Security Implications of Large Language Model Code Assistants: A User Study

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Abstract
Large Language Models (LLMs) such as OpenAI Codex are increasingly being used as AI-based coding assistants. Understanding the impact of these tools on developers’ code is paramount, especially as recent work showed that LLMs may suggest cybersecurity vulnerabilities. We conduct a security-driven user study (N=58) to assess code written by student programmers when assisted by LLMs. Given the potential severity of low-level bugs as well as their relative frequency in real-world projects, we tasked participants with implementing a singly-linked ‘shopping list’ structure in C. Our results indicate that the security impact in this setting is small: AI-assisted users produce critical security bugs at a rate no greater than 10% more than the control, indicating the use of LLMs does not introduce new security risks.

1 Introduction
Large Language Models (LLMs) are deep neural networks trained on massive text corpora [1, 2] to learn the underlying distribution of natural language or structured text. When trained on code, LLMs can be used for code completion, bug fixing, and summarization [3–5], useful features for developers. Recent offerings are thus commercializing LLMs for code, including GitHub Copilot, which after its public release in June 2022 added 400,000 new users in just two months [6].

However, recent work has shown that LLM completions may contain critical security vulnerabilities [7, 8]. This suggests that despite gain in developer productivity, LLM based code assistants should be used with caution (or not at all) due to security concerns. This prior work has evaluated the security of LLM code assuming that its entirely generated by the LLM model (we will call this the autopilot mode). In practice, code completion LLMs assist developers with suggestions that they can accept, edit or reject—a real-world security evaluation must account for the role of developers and how they interact with LLM based code assistants. While programmers prone to automation bias might naively accept buggy completions, other developers might produce overall less buggy code by only accepting safe suggestions and using time saved to fix other bugs.

This leads us to the key question motivating this work: Do developers with access to an LLM-based code completion assistants produce less secure code than the code produced by programmers without this access (Fig. 1)? An affirmative answer to this question could be a significant showstopper for LLM based code assistants. To answer this question, we perform the first security-motivated randomized trial comparing programmers with and without access to a Codex-based code completion assistant powered by OpenAI’s code-cushman-001 LLM.

Our user study in Section 3 had 58 computer science undergraduate and graduate students with programming backgrounds split randomly into ‘control’ (no Codex LLM access) and ‘assisted’ (with Codex LLM access) groups. Given the relative frequency of memory-based errors in low-level languages such as C and C++ (≈70% of CWEs assigned by Microsoft each year [9]), as well as their relative severity (classes of memory related bugs take many of MITRE’s ‘Top 25 Common Weakness Enumeration (CWE) Most Dangerous Software Weaknesses’ list, including positions #1 and #5 [10]), we design a study where the participants were tasked to complete a set of 12 functions that perform basic operations on a linked list representing a “shopping list” in C. To understand the programming patterns in both groups, we created a
cloud-based integrated development environment (IDE) that links to a Codex LLM in the back-end to behave like GitHub Copilot. The IDE logs user inputs and their interactions with the Codex LLM at a fine-grain.

Using the data from our user study, we investigate the impact of LLMs across three research questions:

**RQ1:** To confirm motivation for this research, does a AI code assistant help novice users write better code in terms of functionality?

**RQ2:** Given functional benefits, does the code that users write with AI assistance have acceptable incidence rate of security bugs vis-a-vis code written without assistance?

**RQ3:** How do AI assisted users interact with potentially vulnerable code suggestions—i.e., where do bugs originate in an LLM-assisted system?

Our analysis, presented in Section 4, addresses these questions both quantitatively and qualitatively. We examined completed code for functionality and security, using manual and automated methods. We sought to examine the code for bugs from the Common Weakness Enumeration (CWE) [11] taxonomy. We find that in our setting (low-level C linked list), the security impacts are minimal. We confirm existing findings on the productivity benefits of AI-assistance (RQ1), while finding that the AI-assisted group produced security-critical bugs at a rate no greater than 10% higher than the control group (non-assisted) (RQ2). When investigating the origin of bugs within the assisted users (RQ3), 63% of the bugs originate in code written by humans and 36% of the bugs were present in taken suggestions. In the interests of open science we provide all data open source in [12].

## 2 Background and Related Work

### 2.1 AI code assistants target productivity

Academic and commercial AI code assistant tools are proliferating. Examples include OpenAI’s Codex [3, 5], AI21’s Jurassic J1 [13, 14], Salesforce CodeGen [15] and CodeBERT [16]. These LLMs can write functionally correct code, with studies showing capabilities in solving introductory programming tasks [17, 18] and algorithmic challenges [19].

Recent user studies examine the effects of code LLMs on developer productivity. Vaithilingam et al. [20] measured productivity from a group of developers (N=24) completing code tasks in Python. Each developer used GitHub Copilot to complete one task and the default non-AI based IntelliJSense assistant to complete a different task and discussed which they preferred on three tasks of increasing difficulty. The exact task/assistant choice were randomized across participants. Overall, the participants preferred using Copilot as it helped them get started quicker. Analysis showed that the average task completion time when using Copilot was shorter although this result was not statistically significant—possibly because some participants did not complete the tasks in the allotted time, or due to the small sample size. They found Copilot generates code a lot quicker than typing or finding it from other sources. However, they also theorize that it is often buggy and so time saved writing code may then need to be spent in debugging Copilot generated code.

Imai [21] tasked a group of developers (N=21) to implement code for a ‘minesweeper’ game. The study participants were randomly asked to use (1) GitHub Copilot as a code assistant, (2) a human pair programmer as the ‘driver’ controlling the computer and writing the code, and (3) a human pair programmer as the ‘navigator’ assisting ‘driver’, and reading the code the ‘driver’ is writing and examining it for issues. The study concluded that Copilot tended to result in more lines of code than with the human-based pair-programming in the same amount of time. However, the quality of code produced by Copilot was lower. Pair-programming with Copilot does not match the profile of human pair-programming. The study did not examine whether or not Copilot improves over a developer without a pair programmer.

A study by Ziegler et al. [22] from GitHub examines user perspectives on productivity during usage of GitHub Copilot. Here, a large number of users running the GitHub Copilot technical preview were invited to complete a survey on their perspectives, and a subset of these responded (N=2,047). Here, 84% (1,724-out-of-2,047 completions) self-scored a SPACE-type survey with a positive perspective aggregate. They felt Copilot had a more beneficial effect on their productivity than a negative one. Using internal metrics collected by the tool, GitHub authors determined that the number of suggestions accepted by the users was the greatest indicator of the positive perspective. The more suggestions a developer accepts, the more likely they feel the tool makes them productive. GitHub Copilot user’s acceptance rate of suggestions is 6.6% per hour.

