-off extends to users' choice of development environments. P4, for example, preferred reading code in Notepad, finding VS Code "too complex" with "too many interaction steps." Prior studies [4, 44] similarly report that many screen reader users favor simple editors over feature-rich IDEs, as complex interfaces often hinder accessibility due to increased UI elements and shortcut conflicts. Despite limitations, participants valued streamlined workflows and task efficiency—calling for *more* functional support. Yet, excessive complexity and unpredictability often caused overload—calling for *less* cognitive and interactional burden. This tension highlights the need for customizable, user-centered design. As echoed in prior work [55], supporting users in adjusting interaction complexity may be key to balancing usability and efficiency.

Greater Automation, Increased Risks. While users generally appreciated advanced features such as *Agent mode*, these highly automated interactions also introduced new challenges—particularly concerning transparency, control, and unintended changes. As noted in subsection 5.4, participants emphasized the need for clear and timely status updates during task execution to track AI actions. Similarly, in subsection 5.2, users emphasized the need to examine and verify outcomes, especially for direct file modifications. For instance, P10 described *Agent mode* as "powerful" but noted its tendency to "*randomly change*" content that was not intended to be altered, reducing confidence in AI oversight. This reflects a classic automation paradox: increased system autonomy can diminish users' sense of control and raise concerns about potential errors. To cope with these risks, some participants reported adopting compensatory strategies, such as version control with Git (P2), to maintain oversight and recoverability. These findings echo prior research on human-AI collaboration [17, 40, 79], which stresses the importance of transparency, user agency, and trust.

6.3 For the Future: Towards Accessible Human-AI Collaboration Design

Building on the insights from section 5 and the preceding discussion, we propose actionable design principles and guidelines for future AI tools to achieve more accessible and inclusive human-AI interaction and collaboration:

- **UI Complexity and Consistent Interaction**: Complex UIs and excessive interactions are among the most significant barriers. Designs should prioritize simplicity, predictability, and efficiency, especially for core workflows. While multiple AI modes could be useful, each should have a minimal learning curve, clear transitions between modes, and consistent interactions across views.
- **Transparent Status and Error Recovery**: Users need clear, real-time, and non-visual feedback about AI status, progress, and completed actions, with emphasis on error discovery, understanding, and recovery. Features like undo capabilities, accessible action tracking, and informative error messages are crucial for reducing adoption barriers and enabling screen reader users to confidently explore and leverage new technologies.
- **Beyond Tool Design**: Accessibility should be integrated throughout the entire user journey—from onboarding to everyday use. This involves not only improving tool accessibility, but also

providing comprehensive, screen reader-specific documentation and tutorials. AI can assist by enabling conversational Q&A about new features within the tool. As AI capabilities advance, systems could automatically generate step-by-step instructions and audio demonstrations tailored for screen readers from complex documentation.

6.4 Limitation and Future Work

While our study offers valuable insights into accessible human-AI collaboration, several limitations may be noted. Despite our efforts to recruit a diverse group of screen reader users with programming experience, only two participants identified as female. This limitation reflects broader challenges in achieving gender diversity within HCI and accessibility research, particularly in the domain of programming [28, 53]. Besides, our investigation does not include cognitively impaired users, who may also have the demands to approach data and programs [74, 84]. Future work should explore more diverse and inclusive user backgrounds and usage contexts to provide a more generalized paradigm for accessible human-AI interaction and collaboration.

7 Conclusion

This paper presents a two-week, three-phase longitudinal study exploring screen reader users' engagement with advanced AI code assistants and their impact on programming practice. Our research uncovers how AI code assistants enhance programming capabilities and bridge accessibility gaps. While AI code assistants offer clear benefits, users still need better support for communication, output review, view management, situational awareness, learning advanced features, and maintaining control. Drawing on these findings, we propose actionable implications and practical design recommendations to guide future development of AI-assisted tools that empower screen reader users and foster accessible, inclusive human-AI collaboration. We anticipate that our work can inspire advanced research and engineering efforts to promote an inclusive era of future AI-assisted tools, enabling all users to benefit from the "*vibe*" brought by AI.

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Appendix 1: Changes in Self-Reported Ratings of Using AI Code Assistants

We discussed the results on how users' self-reported Likert scale ratings changed from the initial interview to the follow-up interview (after their two-week exploration) in Figure A.

