

Experimental Analysis of Productive Interaction Strategy with ChatGPT: User Study on Function and Project-level Code Generation Tasks

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The application of Large Language Models (LLMs) is growing in the productive completion of Software Engineering tasks. Yet, studies investigating the productive prompting techniques often employed a limited problem space, primarily focusing on well-known prompting patterns and mainly targeting function-level SE practices. We identify significant gaps in real-world workflows that involve complexities beyond class-level (e.g., multi-class dependencies) and different features that can impact Human-LLM Interactions (HLIs) processes in code generation. To address these issues, we designed an experiment that comprehensively analyzed the HLI features regarding the code generation productivity. Our study presents two project-level benchmark tasks, extending beyond function-level evaluations. We conducted a user study with 36 participants from diverse backgrounds, asking them to solve the assigned tasks by interacting with the GPT assistant using specific prompting patterns. We also examined the participants' experience and their behavioral features during interactions by analyzing screen recordings and GPT chat logs. Our statistical and empirical investigation revealed (1) that three out of 15 HLI features significantly impacted the productivity in code generation; (2) five primary guidelines for enhancing productivity for HLI processes; and (3) a taxonomy of 29 runtime and logic errors that can occur during HLI processes, along with suggested mitigation plans.

Additional Key Words and Phrases: Human-LLM Interaction, Code Generation Productivity, User Study

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1 Introduction

It is widely recognized that developers in various domains utilize Large Language Models (LLMs), particularly ChatGPT, to complete different Software Engineering (SE) tasks [25]. While the practicality and productivity with and without LLMs have been highlighted [44], the challenge of how developers can effectively interact with LLM code assistants for optimal productivity remains understudied.

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Human-LLM interactions can be facilitated through prompts that guide users in designing instructions and providing context for the model [23]. Various prompting techniques have introduced example-based methods (e.g., Zero-Shot or Few-Shot), which are effective for general LLM applications in information retrieval and reasoning [6, 23]. These prompt patterns are actively utilized across various SE tasks, including code and test case generation [26, 29, 43], bug reproduction [22], and program repair [35]. However, most studies assume that these prompting techniques can yield optimal outcomes, which could lead to potential risks of redundant iterations and diminished developer acceptance of the outcomes, indicating lower productivity in SE tasks [44]. For example, developers might repeatedly refine their prompts to generate more accurate test suites or codes, only to discover minor differences each time. This would trap the developer in an inefficient spinning wheel and undermine potential productivity gains.

To address these concerns, we investigated LLM-driven code and test case generation research [13, 26, 29, 33, 43], and empirical analysis studies using LLMs to solve SE tasks [3, 15, 34]. Our findings reveal that (1) the majority of the research focuses on function-level tasks that exhibit limited dependency and diversity; (2) most studies have not taken into account comprehensive Human-LLM Interaction (HLI) features, such as user experience on using LLMs and users' prompt design behaviors, in their analyses; (3) the investigation into errors arising during HLI processes, along with the suggestion of mitigation strategies, has remained understudied.

The first technical challenge presents that all existing studies have focused on function-level code generation and bug fixing. Du et al. [13] addressed the class-level code generation by introducing a class-level code generation benchmark, ClassEval, and noted that the performance of LLMs in class-level code generation is limited due to the dependencies between functions and classes. This suggests that the complexities of real-world engineering tasks, which arise from dependencies, inheritance, and API integrations among various functions, classes, and third-party providers, cannot be adequately addressed by the conventionally utilized function-level SE tasks. Furthermore, many function-level benchmarks are based on a limited number of source datasets, highlighting diversity issues in the codes used for the assessment [32]. Therefore, class or project-level engineering tasks must be considered to evaluate the effectiveness of prompting techniques in addressing the reality gaps.

Next, most existing studies concentrated on analyzing prompt patterns, such as Zero-Shot or Few-Shot, in different SE tasks. However, beyond these prompt patterns, numerous features can influence the HLI processes for code generation. For example, the users' approach to defining the prompt context or the types of prompt context among the test cases or design descriptions should be explored to establish practical guidelines for interacting with LLM code assistants. However, current research has not thoroughly examined the comprehensive features of HLI processes in their analyses.

Lastly, the in-depth analysis of errors and their root causes that occurred during the HLI processes is limited. Although Liu et al. [28] examined various static and runtime errors generated by LLMs through a scalable empirical analysis, the study primarily concentrated on the errors generated during function-level code generation tasks and did not consider user perspective features as root causes. Therefore, the strategies for mitigating errors induced by specific behavioral patterns from users or multi-class dependency issues in runtime or logic errors require further investigation.

In response to these challenges, we designed a user study to seek the answer to the question: **Which prompting strategies are the most productive in completing function-level and project-level code generation practices when interacting with GPT code assistants?** Based on the carefully designed project-level and function-level tasks with test suites, we recruited 36 students and practitioners to interact with assigned GPT models for our study. First, we conducted a comprehensive feature analysis of the HLI processes for code generation. Next, we examined the significant features in detail through a rigorous investigation of the experiment outcomes, which included analyzing the generated code, survey responses, GPT chat logs, and screen recordings of all participants. Additionally, we investigated

791 runtime and logic errors that occurred during our experiments, categorizing them based on their root causes and symptoms, and provided suggestions for minimizing the uncertainties causing errors, particularly in multi-class code generation cases.

Our analysis of the experimental results on code generation productivity, indicating the number of passed test cases within the given timeframe, revealed that (1) Three HLI features have a significant impact on the code generation productivity in the interaction with GPTs compared with other features; (2) Specifically, the Few-Shot prompt pattern, more assignment of time on the debugging than the initial implementation, and the combined CopyPaste and Manual Formulating methods for context curation based on test resources are identified as the most suggested practices to enhance productivity in code generation; (3) GPTs have generated 29 categories of runtime and logic errors, stemming from various user-side, GPT-side faults, with observing specific uncertainties related to the implementation and debuging processes in multi-class code generation.

This study presents the following key contributions:

- Newly introduced two multi-class code generation benchmarks to compare various prompting strategies.
- Analyzed best practices for productive prompting strategies for code generation, encompassing various features in the HLI processes.
- Developed a taxonomy for runtime and logic errors, including their root causes and suggestions for minimizing uncertainties during interaction with GPTs.

The paper is organized as follows: Sections 2 and 3 explain the works related to this study and the background on HLI features used in our experiment. In Section 4, we elucidate the experiment design. Sections 5 and 6 describe the empirical analysis results with discussion points. Finally, Section 7 concludes the study with directions for future work.

2 Related Work

We have investigated research studies that propose automated code or test generation pipeline [13, 26, 29, 33, 43] and empirically investigate SE processes considering the interaction between LLM code assistants and users [3, 15, 34].