A Google study by Tabachnyk et al. [23] used a large number of developers (N>10,000). They found that since the deployment of a proprietary LLM, the fraction of all code added by the LLM has increased to 2.6%, and developers have reduced their coding iteration duration by 6% and reduced their number of context switches by 7%, i.e. the LLM has had a measurable (and positive) impact on developer productivity.

### 2.2 From prompts to suggestions: How LLMs generate code

LLMs such as the GPT-type transformers which underpin Codex [3] function by building probabilistic sequences of tokens based on the frequency of observed tokens in the training data [2]. In other words, they act as an ‘autocomplete’ tool. Given some input sequence, they will find the most probable next token(s) in the output sequence. For instance, if an LLM is given “int main(int argc, char **” as the ‘prompt’, it would likely return “argv” as the ‘suggested’ next token,
as this is a very common sequence in C programs.

In an LLM, ‘tokens’ refer to common sets of individual characters. These are used via ‘byte pair encoding’ [24] to allow the LLMs to ingest more text into their fixed-size input windows. This allows the LLM to process more information. Codex builds on the same tokenizer as GPT-3, extending it to include tokens for runs of whitespace. This makes it work better for code indentation [3]. The average token for Codex is about four characters.

LLMs are not restricted to predicting just one token at a time, however. They are autoregressive, feeding predictions back in on themselves and performing searches across chains of tokens (e.g. beam search is used in GPT-3 [1]). In the code-writing LLMs, this allows for them to write large quantities of code ‘at once’. For example, given the right input prompt containing a well-defined function signature, an LLM may produce an entire function body.

### 2.3 Security concerns of LLM-generated code

Unfortunately, the somewhat naïve mechanisms that underpin LLM suggestion generation discussed in the previous subsection have been shown to problematic outcomes from a security standpoint, for two primary reasons: (1) LLMs may be trained over potentially insecure or buggy code (and will then reproduce those insecurities/bugs), and (2) Code which may be secure in isolation may be insecure depending on the sequence it is executed in relation to other pieces of code.

For an example of (1), consider the use of the ‘MD5’ hash algorithm once widely used to protect secure information such as passwords. MD5 has been cryptographically broken, and so should no longer be used. However, code examples with MD5 remain on open source repositories. Therefore LLMs learn to (incorrectly) suggest MD5 for hashing passwords. For (2), consider storing text in a buffer. This can occur safely using functions such as `snprintf`. However, if that buffer was just `free`-d, then the same line of code calling `snprintf` would result in a use-after-free vulnerability.

The issue of GitHub Copilot’s code suggestions containing security vulnerabilities was first studied by Pearce et al. [8]. They found that as measured by the GitHub CodeQL [25] static analysis tool, 40% of the suggestions in relevant contexts contain security-related bugs (i.e. from MITRE’s Common Weakness Enumeration (CWE) taxonomy [11]). Likewise, Siddiqi et al. [7] showed that for the HumanEval dataset (which examine functional capabilities and not security) GitHub Copilot emits certain CWEs in around 2% of cases as measured by Bandit analysis tool [26].

That said, LLMs may also generate secure code as a replacement for insecure code [27] (i.e. may be used for bug patches). Although this was only shown to reliably work for small synthetic examples rather than for case studies taken from real-world vulnerabilities, where the results were inconclusive, this indicates that the issue of insecure code sugges-

### 2.4 Evaluating Code Security

There are several techniques to determine the security of a piece of code. Identified bugs can be classified into the aforementioned CWE taxonomy [11].

**Static Analysis** tools detect security-related bugs attempts statically at compile-time. Source code is parsed and analyzed for buggy design patterns. Common techniques include access-control analysis, information-flow analysis, and checks for application-programming-interface (API) conformance [34]. Common static analysis tools are listed by OWASP [35], and include GitHub CodeQL [25].

**Run-time analysis** can also occur by using tools such as debuggers and sanitizers like ‘Address Sanitizer’ (ASAN) [36] and ‘Undefined Behavior Sanitizer’ (UBSAN) [37]. These can identify bugs and instrument the underlying code at compile time to help identify the root cause, providing detailed information about the locations and causes of any errors. Unlike static analysis, sanitizers require a proof-of-concept ‘crashing’ inputs which trigger bugs. These can be found by ‘fuzzers’.

**Fuzzers** run the program on concrete, randomly generated inputs in an attempt to uncover bugs and vulnerabilities. Bugs found with fuzzing are generally guaranteed to be true positives, and the proof-of-concept input that demonstrates the bug can be helpful to developers in fixes. Since the release of
“American fuzzy lop” [38] in 2013, fuzzing has received significant attention. Google’s oss-fuzz [39] provides continuous fuzzing for over 650 open source projects. Standards bodies such as NIST recommend fuzzing for secure development practices [40]. Major academic security conferences typically feature a dozen or more papers on fuzzing each year. While a full treatment is beyond the scope of this paper, we direct the reader to the survey by Manes et al. [41].

Manual analysis: Despite the pressing need for automated tooling, manual analysis for security bugs continues to be utilized at all stages of software design [42]. Manual code review is often essential to identify certain classes of bugs [43]. For example, in the study analysing Copilot’s outputs [8], despite their use of GitHub CodeQL in identifying many CWE instances, other CWEs are checked manually.

In this study, we primarily use manual analysis jointly with static and run-time analysis as discussed in Section 4.3.

3 Design of The Security-Focused User Study

3.1 Overview

We seek to determine the impact of LLM assistance on the security qualities of the code written by programmers, comparing against baseline code written by programmers without assistance. Here, completions suggested by an LLM may be accepted by the users and inserted into their source code file. Suggestions may also be accepted and subsequently edited.

Similar to the previous two user studies using LLMs [20, 21], we examined undergraduate and postgraduate students from two software development courses at an R1 research university. We recruited participants by advertising on related social media. We tasked the participants with a programming assignment. Since real-world programming tends to be project-based (i.e. over a collection of related functions) rather than a collection of disparate tasks, we modeled the assignment in this manner. This is similar to Imai’s [21] ‘minesweepeer’ assignment. We prompted participants to complete a “shopping list” program implementation in C. This was chosen as a majority of bugs are memory-based issues in low-level languages such as C/C++ [9]. Participants had to complete 12 functions related to this list (1 provided by us and 11 to complete). By providing a well-defined API (the list of functions), the program can be thought of as 12 separate programming tasks which may be analyzed separately. To minimize the risk of users running out of time, users were given two weeks to complete the assignment.