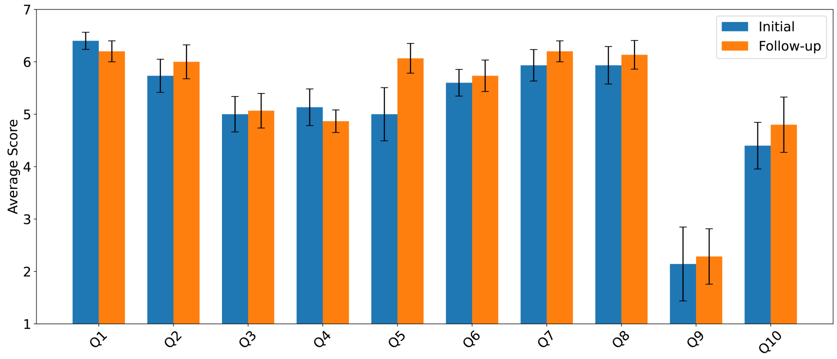

Fig. A. The average changes of users' self-reported score in the initial and follow-up interviews. The error bars show 95% confidence intervals. See Table C for the full list of all questions.

We found that users generally had a positive view of their interactions with the AI code assistant, and their responses to other questions were consistent with the key findings discussed in section 4. While users' responses to most questions were just slightly changed without significant differences between the two interviews, we found for question *Q5—"Copilot's suggestions won't lead me to develop bad coding habits, such as accepting code without fully understanding it."*—users' self-reported scores show significant differences at $p = \mathbf{0.02}, Cohen's\, d = 0.64$, and increase from $Mean = 5.0, SE = 0.50$ to $Mean = 6.1, SE = 0.28$. As discussed in subsection 4.3 and subsection 5.2, this may be attributed to participants' realization, over time, that active engagement in the collaboration with the AI remained necessary. Rather than delegating tasks entirely to the AI, they often took responsibility for reviewing and correcting the outputs, thereby maintaining control over the process.

Appendix 2: List of Questions during Interviews

We present the full phrase of all our questions used in the interview.

Table A shows the think-aloud questions asked in the initial interview.

Table B shows the think-aloud questions asked in the follow-up interview.

Table C shows the questions rated on a 1-7 Likert scale in both the initial and follow-up interviews, where 1 indicates strong disagreement and 7 indicates strong agreement.

Appendix 3: All Users' Interaction Timelines

Finally, we presented all 16 users' interaction timeline during their programming task in Figure B.

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Table A. Question phrases by category for the initial interview.

Category	**Question Phrase**
Background (Pre-task)	How long have you been learning programming? Can you share your work experience? Have you used AI coding assistants before (e.g., GitHub Copilot, ChatGPT)? Which ones? How frequently do you use them? What kind of tasks do you typically use them for? What benefits do you think they provide?
Thinking	What was your overall thought process when completing the task?
Interaction	Did you find learning and mastering GitHub Copilot easy or difficult? What aspects influenced this experience? Can you describe how easy or difficult it is to understand Copilot's suggestions? How do you decide which suggestions to accept or reject? How do you evaluate Copilot's suggestions? How much do you trust Copilot? What could Copilot do to make you trust it more? Have you encountered situations where Copilot generated incorrect answers? How did you handle such situations? Among Copilot's different features (code completion, inline chat, ask, edit, agent mode), which do you prefer and why? Does it vary by situation? Any specific examples? Why didn't you use certain modes?
Copilot's Impact	In your daily programming activities, which tasks or stages do you find most challenging? Please provide examples. Does GitHub Copilot help alleviate the programming challenges you mentioned? Please discuss with specific examples. Additionally, for which tasks do you think Copilot provides the most help?
Difficulties & Expectations	What difficulties or challenges have you encountered while using Copilot? If any, what were they? Would you consider using GitHub Copilot long-term? What additional features or improvements would you like Copilot to provide to help you more?

Table B. Question phrases by category for the follow-up interview.

Category	Question Phrase
Frequency of Use	How often have you used Copilot in the past two weeks? Why?
Modes	Which modes or features did you use more frequently during these two weeks? What specific tasks did you use them for? What benefits or shortcomings did you notice in their usage?
Usage Experience & Impact	Do you think Copilot understands your needs well? How do you prefer to review responses now? Do you find the process of reviewing and accepting responses smooth? Were there any obstacles or inconveniences? After continuous use of Copilot, has your overall impression of the tool changed? What new insights or discoveries have you made?
Challenges & Feedback	During the past two weeks, did you encounter any new difficulties or challenges while using Copilot? After using Copilot for a while, what features or improvements would you most like to see?

Table C. Likert scale questions' IDs and corresponding phrases.