Automated SE Tasks by LLMs. The studies on automated code or test generation have compared various prompting methods and SE processes to complete function-level tasks. Lin et al. [26] developed multi-role LLM agents, such as Architecture Designer and Software Engineer, and assessed different software development processes utilizing these agents on HumanEval. Mathew et al. [29] investigate how integrating Test-Driven Development (TDD) principles into LLM-based code generation can enhance the correctness of the generated code, primarily focusing on the effectiveness of test cases. Piya et al. [33] also introduced a TDD framework that incrementally incorporates manually designed test cases to enhance code correctness. Yuan et al. [43] conducted a comprehensive evaluation of unit test generation by LLMs and proposed a method for improving output quality. Du et al. [13] established a fundamental structure and examples for a class-level benchmark dataset for SE tasks, revealing that existing LLMs struggle to perform class-level SE tasks accurately. However, while these studies predominantly focused on function-level SE practices, Du et al. [13] also emphasized developing a benchmark for class-level practices. They employed Zero-Shot and One-shot patterns and did not explore different prompting methods in experiments.

Empirical Analysis on SE Tasks. Several recent studies have conducted empirical user research on function-level tasks. Rahe et al. [34] examined how programming students interact with LLMs to solve coding exercises. Their study with 37 students noted that students tend to use LLMs to seek knowledge about general concepts or to generate solutions directly. Barke et al. [3] analyzed the empirical usage patterns of 20 users with Copilot while solving

customized experimental task sets. Fakhouri et al. [15] designed a TDD workflow process for developers and validated its effectiveness with 15 developers. Liu et al. [28] conducted a scalable examination on GPT-generated codes for function-level tasks and defined a taxonomy of static and semantic errors. However, these studies primarily focused on function-level tasks, while Barke et al. [3] designed two class-level tasks. Additionally, they did not cover the diverse backgrounds of participants, including programming experience and tool familiarity, and did not fully consider various interaction features, such as prompting methods and artifacts.

Our Study has considered multiple prompting patterns and strategic interaction features with Paid and Free GPT models. We developed project-level tasks to address various dependencies between classes. Additionally, we identified function-level tasks that could not be resolved by a single request to GPTs, which were aimed at addressing the data leakage issue. Lastly, our study recruited participants from diverse backgrounds and experiences. We considered these features, along with the screen recordings and GPT chat logs, when investigating the distinguishing features of productivity achievements in the top quartile group, thus identifying practical guidelines that can facilitate productive interactions with GPTs for coding tasks.

3 Background

3.1 Human-LLM Interaction Features

In formulating HLIs for code generation practices, we defined three main attributes: User, Model, and Interaction by extending the 5W1H HLI catalogue format [18]. Then, we investigated concrete features for each attribute that can affect the engineering productivity with LLM code assistants.

Firstly, the **User** attribute abstracts users' backgrounds and experiences in handling assigned tasks and specifying prompts. For instance, the programming and industry experience features implicitly indicate users' skill levels and confidence in general engineering and industry project tasks. The LLM usage experience feature can reflect users' prompt engineering skills, while the dependency feature indicates the degree of trust in their prompting abilities and reliance on outcomes. The algorithmic experience represents the users' familiarity with algorithm-solving tasks, as most function-level tasks and class-level sub-tasks involve algorithm-solving challenges [8, 12]. We observed that existing studies did not account for user-oriented features in their empirical and quantitative analyses of software engineering tasks. However, we incorporated the user attribute into our analytical features because their backgrounds and experiences may shape the user's overall decision-making regarding interaction strategy, ultimately affecting productivity in completing the assigned tasks.

Next, the **Model** attribute indicates the ontological features of various LLM types, including their accessibility through licensing policies and interaction interfaces, which may influence user experiences in addressing engineering tasks or the quality of outcomes. We employed both the Free and Paid features in our experiment to compare the contributions of the feature with other user-side and interaction-side features in terms of code generation productivity. However, for the interface, we asked all the participants to use the same WebUI to unify other environment settings.

The **Interaction Method and Process** attributes are the primary goals of analysis addressed by existing studies [13, 26, 29]. We defined these attributes to instantiate the conceptual "How to interact with LLMs concretely" feature [18] in the context of code generation tasks. The interaction process outlines specific steps and approaches for conducting HLIs on software engineering tasks, such as following a waterfall development process or a test-driven development approach. The interaction method involves techniques for designing prompts, considering existing pattern templates and various design methods, including copying and pasting specification documents and custom formulation, as well as

Table 1. Overall Attributes and Features of HLIs on SE Tasks

Human-LLM Interaction Features for Software Engineering Tasks	
User Perspective	
Programming experiences	2-4 / 3-5 / 6-10 / 10+ years
Industry experiences	0: None / 1-2 years / 3-4 years / 5+ years
LLM usage experience when conducting coding tasks	0: Never / 25: rarely / 50: half the time / 75: most / 100: always
Dependency on LLMs in final code outcomes	Applying 0-100% of codes generated from LLMs
Algorithm solving experiences in the past 2 years	0-5 / 6-10 / 11-15 / 16-20 / 20+ problems
Model Perspective	
License	Free / Paid
Interaction interface	WebUI / IDE / API
Interaction Perspective	
Interaction process	Waterfall, Test-Driven Development, etc
Prompting pattern	Few-Shot, CoT, Reflection, Alternative Approaches, etc
Prompt design method	Copy Paste / Formulate / Using LLMs on prompting / Pre-existing template
Context Artifact	Requirement specification, Test cases, Architecture, Skeleton codes, etc.

the types of artifacts utilized in curating the context. We explain the prompting patterns in depth in the next Section and the coverage of the features in Section 6.

3.2 Prompting Pattern Templates

Prompting patterns among the other HLI features have been extensively studied by existing research [1, 6, 23, 27, 40]. Among these studies, White et al. [41] categorized prompting strategies and designed a catalog of prompting pattern templates. Based on the templates, we identified two well-known patterns: Few-Shot and Chain-of-Thought (i.e., Cognitive Verifier), as well as two improvement-driven prompting patterns: Reflection and Alternative Approach patterns, which are designed to conduct the reasoning process with LLMs. These Reflection and Alternative Approach patterns facilitate reasoning about self-repairing and feedback loops, which are known to improve code generation qualities [28]. The templates for these patterns are systematically designed to represent the conventional use cases of each template, based on the actual prompts used in existing studies. All the prompt patterns are available in the attached supplement file¹.

First, the **Reflection** pattern intends to get GPTs to automatically explain the reasoning behind the answers they give to the users' questions. This can help better understand how GPTs process the input and the assumptions they make in their outputs. We expect the Reflection pattern to aid in improving outcome codes by explaining the underlying

¹Due to our institution's IP policy, experiment files and logs without personal information are attached for review purposes.