To understand the effects of the LLM suggestions, we randomly split the cohort into two groups. The ‘control’ group were not given suggestions (the LLM was inactive). The ‘assisted’ group were given code suggestions by the LLM. All groups were given identical video instructions to sign in to an online web portal where they complete the assignment in a controlled development environment, with an additional segment that either explains that they would get LLM suggestions and how to accept or reject them (‘assisted’ group), or that they would not get suggestions (‘control’ group). They were told that when they thought they were done, they should upload the program and complete an exit questionnaire for demographic information. We analyzed the completed code for functional and security correctness. This is discussed in Section 4. Our institutional review board approved this study.

3.2 Participant Recruitment

We recruit CS (or related discipline) students for our user study. Prior work has noted that CS students can be reasonable proxies for developers in the context of software engineering user studies. Tahaei et al. [44] found that “recruiting CS students from our University’s mailing list resulted in the highest data quality in terms of programming skills (highest), costs (lowest), number of duplicates (low), and passing attention check questions (high) compared to the other tested crowdsourcing platforms.” Further, Ko et al. [45] note that university students can be appropriate participants when their knowledge and skills fit the one for the target audience. Finally, Salman et al. [46] found that students and professionals do similarly on various code quality metrics.

We selected participants with a range of experience from three sources: (1) an undergraduate junior “operating systems” software class, (2) a senior- and MS-level “Application Security” software class, and (3) an informal student “software chat group” which operates over Discord app. During recruitment, we outlined the goals of this study to measure the impact of the LLM on code writing (see Fig. 11 in Appendix). We informed participants of a US$50 compensation.

In total, 105 participants signed up for this study. The participants were randomly divided into the ‘assisted’ group (which was prompted code generated by the AI code assistant), and the ‘control’ group (which did not). The participants were informed that they could use the Internet to find resources to help them write C code, but they should not ask their peers or others for assistance. Not all participants ended up engaging with the assignment. In total, 58 users signed in to the system and completed code for analysis. We present demographics of these users in Section 4.1.

3.3 Programming Assignment

Summary: The students were tasked with completing a programming assignment that consisted of a shopping list implemented using a singly linked list data structure1. The students were provided with documentation in the form of header files and a README, as well as an instructional video. Other supporting documents included a Makefile as well as 12 basic functional tests and a script such that the students could automatically test their code.

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1https://en.wikipedia.org/wiki/Singly_linked_list
Open source: We open source the assignment in [12].

Justification for the C Language: This study focuses on the security implications of using LLM code assistants by programmers. Given the frequency of memory-related bugs in C [9] such as null pointer references, and array and buffer overflows, we chose the C programming language for the study; these bugs are both consequential (frequently leading to exploitable code and severe errors) and relatively easy for developers to inadvertently express via vulnerable design patterns. Further, unlike modern languages such as Go or Rust, the default compilation toolchains for C does not adequately check for these issues. Finally, all recruited participants should have experience programming in C due to syllabus requirements—i.e., this assignment should not be their first exposure to C.

Instructions: Video and text instructions walked the students through signing in to the development environment, compiling, and their code. We gave the students a folder that contained the files listed in Fig. 2. These contained documentation on what to do and how to do it (README.md, Makefile, list.h), the file they were to complete (list.c), and supplementary testing files to measure their progress and completion (main.c, test.sh, unitests.exp, example_load_file.txt). These were designed similar to an industry-standard setup for programming—i.e., the users had to run make test to build and run tests and evaluate their code. Students were told they could use any resource on the Internet, such as Google and Stack Overflow. But they were not allowed to ask other students. We asked the students to complete as much of the functionality as they could during the two weeks of the study. They were not obligated to finish all functions to be compensated.

Introduction to the implementation: The basic shopping list definition is provided in Fig. 3(a). It is a singly-linked list with each node containing a char* string pointer, a price (float), and a quantity (int). No specific information is provided regarding other properties of these variables. The users are then provided with the function APIs in the remainder of list.h, as #includes and implementation hints at the beginning of list.c (Fig. 3(b)).

Basic functions: The ‘basic’ API functions are presented in Fig. 4. Here, ‘basic’ refers not to the difficulty of the under-
will select all code prior to their cursor and select text in reverse up to a finite amount—ours took up to 1,800 tokens (see Section 2.2). It passes this text to the OpenAI Codex API for the code-cushman-001 LLM. We chose this LLM as it is the fastest to operate and gave us response times similar to GitHub Copilot. To prompt the LLM we used the following parameters. The max_tokens: 64. This was chosen to keep the speed of generation high and the suggestions relatively short (we did not want the LLM to suggest code beyond the function currently being developed). The temperature: 0.6. This somewhat high temperature ensures the LLM does not provide the same answers to all users. This is important as the same starting list.c file is provided to all users, and as our focus is on user acceptance of code suggestions rather than the LLM, it is beneficial if some suggestions by the model are unusual or creative. The top_p: 1.0. OpenAI documentation suggests varying temperature or top_p, not both.

Input (and settings) thus provided, the assistant responds with a code suggestion presented in grey italics (e.g. Fig. 6). The user can accept the suggestion by pressing space bar or reject by continuing to type.

3.5 ‘Autopilot’- Automated task completion

In addition to the two user groups, we created 30 solutions that were generated entirely by the Codex model as an ‘autopilot’ group. We produced ten solutions from each of the three code models offered by OpenAI: code-cushman-001 (max 2048 tokens), code-davinci-001 (max 4096 tokens) and code-davinci-002 (max 8000 tokens). The last LLM is capable of filling in the middle given a prefix and suffix [47]).

We queried the LLM to generate code for one function at a time in the order they appear in the template list.c file, requesting 512 tokens with a stop sequence of “\n”\n”. The prompt included the function declaration and as much of the previous file context as would fit in the LLM’s context window (minus 512 tokens to allow room for the generated response), including any code previously generated by the LLM. The temperature and top_p were set to the same values as in the AI assistant IDE plugin (0.6 and 1.0). After generating a function, we check if the result compiled. If compilation failed, we request another completion, up to a maximum of 10 attempts per function. If no code compiled, we used the template’s implementation of the function, which just returns
EXIT_FAILURE. This procedure models a user that relies on the AI assistant, accepting suggestions unconditionally, with minimal checks to see if the code compiles. Moving on to the next function once it seems to work and giving up if it fails after several attempts. This is our baseline to compare control and AI-Assistant groups. The initial file was identical to the starting template with one exception: we added a comment near the top of the file that listed the members of the node structure, which is defined in a header and is otherwise not visible to the model, as noted here:

```c
// Members of the node struct:
// char item_name, float price, int quantity, node * next
```

Without this addition, an unassisted LLM model must guess the member names, creating unusable solutions. This intervention is realistic since our goal is to mimick a hands-off human user. Two users in the ‘assisted’ group independently deployed this strategy by copying the struct definition from the header file into `list.c` (commented out).