QID	Phrase
Q1	Copilot's code suggestions make me more efficient in completing programming tasks.
Q2	Copilot helps me improve my programming skills and inspires new ideas.
Q3	I can predict when Copilot will generate useful results.
Q4	I trust Copilot's code suggestions and am willing to use them directly.
Q5	Copilot's suggestions won't lead me to develop bad coding habits, such as accepting code without fully understanding it.
Q6	I can efficiently interact with Copilot via keyboard shortcuts or other methods.
Q7	Copilot's suggestions are easy to understand and review using a screen reader.
Q8	I feel that I am actively leading the collaboration with Copilot, instead of passively following its suggestions.
Q9	Code completion distracts me and makes me feel troubled while programming.
Q10	I prefer Copilot to provide suggestions automatically rather than manually triggering them.

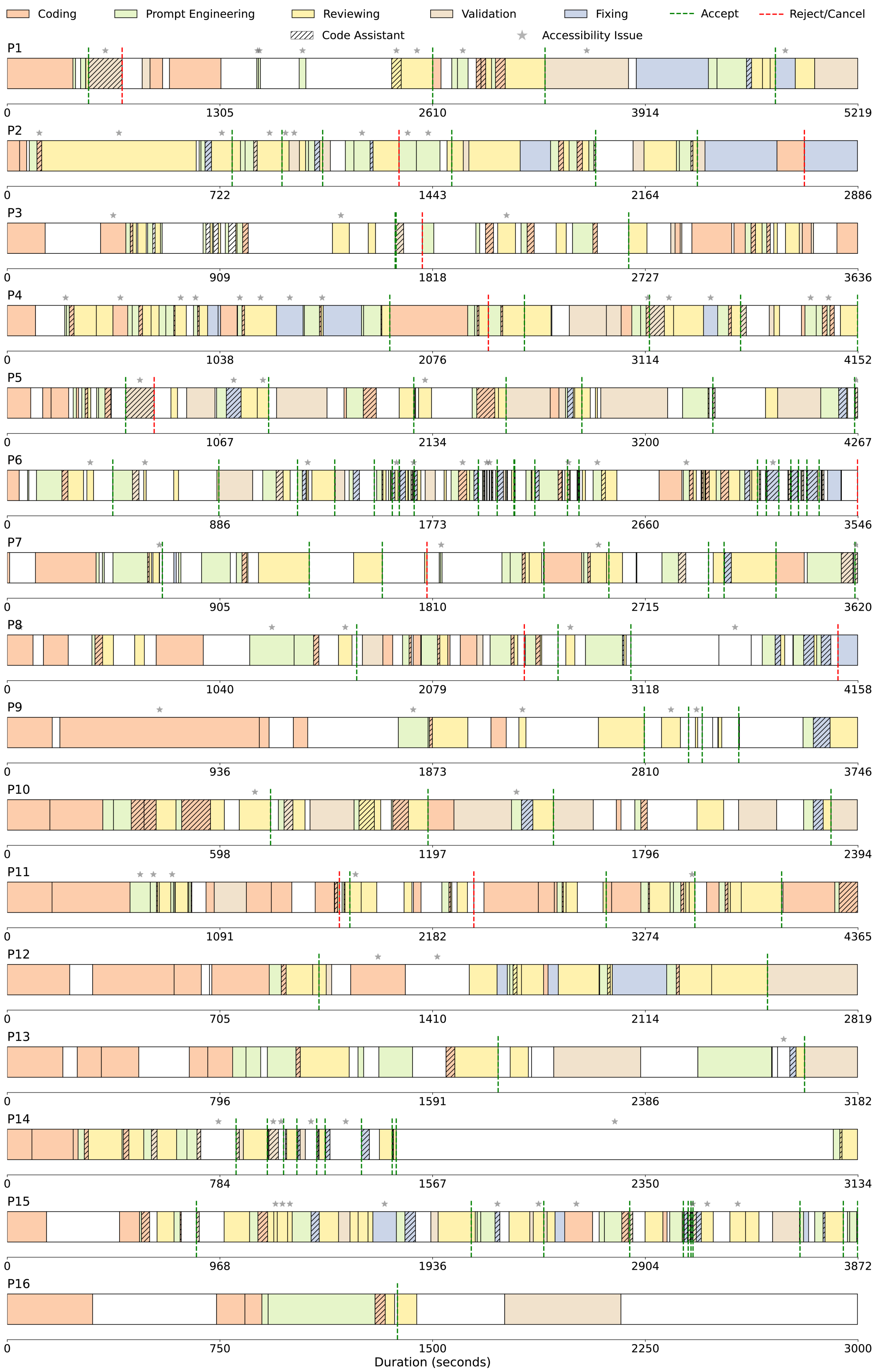

Fig. B. All users' action timelines during their programming task.