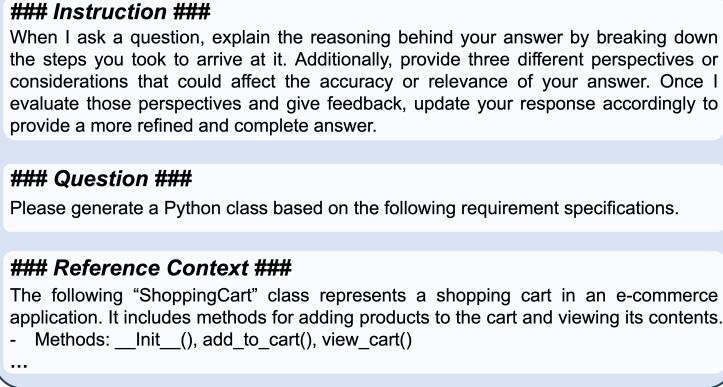


Fig. 1. Example prompt template for the Reflection pattern

logic to users, allowing them to verify correctness and debug any issues. Fig. 1 illustrates the prompt template example for the reflection pattern used in our experiment, containing the pre-defined Instruction part to explain the Reflection pattern, and the Question and Reference Context parts where users can add any request and context information.

The **Alternative Approach** pattern aims to ensure that GPTs provide multiple methods for accomplishing a task. This prompting pattern is motivated by users becoming fixated on pursuing only a single approach. This pattern aims to help users recognize alternative methods they may not have considered, enabling them to choose the most suitable option. We anticipate that this prompt pattern can offer various approaches for developing or fixing code, allowing users to select the best solution.

The **Cognitive Verifier** (a.k.a Chain-of-Thought) pattern enables GPTs to subdivide an original question into smaller questions that can ultimately yield a better answer to the original one. This pattern employs a divide-and-conquer strategy based on the premise that GPTs can reason more effectively when a question is divided, and the answers to these smaller questions can be combined to form a solution to the original question. Although this pattern can determine the number of questions GPTs should ask users, it means that users must answer those questions to receive appropriate answers from GPTs.

Lastly, we defined the well-known **Few-Shot** template by adding two pre-defined request-and-answer examples in the Example part below the three-part structure described in Fig. 1. Since optimizing prompt design is not within the scope of our study, we focused on establishing a conventional template with two fixed examples for each task in this Few-Shot pattern. The number of examples was determined based on existing research [22, 26, 29, 35, 43]. For each task, we included one specific example of generating partial classes or functions alongside one general example. To minimize the variance caused by the prompt pattern templates, we asked participants not to modify the order and number of examples in the Example part when using this pattern. Still, we allowed users to add any context in the Reference Context part. One example of a Few-Shot pattern template usage is explained in the Appendix.

4 Experiment Design

This section outlines our user-participating experiment process, function and project-level coding tasks, and concrete research questions with corresponding productivity measures adopted in our experiment.

4.1 Research Questions

The following Research Questions (RQs) are defined to explore the most productive strategy for interacting with GPTs on code generation at the function-level and project-level tasks:

- RQ1. Which features of HLIs have the most significant impact on code generation productivity?
- RQ2. What best practice guidelines can be established for strategic interactions with GPTs to enhance productivity?
 - RQ2-1. Which prompting patterns yield the highest productivity for both function-level and project-level software engineering tasks?
 - RQ2-2. What features distinguish the Best quartile group from the other groups?
- RQ3. What errors occur during HLI processes for code generation?

RQ1 aims to investigate the overall contributions of the HLI features defined in this study to code generation productivity. We used the Test Passed Rate (TPR) as our primary measure of code generation productivity. Through a systematic statistical analysis, which includes the ElasticNet model [45] and follow-up post-hoc analysis, we calculated the contributions of each categorical and numeric feature within the HLI processes and provided comprehensive insights into the significance of these features.

RQ2 focuses on investigating key aspects of HLI strategies and providing best practice guidelines for using ChatGPT to enhance code generation productivity. **RQ2-1** aims to examine the relationship between the prompt patterns and their impact on TPR productivity. In **RQ2-2**, we conducted a group-wise comparison of different features between the Best quartile group and the other quartile groups. We analyzed context curation methods, such as context design methods (e.g., Copy-Paste, Manual-Formulating, etc.) and different types of contextual artifacts (e.g., design document, test cases, etc.) that can affect the productivity of interactions. We identified the first quartile group of TPR as our best practice group. We thoroughly analyzed the screen recordings and GPT communication logs of participants in this group, comparing them with those of participants in other groups. The findings from these research questions provide clear guidelines for HLI best practices for multi-class code generation with GPT assistance.

RQ3 concentrates on the empirical analysis of errors detected in the user study to categorize the types of errors, identify the root causes of errors, and suggest mitigation strategies for identified errors. We first define a taxonomy of HLI errors and outline the types, frequencies, and symptoms of the 791 identified errors. Then, we analyzed the root causes of the errors and identified whether the errors are user-side or GPT-side faults by thoroughly reviewing the participants' outcome codes, chat logs, and screen recordings. We believe these findings offer valuable insights into error handling in code generation, particularly in the context of using GPT models.

4.2 Overall Experiment Process

Our experiment aims to identify the most productive prompting strategy for completing code generation tasks. We have designed problem-solving tasks at the function and project levels, distributed the design documents with skeletons to users, and asked them to generate code within a specified time.

Fig. 2 illustrates the **Experimental Process**, outlining the first 15 minutes to introduce the experiment to participants and explain the assigned prompt patterns, 70 minutes for actual task solving, and the last 15 minutes for surveying the in-detail background and subjective evaluations on prompting patterns and their design methods. The experiment was conducted online and offline, depending on the participants' circumstances. The introduction session aims to explain the experiment process, rules, and tasks with prompt patterns, through prepared materials.

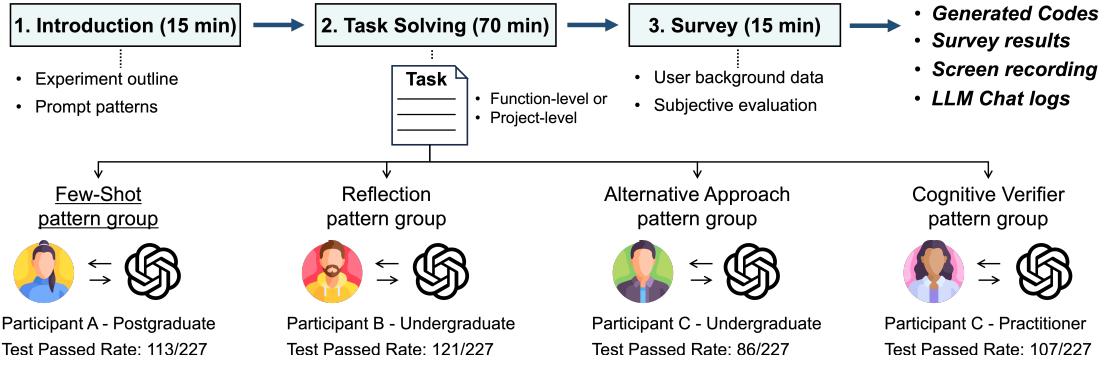


Fig. 2. Overall experimental process and example outcomes of interactive problem solving on project-level tasks

For the **Participant Recruitment**, we disseminated our experiment through various methods, like hands-on flyers and LinkedIn, and recruited 36 participants via the Upwork platform [20]. Our recruitment criteria require more than two years of Python programming experience. We recruited participants globally with diverse backgrounds, including undergraduate and postgraduate students and practitioners with industry experience. We evenly distributed the participants into four comparison pattern groups based on their backgrounds and project logs on Upwork.