We will present results for Autopilot group where appropriate, except for manual security analysis (Section 4.3), which was too time-consuming to expand to full set of 30 Autopilot solutions. Instead, we audited five Cushman LLMs.

### 3.6 Experimental Infrastructure

To ensure that the IDE used in the study presented a consistent environment for all users, we provided a containerized cloud-based IDE. Within this environment, we ensured that Visual Studio Code was pre-installed and opened automatically to the project on sign in to the tool. Each user was randomly assigned to ‘control’ or ‘assisted’ groups. The LLM would either provide suggestions or not - the users did not have to set this up themselves. Fig. 12 (in the Appendix) presents a snapshot of the IDE running in the Firefox web browser.

Using the custom IDE made it straightforward to add data collection for active participants, and prevent usage of the IDE being connected to other language models. In addition to the ‘final form upload’, which collected the self-reported ‘finished’ `list.c` files (as well as collected the study’s demographic information), we also took snapshots of the complete `list.c` file environment every 60 seconds that the file was open. This allowed us to track changes over time. In addition, we recorded when suggestions from the Codex-based AI assistant were taken or when they were rejected.

### 3.7 Statistical Tests

We use standard statistical hypothesis tests to analyze results. We check if LLM code assistants improve code quality without exacerbating security. Analogously, in medical settings, it is required to show that a treatment is effective (code quality) while not exacerbating side effects (security). Standard comparative tests are used to establish efficacy – i.e., that the mean efficacy of the treatment is higher than the control. For side effects, non-inferiority tests are used—the test seeks to establish that the side effects are within a “maximum clinically acceptable difference” that one is willing to tolerate [48].

We describe the two tests below.

**Comparative hypothesis test:** Given treatment and control groups with means $\mu_1$ and $\mu_0$, respectively, and assuming (without loss of generality) that smaller means are better, a comparative hypothesis test seeks to reject the null hypothesis $H_0$ in favor of the alternate $H_1$.

- Null hypothesis ($H_0$): Treatment and control groups have the same mean, i.e., $\mu_1 = \mu_0$.
- Alternate ($H_1$): Treatment group has a lower mean than control, i.e., $\mu_1 < \mu_0$.

A comparative test establishes that the treatment is “better” than the control. We use this test to compare assisted (i.e., treatment) and control groups in terms of number of compiling functions and unit tests passed\(^2\).

**Non-inferiority hypothesis test:** Under the same assumptions as above, the null and alternate hypotheses of a non-inferiority test are:

- Null hypothesis ($H_0$): The treatment mean is more than $\delta\%$ larger than control, i.e., $\mu_1 > (1 + \frac{\delta}{100}) \times \mu_0$.
- Alternate ($H_1$): The mean of the treatment group is less than $\delta\%$ larger than control, i.e., $\mu_1 < (1 + \frac{\delta}{100}) \times \mu_0$.

where $\delta$ is the tolerance threshold. We use non-inferiority tests to compare bug incidence, measured as CWEs/LoC (Equation 1, Section 4.3.2) and average CWEs/function (Equation 2), in the assisted and control groups.

There is no commonly accepted threshold for the amount of decrease in code security that is considered acceptable for a new programming tool. Different organizations may make different choices depending on their threat model. For this study we pick a threshold of 10% (i.e., we test the hypothesis that AI assistance introduces no more than 10% more vulnerabilities per line of code), but we make our data and analysis available so that other thresholds can be tested if desired. With $\delta = 10\%$, rejecting the null confirms that the bug incidence in the Codex assisted group is at worst 10% greater than the control group. That is, Codex assistance does not exacerbate security “too much.”

### 4 Study Results and Analysis

#### 4.1 User Population (Demographics)

As previously noted (Section 3.2), 58 participants signed up to the study and completed code for analysis. As part of the study

\(^2\)In both cases, larger is better so the hypothesis test is modified accordingly.
the participants completed a brief demographic questionnaire. Table 1 shows the academic enrolment information for the users, broken down by study group. As can be seen, there was a good balance between undergraduates (UG), postgraduates (PG), and others (e.g. recent graduates), across the two study groups (‘control’ and ‘assisted’).

To examine pre-existing participant knowledge, we asked the three questions presented in Table 2. The first question checked if this assignment was similar to previous assignment(s) completed by the participants. This had a good mix of responses, with about half of each of the ‘control’ and ‘assisted’ groups each reporting having written a linked list in C before. The latter two questions aimed to validate our goals with participant recruitment (i.e., they should have some experience with C and knowledge of the linked list data structure). The majority of participants in both study groups had both written C code before and had previously or were currently taking a data structures or algorithms class.

### 4.2 RQ1 - Functionality

We assess functionality of the code using unit tests. Besides the 11 Basic Tests (see Fig. 7) that we provided to the participants, we wrote 43 Expanded Tests to exercise edge cases (e.g., adding an element to the head of the list, providing the same position for both arguments to list_swap_item_positions), invalid parameters (e.g., NULL pointers, zero/negative indices), and validating that return value and state of the list are correct after each API call.

**Split Testing:** We faced two challenges in automatically testing the functionality of submitted code. First, many submissions did not compile (19/58 = 32.8%). This includes 9/30=30% in the Assistant group and 10/28=35.7% in the Control group. Second, the tests in the test suite may need to use other API functions in addition to the one under test (e.g. a test for list_delete_item_at_pos might need to create a nonempty list by using list_init and list_add_item_at_pos). If there is a serious bug in one of the core functions, it will cause all tests that depend on it to fail (even if the function under test itself is correct). It is difficult to measure functionality of the program as a whole.

Our testing procedure solves both of these problems by splitting the user’s code into individual functions (one per API, including any required helper functions or data structures). For each function under test, we create a version of the submitted code where the other API functions are replaced by our own known-good reference implementations. If an extracted function does not compile, we mark it as non-compiling and mark its associated tests as failing. As the template code “implements” each function by returning EXIT_FAILURE, and some tests expect failure, unmodified code may spuriously pass some tests. So, we also require code modification.

Our tests thus automatically measure four distinct quantitative aspects of functionality for each submission: (i) % functions that were implemented, (ii) % functions that compiled, (iii) % basic tests passing, and (iv) % expanded tests passing. The four measures are shown for each group (‘control’, ‘assisted’, and ‘autopilot’) in Figure 7.