The **Task Solving** phase was executed by distributing the design documents, prompt pattern templates, and skeleton Jupyter Notebook files or problem links to participants. We assigned function-level tasks to 12 participants and project-level tasks to 24 participants. Additionally, we strictly limited participants' manual coding only when GPTs could not generate the expected outcomes after three request attempts. This concentrates on interactions with users and GPT code assistants and their outputs while preventing situations where biased contributions from users or GPTs affect the completion of SE tasks. The detailed task and test suite design are specified in Section 4.3.

For the **GPTs** that participants interacted with, we considered the Free-tier and subscription-tier (i.e., Paid) GPTs they primarily use in their regular practices. Based on the Expression of Interest questions on Upwork, we assigned participants Free or Paid models according to their preferences in this experiment. Overall, 18 participants utilized free-tier GPTs, such as GPT-3.5 or GPT-4o-mini, while the other half adopted the Paid 4o model. The concrete distributions of GPT models by tasks and prompt pattern groups are illustrated in Section 5.1.

The **Survey** aims to gather specified user background information and their subjective assessment of prompting strategies. We have designed 30 multiple-choice and text-entry questions that collect specific attributes that can influence the interaction strategy and processes between participants and GPTs, as detailed in Table 1.

The final question set evaluates participants' subjective views on their interaction strategies. We provided sample scales to assess the subjective productivity, accuracy, and efficiency of the participants' prompting strategies, such as None, Rarely, Moderately, Mostly, and Strongly. Additionally, we asked them to share specific experiences where GPTs produced outcomes with improved or diminished qualities. The last questions of our survey inquired whether they would like to adopt these prompting strategies in their future studies and their comments on the experiments.

4.3 Task Design: Function and Project-level

Our study specified concrete design documents for function and project-level tasks. We thoroughly designed test cases aligned with the specifications and skeleton codes for convenient distribution and immediate task-solving execution.

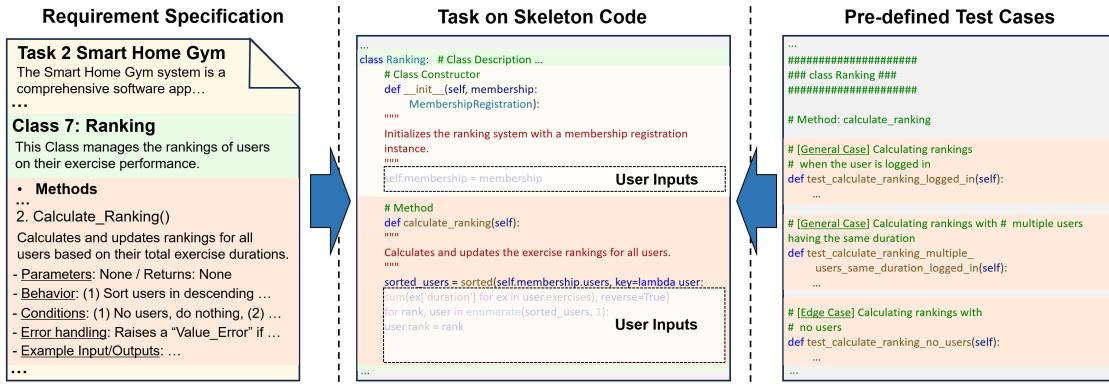


Fig. 3. Example design specification along with the corresponding skeleton code snippets and test cases

Function-level Tasks. Several benchmark datasets, such as HumanEval [8], are available for assessing the code generation accuracy of GPTs. However, we decided not to utilize the problems in existing benchmarks because their tasks have been segmented, indicating each task only contains a single requirement for code generation or fixing. Since our work focuses on analyzing interactions between GPTs and engineers, we determined that these segmented SE tasks could not entirely capture potential interactions, and additional processes would be necessary to curate or combine them. Moreover, there may be data leakage concerns where GPTs directly respond to answer codes.

Utilizing existing problems from popular coding challenge platforms, such as LeetCode [24] and HackerRank [19], can offer an accessible range of coding tasks at various levels of difficulty [3, 38, 44]. After rigorously reviewing the problems from these platforms on several GPTs regarding the data leakage issue, we selected five problems, including two Easy, two Medium, and one Hard-level difficulty. Based on our empirical practices and common understanding, Easy-level problems typically take 10 to 15 minutes, Medium problems require 20 to 30 minutes, and Hard ones generally need more than 1 hour of manual coding to pass all the test cases. Therefore, we have designed a demanding task set that an engineer would not typically be able to complete to pass all 72 test cases across the five problems in 70 minutes. The problem list is detailed in the attached material².

Project-level Tasks. While function-level tasks address the problem-solving capabilities of GPT code assistants and engineers, class or project-level (i.e., multi-class) tasks can present architecture, dependency, and integration challenges in SE processes. In particular, we considered several dependency features for task development, including composition, aggregation, and association in object-oriented principles [5, 17]. To the best of our knowledge, we first specified two project-level SE tasks, E-Commerce App and Smart Home Gym, addressing the multi-class dependency features and data leakage issue. We specified the rigorous specification of classes and methods, manually designed test cases based on the equivalent partitioning method [7] covering both general and edge cases, and skeleton codes in Jupyter Notebook to facilitate direct task solving and assessment.

Our project-level tasks consist of design document, skeleton code for task solving, and executable test cases for corresponding requirements. Examples of each component are illustrated in Fig. 3. First, our specification documents for each project-level task outline the project's abstract and goals, provide an overview description of each class, and detail method specifications. In particular, the method specifications clearly state the essential features and guidelines for

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developing the correct functions, including parameter and return information, specific behaviors, special requirements, error-handling guidelines, and example inputs and outputs. We have designed 5 classes with 14 methods for the E-Commerce scenario task and 7 classes with 22 methods for the Smart Home Gym task. We did not include any UI-related requirements or implementations in the tasks.

The middle part of Fig. 3 provides an example skeleton code for the Ranking class in the Smart Home Gym task. Following the class specification format proposed in ClassEval [13], we designed the skeleton code to include descriptions of classes and methods, parameter details, and sections for user input. Additionally, the dependency examples between the Ranking and Membership classes are demonstrated in the two functions included in the skeleton code. We have concentrated on developing task components that can evaluate the capability of GPT’s code generation in managing software code dependencies for project-level tasks.

Lastly, we designed a test suite for each project task by applying the equivalent partitioning method [7], considering all the requirements and their input spaces. We categorized the test cases into general and edge cases. The general cases aim to evaluate the expected functionalities of the developed classes and methods, while the edge cases focus more on assessing the implementation of special requirements (E.g., No-user case) and error-handling guidelines. In total, we designed 128 test cases for the E-Commerce App and 100 test cases for the Smart Home Gym task. We ensured that the test suite for each task achieved 100% branch coverage in our sample codes. Additionally, we empirically checked that the test suites achieved an average line coverage of 91.85%, excluding non-executable code, and an average branch coverage of 99.83%, excluding redundant conditional branches, in the final code sets from participants. The test cases are also included in the distributed Jupyter Notebook files, allowing participants to conveniently execute the tests to evaluate and improve the code generated by GPT assistants. A more detailed project-level task example is described in the Appendix, and all the files are provided in the attached file.