**Results:** We see systematic differences between the ‘as-

![Figure 7: Functionality for each group. Each group has to implement 11 functions and 11 basic tests. We had 43 expanded tests. We show per group, the average % of functions Implemented, regardless of whether they compiled or not, the average % of those functions that Compiled, the average % of each group that passes the 11 Basic Tests and the average % that passes the 43 Expanded Tests from each group.](image-url)
sisted’ and the ‘control’ group, the ‘assisted’ group had a small but consistent advantage over the ‘control’ group. The ‘autopilot’ group outperformed both ‘assisted’ and ‘control’ groups on functions implemented and compiled—this is by design since our autopilot code generation procedure repeats several times till code compiles. Interestingly, ‘autopilot’ slightly underperformed ‘assisted’ on basic tests, but slightly over performs on expanded tests. In other words, the AI code assistant does help the users write better code in terms of functionality.

Finally, the ‘assisted’ group wrote more code overall (280.9 average lines of code compared to 247.5 LoC in the control group). We note, however, that due to the small sample size none of these comparisons reach statistical significance at the standard $p < 0.05$ level (as tested using Fisher’s exact test for the completion data, which is a binary variable, and Welch’s t-test for the remaining comparisons).

4.3 RQ2 - Security Analysis

Although there are many different tools available for finding security-relevant flaws in C source code (as discussed in Section 2.4), we found that none of them were appropriate for our use case. Static analysis tools such as CodeQL [25] gave rates of false positives and negatives too high for our purposes. Meanwhile, fuzzing the participant code created records difficult to deduplicate (this is an open research problem [41]). Further, as fuzzing is dynamic, any vulnerability causing a crash along a program path rendered vulnerabilities later in the path unreachable, underestimating the true vulnerability count. For these reasons, we opted to manually audit the 58 user-generated submissions, and five of the code-cushman-001 LLM answers for comparison, a process further discussed here.

4.3.1 Bug Data Encoding

Working one function at a time, a panel of three of the co-authors collectively read through blinded copies of submitted source code, annotating security-relevant bugs as comments. This process was guided by compiler logs and the basic and vulnerability count. For these reasons, we opted to manually audit the 58 user-generated submissions, and five of the code-cushman-001 LLM answers for comparison, a process further discussed here.

Example bug finding process: One study participant provided the code exactly as it appears in Fig. 6 for list_item_to_string. This was a second-year UG student who had written C code before and took an algorithms class. They were in the ‘assisted’ group.

This code passes basic functional tests. However, it has three CWEs. The first weakness is CWE-476: NULL Pointer Dereference. This can occur in the case where str is NULL when this function is called (this is not checked for in the code, and the API cannot guarantee the values it will be passed as arguments). This CWE is ranked at position #11 on Mitre’s 2022 ‘Top 25’ list [10]. The next weakness is CWE-758: Reliance on Undefined, Unspecified, or Implementation-Defined Behavior. This can occur when head->item_name is NULL, and occurs because sprintf does not define what should happen when NULL is passed to the ‘%s’ argument. This is a minor (some would say negligible) issue, as in the standard libraries for gcc sprintf will print it as (null).

The third and final weakness is the most serious. It is CWE-787: Out-of-bounds Write, ranked as #1 on Mitre’s ‘Top 25’ list. This occurs because the function sprintf to an externally allocated string. What is the length of this string? It is defined in a #define at the top of list.c (see Fig. 3(b), line 7). This is important because head->item_name is a user-controlled value, meaning they could store a very long string in here which would run off the end of the buffer. The only safe way to implement this function is to use sprintf with the n set to the value of this #define. This function is scored as passing the basic tests, failing extended tests (they pass in NULL as str for one case), and features three CWEs, two ranked as severe.

4.3.2 Metrics

We analyze the quality of each user’s submission using the bug per line-of-code (LoC) as our metric. Since we associate each bug with a CWE, we will use CWEs/LoC as the metric. Since most users submitted valid implementations for a subset of the 11 functions they were tasked with implementing, we compute CWEs/LoC over those functions. We adopt two notions of validity: (1) the function compiles or (2) it compiles and passes unit tests.

The CWEs/LoC are computed as follows. if $E_{ij}$ is the number of CWEs in function $j$ of user $i$’s submission, $V_{ij} \in \{0, 1\}$ is a binary variable that is one only if user $i$ submitted valid code for function $j$, and $L_{ij}$ are the LoCs written by user $i$ for function $j$, then the $\text{CWEs/LoC}$ for user $i$ are:

$$M^i_j = \frac{\sum_{j=1}^{11} E_{ij} V_{ij}}{\sum_{j=1}^{11} L_{ij} V_{ij}}. \quad (1)$$

We report CWEs/LoC in ‘assisted’ and ‘control’ groups by averaging $M^i_j$ over users in these groups. We compute Severe CWEs/LoC metric focusing on the top-25 security CWEs reported by Mitre [11]. The results are shown in Figure 8.

Since our methodology allows us to test each function independently, we can compare CWE incidence rates on a per function basis. For this, we compute the average CWEs
4.3.3 Topline results—CWEs/LoC

Figure 8(a)-(b) shows boxplots of the CWEs/LoC over compiling functions and functions passing unit tests for the three groups, while Figure 8(c)-(d) do the same for severe CWEs. For all four cases, we found that the ‘assisted’ group has fewer bugs compared to ‘control’, with up to a 22% lower mean for the ‘assisted’ group compared with the ‘control’ for severe CWEs over passing tests. For severe CWEs, the comparisons are also statistically significant using non-inferiority tests with \( \delta = 10\% \), i.e., we can conclude that severe bugs/LoC for the ‘Assisted’ group are no more than 10% greater than in the ‘Control’ group.

4.3.4 Per function CWE rates

Our topline results suggest that CWE incidence in ‘assisted’ and ‘control’ groups are close. We now check whether these groups differ at the function level, i.e., whether Codex assisted users introduce more bugs in certain functions compared to the control group or vice-versa. The per-function CWE rates (see Equation 2 to see how compute this), of severe CWEs (those within Mitre's ‘Top 25’) written by the three study groups are presented in Table 3. We present the results for (a) all functions that compile, and (b) the compiling functions that then go on to pass the basic suite of tests. We present the number of passing functions from each group, as well as the number of CWEs found in those functions. The rate is the division of these two numbers (see Equation 2). Security-related errors within functions that pass tests are naturally more concerning than those in functionally-buggy code, as code that appears to be functional has a higher chance of being deployed as-is.

As can be seen, the results for individual function vary across groups. Functions for which the ‘assisted’ group has 10% higher rate of bugs compared to ‘control’ are highlighted in blue. Over functions that pass unit tests, ‘assisted’ users have more bugs for functions that perform input/output operations on the linked list (\( \text{list\_load}, \text{list\_save} \) and \( \text{list\_print} \)). Conversely, functions for which the ‘control’ group has 10% higher rate of bugs compared to ‘assisted’ are highlighted in blue. All three functions, \( \text{list\_deduplicate} \), \( \text{list\_remove\_item\_at\_pos} \) and \( \text{list\_find\_highest\_cost\_item\_position} \), involve pointer manipulations and/or more complex logic.