When experimenting with project-level tasks, we strictly limited the order in which participants should solve tasks and the transitions between the tasks. The E-Commerce App was designated as Task 1, and participants could move on to the second Smart Home Gym task only if they passed 121 out of 128 test cases in Task 1, indicating a 95% pass rate. We defined this rule to ensure that all participants have the same conditions and to set a realistic environment for task-solving practices rather than frequently transitioning from one task to another. The task execution order is fixed for assessment purposes in this experiment, while the problem order in the benchmark will be randomly given to mitigate the learning effect of LLMs.

4.4 Productivity Measures for GPT Outcomes

Software engineering productivity for human engineers has been extensively studied in previous research [4, 21, 30, 36]. These studies have highlighted the importance of considering various factors when assessing SE productivity, such as correctness, efficiency, maintainability, security, and subjective evaluations, including developer satisfaction. For example, correctness has been measured by test-pass or requirement-completion rates, while the time-to-completion metric can be used to measure efficiency. Recent studies utilized the SE productivity measure to evaluate the code generation productivity of GPTs [3, 10, 44]. These studies concentrated on the correctness aspect of GPT code generation; thus, they primarily employed the Pass@K [8] or Test Passed Rate methods. In our experiment, we assessed the productivity of GPT code assistants by first applying the Test Case Passed Rate over 70 minutes and then using time-to-completion if all test cases were satisfied.

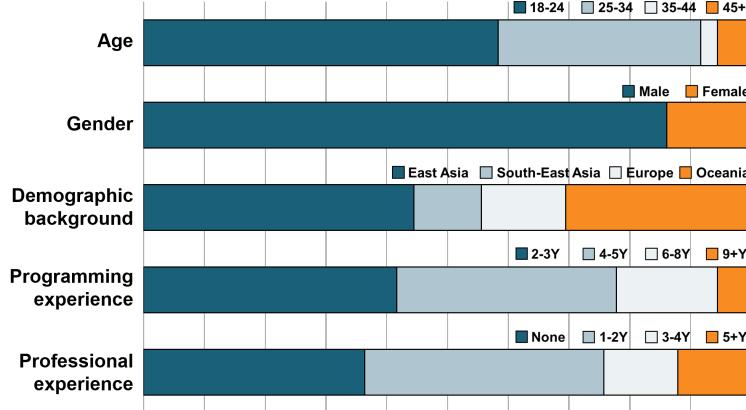


Fig. 4. Overview of participant background statistics

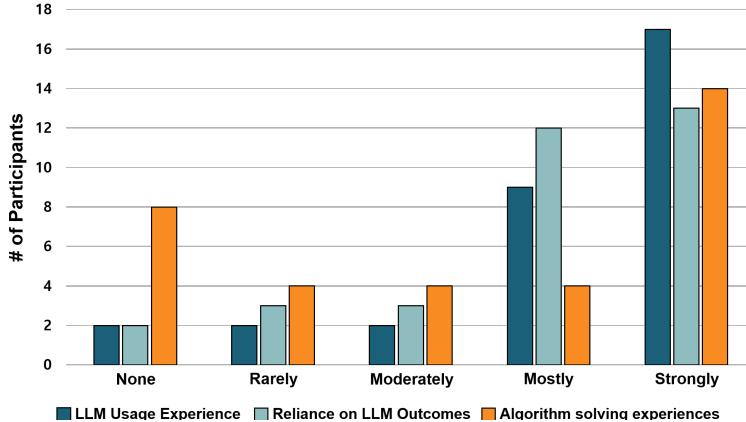


Fig. 5. Overview of GPT usage and task-solving experience

5 Experiment Results

5.1 Statistics of Experiments

Fig. 4 and 5 illustrate the statistics of participants in our experiment. Fig. 4 presents a 100% Stacked Bar Chart showing the backgrounds of the 36 participants. Among these, 21 participants (58%) are in the age range of 18-24, 12 participants are aged 25-34 (33%), one participant is aged 35-44, and two are aged 45 and older. A total of 31 male participants and 5 female participants participated in our experiment. Next, 16 participants were from East Asian backgrounds, 4 were from Southeast Asia, 5 were from Europe, and 11 were from Oceania. 15 participants have 2-3 years of Python programming experience, 13 have 4-5 years, while 9 participants have over 6 years of experience, including 2 with more than 9 years. In terms of professional experience, 12 participants have none, indicating they are undergraduate students, 14 have 1-2 years of experience, and 9 participants have more than 3 years of industry or research engineering experience, with 4 having over 5 years. Our experiment considered various user background factors and covered a diverse spectrum of users. The participants are evenly distributed regarding their programming and professional experience across the comparison groups.

We classified participants' status based on their academic and industrial experiences, as we deemed it more appropriate than categorizing them by their current status in our analysis. For example, one participant has over 9 years of industry experience and is a Ph.D. student, while another has 2 years of industry experience and is a 4th-year student. We utilized the categorized results to investigate whether academic or industry experience can serve as distinguishing features of optimal productivity in conducting software engineering tasks. To clarify the status of participants, our experiment consists of 18 undergraduate students, more than 2nd-year (3: Function-level/15: Project-level), 8 graduate students, including Master's and Ph.D. programs (6: Function/2: Project), and 10 practitioners (3: Function/7: Project).

Fig. 5 illustrates the number of participants whose responses are categorized into five intensity levels based on their experience with GPT usage, reliance on GPT results, and experiences in task-solving for the last 2 years, including algorithm problems. For the GPT usage experience in real-world SE tasks, 26 participants stated that they mainly or strongly utilize GPTs. In comparison, only two participants indicated that they rarely use GPTs or not at all. In the reliance on code outcomes from GPTs, 25 participants answered they mostly or absolutely rely on GPT code outcomes. Lastly, for the task-solving experiences, the participants are nearly divided into two groups: familiar for the highest two groups, with 17, and non-familiar for the lowest two groups, with 12, based on their task-solving experiences over the past two years. We believe these background experiences may affect the decision on strategies of high-level task-solving processes, thereby contributing to the productivity of solving SE tasks with GPT assistants.

Additionally, we assigned both Free and Paid GPTs to participants across four prompt pattern groups, considering function and project-level tasks. In total, 18 participants utilized Free-version GPTs, including models like 3.5 or 40-mini, while the remaining 18 used Paid-version models such as 40 or 01. For every 9 participants in each group, we ensured that at least four were assigned to use both the Free and Paid versions. Furthermore, we assigned at least one Free and one Paid model to each function and project task subgroup. For instance, we allocated four Free models and five Paid models to the Few-Shot pattern groups, where two Free models and one Paid model were assigned to the Function-level task subgroup, and two Free and four Paid models were used for the Project-level group. Considering the varying circumstances of each participant regarding subscriptions to and use of GPT models, we distributed Free and Paid models across each categorical group in our experiment.