In terms of absolute CWE rates, for the ‘control’ and ‘assisted’ groups, \( \text{list\_add\_item\_at\_pos}, \text{list\_remove\_item\_at\_pos}, \text{and} \text{list\_update\_item\_at\_pos} \) feature significantly higher incidence rates of severe CWEs (\( \approx 50\% \) greater than the ‘average’ function rate). This likely reflects the increased difficulty when working with these functions with regard to pointer and string manipulations (notoriously fiddly in C). For interest, we also include Table 7 (in the Appendix) which presents the number of each type of CWE identified in the different functions by each study group.

4.3.5 CWE incidence rates

Figure 9 shows the prevalence of the ten most commonly appearing CWEs in user submissions. CWEs drawn from MITRE’s list of top-25 most severe CWEs are annotated in red in the figure, and the CWEs are described in Table 6 along with their severity rank. If a CWE does not have a first-order severity, the possible second-order severity is presented alongside. For instance, with CWE-401, which is unranked, the downstream effect is CWE-400, ranked at (#23).

CWE-787 (out-of-bounds write), the most severe CWE, is about equally prevalent in the ‘control’ and ‘assisted’ groups,
Table 3: Counting the # of Severe CWEs identified in each function/group. N = (N)umber of submitted functions which compile / which pass the tests. Rate is the average of the Severe CWEs count per function in this group. Yellow cells indicate ‘control’ has 10% higher rate of bugs than ‘assisted’, Blue is reverse. The ‘Autopilot’ group in this Table describes only the first 5 code-cushman-001 answers.

| Function                                      | Group      | N | # CWEs | Rate | N | # CWEs | Rate |
|-----------------------------------------------|------------|---|--------|------|---|--------|------|
| list_add_item_at_pos                          | Control    | 20| 61     | 3.05 | 12| 38     | 3.17 |
|                                               | Assisted   | 26| 58     | 3.30 | 10| 33     | 3.32 |
|                                               | Autopilot  | 5 | 13     | 2.5  | 1 | 2      | 2.0  |
| list_cost_sum                                 | Control    | 13| 12     | 0.92 | 10| 10     | 1.0  |
|                                               | Assisted   | 16| 14     | 0.88 | 14| 14     | 1.0  |
|                                               | Autopilot  | 5 | 9      | 1.8  | 4 | 8      | 2.0  |
| list_deduplicate                              | Control    | 12| 20     | 1.67 | 4 | 7      | 1.75 |
|                                               | Assisted   | 15| 14     | 0.93 | 3 | 5      | 1.67 |
|                                               | Autopilot  | 5 | 4      | 0.8  | 1 | 2      | 2.0  |
| list_find_highest_price_item_position         | Control    | 14| 14     | 1.0  | 8 | 11     | 1.38 |
|                                               | Assisted   | 19| 12     | 0.63 | 11| 09     | 0.82 |
|                                               | Autopilot  | 2 | 14     | 2.45 | 1 | 1      | 1.0  |
| list_item_to_string                           | Control    | 21| 47     | 2.24 | 13| 29     | 2.23 |
|                                               | Assisted   | 26| 56     | 2.15 | 20| 43     | 2.15 |
|                                               | Autopilot  | 5 | 10     | 2.0  | 4 | 6      | 1.5  |
| list_load                                     | Control    | 12| 19     | 1.58 | 4 | 6      | 1.5  |
|                                               | Assisted   | 17| 27     | 1.89 | 4 | 8      | 2.0  |
|                                               | Autopilot  | 5 | 0      | 0.0  | 0 | 0      | 0.0  |
| list_print                                    | Control    | 24| 16     | 0.67 | 9 | 4      | 0.44 |
|                                               | Assisted   | 27| 22     | 0.84 | 13| 10     | 0.70 |
|                                               | Autopilot  | 5 | 2      | 0.4  | 1 | 1      | 1.0  |
| list_remove_item_at_pos                       | Control    | 13| 49     | 3.77 | 10| 43     | 4.3  |
|                                               | Assisted   | 19| 74     | 3.89 | 14| 51     | 3.92 |
|                                               | Autopilot  | 5 | 16     | 3.2  | 3 | 9      | 3.0  |
| list_save                                     | Control    | 14| 4      | 0.29 | 7 | 1      | 0.14 |
|                                               | Assisted   | 14| 5      | 0.29 | 7 | 2      | 0.25 |
|                                               | Autopilot  | 5 | 0      | 0.0  | 0 | 0      | 0.0  |
| list_swap_item_positions                      | Control    | 12| 26     | 2.17 | 5 | 11     | 2.2  |
|                                               | Assisted   | 20| 43     | 2.15 | 6 | 7      | 1.17 |
|                                               | Autopilot  | 5 | 15     | 3.0  | 1 | 1      | 1.0  |
| list_update_item_at_pos                       | Control    | 14| 38     | 2.14 | 10| 36     | 3.6  |
|                                               | Assisted   | 24| 88     | 3.67 | 16| 60     | 3.75 |
|                                               | Autopilot  | 5 | 16     | 3.2  | 3 | 13     | 4.33 |
| Totals                                        | Control    | 139| 290   | 2.09 | 84| 180    | 2.14 |
|                                               | Assisted   | 204| 455   | 2.21 | 124| 278    | 2.24 |
|                                               | Autopilot  | 67| 99     | 2.02 | 18| 43     | 2.39 |

Figure 9: Top 10 CWEs per group and their prevalence as % of total CWEs. CWE descriptions are in Table 6.

but far less prevalent in the ‘autopilot’ group. This is likely due to the main root cause of CWE-787, which was, by far, most frequently caused by the use of sprintf rather than snprintf (e.g. in list_item_to_string as previously discussed in Section 4.3.1). The human-based ‘control’ and ‘assisted’ often made this error, whereas while the ‘autopilot’ code also made this error it was less frequent.