5.2 RQ1: Overall HLI Feature Analysis on Code Generation Productivity

This RQ aims to analyze the overall contribution of HLI features defined in this experiment and obtain insights into which features most significantly impact the code generation productivity (i.e., Test Passed Rate (TPR) values) in HLI processes with GPTs. In total, we utilized 15 features in our comprehensive analysis, which included eight user-side features, one model-side feature, and six interaction-related features from 36 participants in the function and project-level tasks.

For the user features, we collected the categorical variables of age, current status, gender, programming experience, and industrial programming experience, as well as the numeric scores for self-evaluation of GPT usage experience, dependency on GPT outcomes, and algorithm-solving expertise over the past two years, through the carefully designed survey results. We also incorporated the model-side features indicating whether users were assigned to use the Paid or Free tiers of GPTs. In terms of interaction features, we analyzed different prompting patterns, including Few-Shot, Reflection, Alternative Approach, and Cognitive Verification. Moreover, we utilized context curation methods characterized by four distinct features: Copy-Paste, Manual Formulation, Use of GPTs, and Utilization of External Templates. Lastly, we involved the strategic process feature, specifically the ratio of the time spent on the initial development phase to that spent on the debugging phase. These context curation and interaction process features were identified through a detailed review of participants' screen recordings and chat logs.

Table 2. Function-level Task Evaluation Results

Feature	β -EN	β -DL (95% CI)	p-value	Bootstrap
Prompt Pattern: Few-Shot	+0.058	0.061 (+0.024 ... +0.098)	0.002	91%
Time Distribution Strategy	+0.034	+0.036 (+0.007 ... +0.064)	0.014	92%
Algorithm Solving Experience	-0.033	-0.030 (-0.061 ... -0.004)	0.028	88%
Paid Tier	+0.021	+0.018 (-0.011 ... +0.043)	0.19	47%
Other 11 Features	0	-	-	<40%

We developed a rigorous statistical analysis process to derive reliable insights from the feature analysis. First, we preprocessed all numeric and categorical feature values into normalized formats. For categorical features, we used mean encoding for ordered features and one-hot encoding for nominal features. For instance, the age group of 18-24 was averaged to approximately 21 years, and the Gender category is encoded to 1 for female and 0 for male. Numeric values were standardized using z-scores. Next, we employed the One-standard-error Elastic-Net regression model, a well-regarded feature analysis technique known for its effectiveness in reducing biased analysis [45]. Following that, we applied the Debiased Lasso method to calculate the significance and 95% confidence intervals of the initially selected features [2, 39]. Lastly, we incorporated bootstrap-based stability selection methods. We performed 200-bootstrap stability selection to estimate coefficient uncertainty and check whether the features appeared in more than 80% of resamples [14, 31]. These post-hoc analysis methods address the issue of a relatively small sample size and ensure the confidence and power values of the statistical outcomes.

Table 2 presents the results of the statistical analysis, focusing on the comparative contributions of each feature to the TPR values. The second column value, β -EN, means the coefficients of features from the ElasticNet model trained on our experimental data. The third, β -DL, and fourth, p-value, columns indicate the 95% confidence intervals and the significance of each feature inferred from the Debiased Lasso algorithm. The last column presents the bootstrap selection rates, which are used to estimate the confidence of the statistical outcomes.

The results presented in Table 2 indicate that three key features significantly influence code generation productivity: the prompting pattern (particularly Few-Shot), the time ratio between the initial implementation and the debugging phase, and the algorithm-solving experience of users. Among these, the prompt pattern feature has the most substantial impact on productivity, demonstrating stable reliability on outcomes. Furthermore, the time distribution strategy between the initial development and debugging phases highlights that interactions with GPTs also play a crucial role in enhancing productivity.

The analysis of the algorithm solving experience reveals a statistically significant negative impact on code generation productivity. We found that this negative impact has been related to the context curation methods of participants with high algorithm solving experience. Additionally, the regression analysis results suggest that Paid GPT models may enhance productivity, although this contribution is neither statistically significant nor confident compared to the three features mentioned earlier. The other features have not demonstrated any statistical evidence of significant contributions. Based on this overall analysis, we conducted further investigation into the prompting pattern feature,

Table 3. Function-level Task Evaluation Results on Prompt Patterns

Metrics		Few-Shot	Reflection	Alternative Approach	Cognitive Verifier
Test Passed Rate	Min	1.0	0.90	0.92	1.0
	Avg	1.0	0.97	0.97	1.0
	Max	1.0	1.0	1.0	1.0
Subjective Productivity	Min	80	80	80	80
	Avg	93.33	86.67	86.67	93.33
	Max	100	100	100	100
Subjective Accuracy	Min	20	80	80	60
	Avg	66.67	93.33	86.67	73.33
	Max	100	100	100	100
Subjective Efficiency	Min	40	80	60	80
	Avg	73.33	86.67	80	93.33
	Max	100	100	100	100
Future Usage Preference	Min	80	80	80	80
	Avg	93.33	86.67	86.67	93.33
	Max	100	100	100	100

which is described in Section 5.3.1, analyzed the time distribution strategy, as well as model feature and other interaction features, is explained in Section 5.3.2, and the algorithm solving experience with relationship to context curation methods and HLI errors is further elucidated in Section 5.4.

The two HLI features, Few-Shot pattern and the time distribution strategy during the interaction process, have shown a statistically significant relationship with code generation productivity when using GPTs. Also, our findings indicate that the algorithm solving experience feature has a significantly negative impact on productivity with GPTs. In contrast, the GPT tier may enhance productivity, but it lacks a statistical foundation.

5.3 RQ2: Best Practice Guideline on HLIs for Code Generation

Based on our high-level findings regarding the key features that contribute to productive HLIs in code generation, we conducted an in-depth investigation to identify the best practices for interacting with GPTs for code generation tasks.

5.3.1 RQ2-1: Analysis on Prompt Patterns. Tables 3 and 4 present the productivity calculation and subjective evaluation results of different prompt patterns for function and project tasks, respectively. While the TPR primarily serves as a comparison metric for different prompting patterns, the subjective evaluation results are also used as supplementary scores, indicating practical scores regarding productivity, accuracy, efficiency, and future usage preference.