CWE-416 (use after free), the second most severe CWE we found, is however more prevalent in the ‘assisted’ group compared to the ‘control’. This appears to be due to mistakes frequently made by this group when creating and modifying nodes, primarily concerning the handling of the char* item_name fields. Here, when creating a new shopping list node, the item_name is passed in as an argument. There are several ways that this name could be embedded within the new node. The naïve way would be to simply copy the char* pointer values. This is unsafe, as the API is not provided any guarantees about the memory location this is pointing to. As

such, it is not safe to assume that this value will persist beyond the call of this function, i.e. performing a simple pointer copy may lead to CWE-416 if that memory is later freed (there will now be a dangling pointer to the freed memory). Without guarantees, the only ‘safe’ way to manage the item_name variable is to perform a copy of the string into a new variable. There are two reasonable ways to do this—the first (and easiest) would use strdup, and the second would use strlen followed by a malloc(strlen+1) followed by a strcpy. The ‘assisted’ group were more likely to make the pointer copy mistake. The ‘control’ group has a higher chance of correctly intuiting the limitations of the pointer variable.

CWE-476 (NULL Pointer Dereference) was the most commonly observed. This is because the API of the shopping list does not guarantees that the contents of the variables are passed to the implementation. Every single pointer should always be checked against NULL. Special cases are where a function takes a double-pointer, such as list_add_item_at_pos taking node** head. Here, both head and head* need to be checked against NULL. Such requirements were often missed by all participants, human or LLM. These had downstream effects. For example, it causes a large proportion of the CWE-758 instances (Reliance on Undefined Behavior). This CWE was frequently observed when working with standard library functions that may ingest NULL pointers (e.g. printf, strcpy, strlen).

4.3.6 Observations

The impact of code suggestions on cybersecurity (RQ2) is less conclusive than the impact on functionality (RQ1). Table 3 suggest that certain kinds of functions may be more or less difficult to write safely depending on their complexity and the experience of the developer—it appears that the LLMs
may sometimes reduce the incidence rates of bugs, and sometimes increase them. Meanwhile, aggregating the CWEs per participant LoC (Fig. 8) suggests that perhaps there may be a slight benefit to using LLMs, with Fig. 8(d) in particular highlighting that as code is made to pass tests it may be made more secure with the help of the LLM. This is contrary to literature [7,8] which suggests that LLMs should be used with care due to their habit of suggesting vulnerable patterns.

4.4 RQ3 - On the Origin of Bugs

To better understand how LLM assistance contributed to the code written by users in the Assisted group, we created a visualization tool (shown in Figure 10) that colors each user’s code based on the accepted suggestions logged during the experiment (ignoring code from our provided initial template). The tool takes each suggestion in reverse chronological order (most recent first) and attempts to match it to a portion of the final document, initially using exact string matching and then attempting approximate matches up to a normalized edit distance of 50%. For code that originated from the LLM one can hover over the code to show the original suggestion.

Using this tool, we examined each of the 564 security vulnerabilities we identified in Section 4.3.5 and coded them as originating from a Codex suggestion or as introduced manually by a human user (Table 4). We found that humans introduced 356 of the bugs in our dataset (63%), while only 36% were introduced by the language model and present in the user’s code verbatim (16%) or with modifications (20%). Overall, 60% of the non-template code was written by a human. This accords with our findings in Section 4.3.5: the rate at which vulnerabilities are introduced by the LLM is similar to the rate at which they are introduced by humans. This makes sense given how the models are trained: they attempt to predict the most likely continuation of their input, and so the quality of the code they output tends to match the quality of their input.

We can qualitatively examine the origin of a single bug. As an example, consider the potential use-after-free CWE-416 discussed in Section 4.3.5. We choose this to analyze as it is a bug which is straightforward to test for using a custom automated script. How do users interact with buggy suggestions from the LLMs, and how bugs might ‘amplify’ via LLM suggestions if present in code.

We scan the document and suggestion snapshots recorded during the user study, looking for the first recorded incident of the CWE-416 bug—that is, the first time that a new node’s item name is incorrectly set directly to the function argument item_name (i.e. without using a proper string copy mechanism). This can occur in a LLM suggestion, or alternatively, it could have been written by a user before the LLM gets a chance to suggest it. We then count the number of times that the bug was present in suggestions by the LLM, as well as the number of suggestions containing the bug that were accepted by the user. As user acceptance of suggestions is still not fully reflective of the final state of the code (as accepted code may be further edited after acceptance), we also scan the final ‘finished’ code files to count the number of these bugs present. This bug can occur in more than one location—both list_add_item_at_pos and list_update_item_at_pos need to properly copy in item names, and depending on function structure, may appear multiple times even within the same function.

We report results of this investigation in Table 5. Looking at this bug, in most cases it comes from the LLM suggestion originally, and even when it appears in the document first, the LLM will go on to suggest the bug. Users that had the highest number of this bug had the highest number of buggy suggestions provided and also accepted the highest number of suggestions. This table provides some insights into the usage of the LLM in general: users ‘1f1c’, ‘2125’, ‘a5ba’, and ‘dc47’ self-author the bug without suggestions and do not go on to accept buggy suggestions from the LLM (nor in many cases even generate relevant suggestions).

5 Discussion

5.1 Implications for LLM Assistants

Functionality (RQ1): our results corroborate recent studies that have suggested that LLM assistants improve developer productivity [22, 23]. While we do not directly mea-
Table 5: Origins of CWE-416 potential ‘use after free’ bug where item_name is improperly copied into a shopping list node by users in ‘assisted’ group.

| Participant UUID | First location of bug (document / suggestion) | # Bug suggestions | # Bug suggestions accepted | # Bugs in final file |
|------------------|---------------------------------------------|-------------------|--------------------------|---------------------|
| 0640             | Suggestion                                  | 5                 | 3                        | 3                   |
| 171e             | Document                                    | 5                 | 0                        | 2                   |
| 2125             | Suggestion                                  | 4                 | 0                        | 2                   |
| 26e4             | Suggestion                                  | 3                 | 1                        | 2                   |
| 3533             | Suggestion                                  | 2                 | 1                        | 1                   |
| 36de             | Suggestion                                  | 69                | 5                        | 4                   |
| 3c1f             | Suggestion                                  | 2                 | 2                        | 2                   |
| 514e             | Document                                    | 1                 | 1                        | 1                   |
| 7193             | Suggestion                                  | 13                | 1                        | 2                   |
| 74bd             | Suggestion                                  | 4                 | 2                        | 2                   |
| 925c             | Suggestion                                  | 8                 | 2                        | 1                   |
| a39d             | Suggestion                                  | 10                | 2                        | 2                   |
| a4b3             | Suggestion                                  | 11                | 5                        | 4                   |
| a5ba             | Document                                    | 0                 | 0                        | 1                   |
| a80d             | Document                                    | 6                 | 3                        | 3                   |
| a974             | Suggestion                                  | 12                | 5                        | 3                   |
| b599             | Suggestion                                  | 8                 | 2                        | 2                   |
| b96f             | Suggestion                                  | 4                 | 1                        | 2                   |
| c23b             | Suggestion                                  | 20                | 10                       | 5                   |
| dac3             | Document                                    | 10                | 2                        | 2                   |
| dc47             | Suggestion                                  | 1                 | 0                        | 2                   |
| dfac             | Suggestion                                  | 13                | 1                        | 1                   |
| ec83             | Document                                    | 11                | 3                        | 3                   |
| fd62             | Suggestion                                  | 12                | 1                        | 1                   |

Sure productivity, the fact that ‘assisted’ users submitted more lines of code and completed a greater fraction of functions suggests enhanced productivity. One surprising result was the relatively high quality of code produced in ‘autopilot’ mode (albeit for a relatively simple task).

Security (RQ2): Prior work called into question using LLM assistants because they introduce security-critical bugs/CWEs. But it did not explicitly compare CWE incidence with human-generated code. We find no conclusive evidence to support the claim LLM assistants increase CWE incidence in code in general, even when we looked only at severe CWEs. Our results indicate that the security impact in this setting is small: AI-assisted users produce critical security bugs at a rate no greater than 10% higher than the control, indicating that LLMs do not introduce new security risks. This suggests that security concerns with LLM assistants might not be as severe as initially suggested, although studies with larger sample sizes and diverse user groups are warranted.

Bug origins (RQ3): Our results indicate that users interact with the model in interesting ways. Users provide prompts which may include bugs, accept buggy prompts which end up in the ‘completed’ programs as well as accept bugs which are later removed. In some cases, users also end up with more bugs than were suggested by the model! In addition, the users that accepted the most bugs from the LLM also had the most bugs in their final files, further suggesting that the use of a buggy LLM may lead users toward buggy code.

5.2 Threats to Validity

User selection: This study recruited university students rather than experienced developers. While this could have led to changes in behavior and code performance, a separate study of GitHub users [49] found that there was no difference between experienced software developers and students regarding security-aware coding. In addition, we observe a defect density of 0.15 bugs/LoC which while greater than reported figures of 0.07 bugs/LoC [50], is reasonable given that our users were working within time constraints.

Code assignment difficulty: We designed both the assignment and chose the programming language with the intention of examining how the developers might miss bugs in their designs. As such, the singly-linked shopping list has a number of unusual traits and a non-optimal API. This increases the difficulty of the assignment, which may itself have an impact on the study results—if a developer is unable to ‘solve’ the coding challenge at hand, they may get frustrated and hand in a substandard solution. Further, C is considered a more difficult programming language for inexperienced programmers than other languages [51] such as Python or MATLAB. It is possible that the use of other languages instead of C would yield different results from this study.

Data capture: Due to limitations of the cloud-based IDE, it was not possible to capture all data from participants. For instance, rather than capturing every keypress from the users, we were restricted to taking ‘snapshots’ of their development over time (every 60 seconds). This limits the kind of fine-grained analysis that might have been possible with more pervasive measurements.

6 Conclusions

In this paper we set out to investigate the cybersecurity impact of LLM code suggestions on participants writing code in a user study. With N=58 users, we determined that the LLM has a likely beneficial impact on functional correctness; and does not increase the incidence rates of severe security bugs in our context. This is somewhat surprising given the existing published studies on how vulnerable code can be suggested by the models [7,8]. When considering the origin of bugs that were found, the data suggests that the users do not use the extra productivity benefits to fix bugs in their code—although suggestions are being modified (e.g. variable names), if a suggestion contained a bug it may not be fixed. This suggests that further research needs to be undertaken on highlighting problematic lines of code (‘nutritional labels’) to encourage users to check for security in real-time, as well as improving code LLMs so that they can produce code that is more secure than the user’s existing code.

13
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Appendix

Large Language Models such as GitHub Copilot and OpenAI Codex have recently been commercially released with the goal of helping developers write software code. While the marketing material touts the benefits of these “AI Pair Programmers”, the actual impacts of these models is yet to be formally investigated. In this research, we aim to begin this exploration by challenging participants such as yourself with completing a range of programming questions similar to those posed at the undergraduate level in computer science and software engineering courses. The research question is simple: Half the participants will have assistance via a language model (OpenAI Codex) and the other half will not. Will one group outperform the other?

Figure 11: Introductory paragraph to the recruitment material. Fig. 12 illustrates the virtual study environment, Visual Studio Code running in a web-based container in the Firefox Web Browser.
Table 6 lists the most common CWEs from each study group with their descriptions, downstream-CWEs if they are severe, and the MITRE ‘top 25’ rank.

Table 6: Top 10 most common CWEs in each study group, along with downstream severe CWEs if a non-severe CWE would lead to a different severe CWE.

| CWE ID  | Description                  | 'Top 25' Rank |
|---------|------------------------------|---------------|
| CWE-476 | NULL Pointer Dereference     | 11            |
| CWE-758 | Reliance on Undefined Behavior | -             |
| CWE-401 → CWE-400 | Missing Release of Memory Uncontrolled Resource Consumption | 23 |
| CWE-252 | Unchecked Return Value       | -             |
| CWE-416 | Use after Free               | 7             |
| CWE-787 | Out-of-bounds Write          | 1             |
| CWE-843 → CWE-119 | Access using Incompatible Type Improper Restriction of Buffer Ops | 19 |
| CWE-457 → CWE-119 | Use of Uninitialized Variable Improper Restriction of Buffer Operations | 19 |
| CWE-835 | Infinite Loop                | -             |

Table 7 presents the severe CWE counts per function by study group. In this table, any bugs were associated with their most severe CWE (according to Table 6). The N for each category refers to the (N)umber of compiling functions from participants. Rate refers to the count of this CWE divided by the N. As it is included for reference only, the ‘Autopilot’ group refers only to the first 5 answers from code-<user>-

Figure 12: The study environment: Visual Studio Code running in web-based container, shown in the Firefox Web Browser.
| Function Name                  | Group       | Observed CWE                                                                 |
|-------------------------------|-------------|-------------------------------------------------------------------------------|
|                              |            | N  | #this CWE  | Group  | Observed CWE                                                                 |
|                              |            |    |            |        | N  | #this CWE  | Group  | Observed CWE                                                                 |
|                              |            | 42 | 18          | Control| 18 | 0.14       | 1.8    | 0.45                                                                 |
| list_add_item_at_pos         | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_cost_sum                | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_deduplicate             | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_find_highest_price_item_position | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_item_to_string          | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_load                    | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_print                   | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_remove_item_at_pos      | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_save                    | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_swap_item_positions     | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
| list_update_item_at_pos      | Control     | 18 | 0.18       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Assisted    | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |
|                              | Autopilot   | 18 | 0.14       | 0.06   | 19 | 1.17       | 1.9    | 0.45                                                                 |