Function-level Task Analysis. The experiment results on function-level tasks presented in Table 3 show that 10 out of 12 participants completed all 72 test cases designed for the five tasks within 70 minutes. The remaining two participants also achieved TPRs of 90% and 92%. Additionally, we found that the unsolved test cases are not just from the Hard problem; they consist of one or two edge cases from multiple problems. This indicates that GPT code assistants

Table 4. Project-level Task Evaluation Results

Metrics		Few-Shot	Reflection	Alternative Approach	Cognitive Verifier
Test Passed Rate	Min	0.41	0.11	0.07	0.16
	Avg	0.48	0.33	0.33	0.32
	Max	0.52	0.53	0.48	0.39
Subjective Productivity	Min	5	29	0	40
	Avg	62.17	66.17	53.33	65.17
	Max	100	100	91	96
Subjective Accuracy	Min	5	33	20	50
	Avg	60.33	62.17	63.83	67.67
	Max	85	100	100	83
Subjective Efficiency	Min	50	61	40	20
	Avg	70.67	74.17	72.83	59.67
	Max	92	98	95	91
Future Usage Preference	Min	30	21	20	23
	Avg	59.00	51.50	54.33	65.67
	Max	85	83	81	81

can effectively provide solutions for function-level requirements, regardless of the difficulties, but have limitations in addressing all edge cases. Notably, participants employing Few-Shot and Cognitive Verifier patterns demonstrated slightly higher productivity than those using Reflection and Alternative Approach patterns.

The subjective evaluations of each pattern also reveal results similar to those of the TPR. The Few-Shot and Cognitive Verifier patterns received the highest average scores in surveys on subjective productivity and future usage preferences. This indicates that participants who used the patterns experienced an improvement in productivity while solving function-level tasks and strongly preferred utilizing them in future practical scenarios. In the subjective accuracy survey, participants who used the Reflection pattern reported experiencing highly accurate code from GPTs. Conversely, the Cognitive Verifier received the highest efficiency ratings.

Project-level Task Analysis. On the other hand, the experimental results from project-level tasks, as detailed in Table 4, reveal the relative difficulties that participants experienced in solving tasks with GPT code assistants. Overall, the maximum TPR is 0.53, indicating that only about half of the project-level design requirements, 121 out of 228 test cases, were resolved within 70 minutes. The minimum TPR identified in the project-level task-solving case is 0.07, indicating that the participant and GPT assistant developed codes that passed only 16 test cases despite the participant communicating intensively with the GPT for over 70 minutes.

In project-level task results, participants using the Few-Shot and Reflection patterns achieved the highest average and maximum TPR values, respectively. Especially, the Reflection pattern recorded the highest scores in subjective evaluations of productivity, accuracy, and efficiency from the participants. The Cognitive Verifier and Few-Shot patterns obtained the top average and maximum scores for future preferences, respectively.

Fig. 6 illustrates the distribution of TPR results for each prompt pattern group. The results indicate that while the Reflection pattern groups achieved the highest TPR score, the Few-Shot group exhibited significantly higher TPR

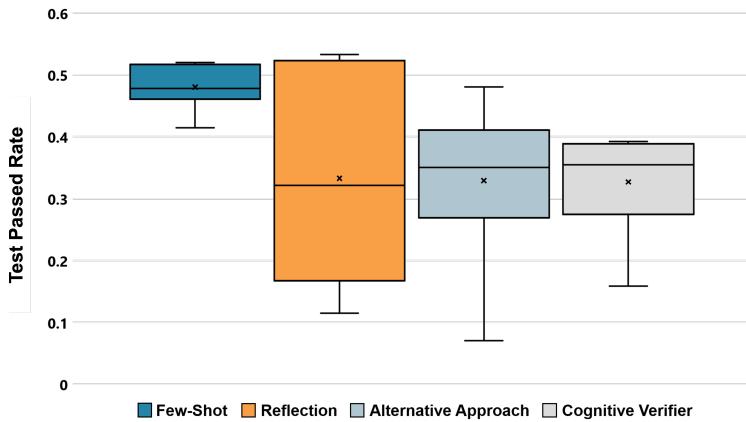


Fig. 6. Productivity comparison results of prompt pattern groups in project-level SE tasks

distributions than the other groups. As a result, we performed the Wilcoxon Ranksum test [42] between the Few-Shot group and the other groups. This analysis revealed that the Few-Shot group's TPR distributions have statistically significant differences compared to the Alternative Approach and Cognitive Verifier groups (i.e., p-values: 0.02 and 0.0005, respectively), whereas no statistical significance was observed compared to the Reflection group.

We further examined the screen recordings and GPT Chat logs to identify the distinguishing features of the Reflection and Few-Shot patterns in comparison to the other Alternative Approach and Cognitive Verifier patterns. We observed that the average number of requests for completing each class's development using the Reflection and Few-Shot patterns is lower than that of the Alternative Approach. For instance, in the Reflection and Few-Shot patterns, participants requested an average of 3.5 prompts and a maximum of 5 prompts to complete the code generation and fixing processes for a single class within the project task. In contrast, the other pattern groups had an average of 5.4 requests and a maximum of 7.3, requiring approximately 50% more requests. This is primarily due to the internal processes of these patterns that necessitate participants responding to the sub-questions. While this difference may seem trivial in function-level tasks, in project tasks that involve iterative and progressive development and debugging of code within a limited timeframe, the inefficiency of requesting more prompts results in a relative decrease in productivity.

The Few-Shot pattern demonstrated high productivity on average in both function and project-level SE tasks. The Reflection pattern yielded the best productivity in project-level tasks and received the highest subjective evaluations from participants. While the Cognitive Verifier pattern showed high productivity in function-level tasks, the Cognitive and Alternative Approach patterns are inefficient in iterative and progress SE tasks due to their interplay of execution processes.

5.3.2 RQ2-2: Quartile Group-Wise Analysis. In this RQ, we concentrated on thoroughly examining the prompting practices for the first quartile group in the project-level task experiment. During the function-level tasks, we observed that most participants interacted with GPT assistants approximately three times to complete a task; consequently, there were fewer than 20 communications across all function-level tasks, including initial implementation and fixing. In contrast, the project-level logs contain an average of 51.9 and a maximum of 82.3 requests, incorporating a variety of

Table 5. Experiment and survey results of the first-quartile group

Rank	TPR	Prompt pattern	GPT Tier	Programming experience	Professional experience	Algorithm solving experience	Context curation	Time Distribution	Unique Strategy
								Development	Debugging
1	0.533	Reflection	GPT-Paid	4-5 years	1-2 years	<5 problems	CopyPaste, Formulate	19.17	50.83
2	0.520	Reflection	GPT-Paid	6-8 years	3-4 years	6 to 10 problems	CopyPaste, Formulate	15	55
3	0.520	Few-Shot	GPT-Paid	4-5 years	1-2 years	20+ problems	CopyPaste, Formulate	27	43
4	0.515	Few-Shot	GPT-Paid	2-3 years	None	11 to 15 problems	GPT-driven, Formulate	13.5	56.5
5	0.480	Few-Shot	GPT-Paid	6-8 years	3-4 years	6 to 10 problems	CopyPaste	15	55
6	0.480	Alternative Approach	GPT-Paid	2-3 years	1-2 years	<5 problems	CopyPaste	29.17	40.83

strategic prompting practices. We investigated the interaction features with GPT assistants in the first quartile group and compared them with the other participants to identify key differences.

Table 5 provides detailed information about the top six participants by analyzing their code outcomes, survey results, screen recordings, and chat logs with GPTs. The second through fourth columns display the experiment results for the top six participants and their assigned prompt patterns with GPT models. The fifth through seventh columns present background information about the participants. The eighth column highlights the types of context curation methods that the participants utilized alongside their predefined prompt patterns. The last three columns, Time distributions and Unique features, aim to explain the strategic aspects of prompting compared with the other quartile groups.

Context Curation Methods. The first aspect of prompting strategies, alongside the prompt pattern, is the context curation method, which determines how participants crafted the prompt context. We categorized the primary curation methods into four types: CopyPaste, Manual Formulation, GPT-driven automated prompting, and other prompting patterns. As indicated in the eighth column of Table 5, five out of the top six participants employed CopyPaste to extract contextual information from existing materials. Notably, the top three participants used CopyPaste for the context and integrated their understanding of the materials or specific requirements.

For instance, the Rank-1 participant instructed the GPT to understand the prompt pattern template and strictly adhere to the Reflection pattern before beginning the task-solving. The participant outlined the expected behaviors and outcomes for the Reflection role to the GPT and then utilized our templates and materials to design task-solving prompts. This method is also evident in the logs of the Rank-3 participant, who set aside time in the beginning to explain the requirements and ensure that the GPT understood them before requesting code development or bug fixing, aiming to obtain more accurate answers. Besides, the Rank-4 participant employed GPT-driven automated prompt generation. The GPT was asked to design prompts after the participant provided the prompt template and all the design document data. The participant then directly used or manually crafted parts of the prompts generated by the GPT to generate and fix the code.

Based on the implications, we compared the TPR results from participants who only used CopyPaste with those who combined CopyPaste with the manual formulation. We found that the eight participants using CopyPaste and Formulating resolved an average of 95.88 test cases, with a minimum of 63 and a maximum of 121 test cases passed. In contrast, the other eight participants who solely copy-pasted the provided materials achieved an average of 77.25 test cases, with a minimum of 36 and a maximum of 109 test cases. Although we could not find statistically significant differences in

their distributions from the Wilcoxon Ranksum test [42], this still suggests that enhancing the understanding of the provided contexts or specifying clear roles and expected outcomes can increase the code generation productivity by approximately 24% on average.

While the accessible CopyPaste method for adding reference context using provided materials has been widely used, our experimental results explain that manually formulating additional context can further enhance productivity when interacting with GPT assistants. The manual method is particularly effective for clarifying your understanding of the requirements and issues, or specifying concrete behaviors and expected outcomes.

Next, we conducted several statistical evaluations as part of our detailed investigation. These included the Wilcoxon Ranksum test, Fisher's exact test [16], Cramer's V test [11], and Cliff's δ test [9]. We compared the HLI features of the first quartile group with those of the other participants, which encompassed all user-side, model-side, and interaction-side features. The results revealed that the **GPT Tier** and **Time Distribution** features had statistically significant differences between the data distributions of the first quartile group and those of the other participant groups. Based on these statistical findings, we also identified a difference in context artifact types among the participants in the first quartile group through a careful examination of their screen recordings and chat logs.

GPT Tier. We found that all participants in the first quartile group used the Paid 40 model, as outlined in Table 5. Additionally, we observed significantly different distributions of GPT models (i.e., p-value: 0.001, Cramer's V: 0.539 — Large, post-hoc power: 85%) between the first quartile and other groups from the statistical analysis. This result might raise a concern that the GPT Tier is the most significant factor in our experiment. However, as described in Section 5.2, the GPT Tier feature does not present statistical significance or confidence in its impact on TPR values compared with prompt patterns and strategic time distribution features. Additionally, the other 12 Paid model users are distributed across the second, third, and last quartile groups, while the second quartile group contains four out of six Free model users. The details of the experimental analysis on the GPT Tier feature are further discussed in Section 6.

While Paid GPTs may offer better productivity opportunities, this has not been proven to influence code generation productivity significantly.

Time Distribution in Initial Development and Debugging Phases. We measured participants' time distributions on initial code generation and iterative code fixing for the generated codes. Our statistical analysis results regarding the ratio of time spent on fixing versus generating code revealed that the first quartile group dedicated significantly more time to debugging the generated code than the other 18 participants (i.e., Wilcoxon Ranksum p-value: 0.014, Cliff's δ : 0.73 — Very Large, post-hoc power: 82%). Fig. 7 shows the ratio of minutes participants spent on code fixing compared to initial code generation. On average, the first quartile group spent three times as many minutes in the fixing phase as in the initial generation phase. This indicates they utilized approximately 17 minutes for code generation based on the design document and then allocated 50 minutes to refine the code based on test results. In contrast, most participants in the other quartile group spent about half the time generating their initial code, which still contained several errors, and they could not resolve them within the given time.

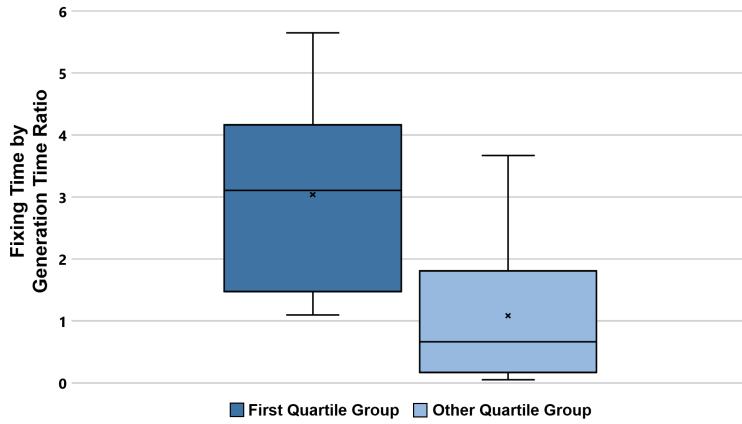


Fig. 7. Initial implementation and code fixing time ratio of different quartile groups

It is advisable to swiftly transition to the code-fixing phase and iteratively refine the code with GPT assistants. GPT-generated codes, especially those involving multiple classes, often contain several faults, even after users spend significant time generating them.

Context Artifact. Another feature we observed during the debugging phase is the context artifact that participants provided GPTs to explain failures. We found that participants primarily used design documents or test case codes. As noted in the last column of Table 5, most participants in the first quartile used test results and test case codes to debug the failures. For example, the Rank-5 participant asked the GPT to filter the list of failed test case messages and address them individually by copy-pasting each message along with the corresponding test case code and specific class codes. Furthermore, we found that 10 participants in the top 12 ranks primarily used the test case codes instead of the documentation during the fixing phase.

Our analysis revealed that utilizing test case codes can facilitate more accurate debugging of the code with GPTs than relying on design documents.

5.4 RQ3: Empirical HLI Error Analysis

The last RQ focuses on examining the identified errors in our experiment. In our user study, participants executed a total of 6,336 test cases. They encountered 791 errors, consisting of 420 runtime errors, 255 logic errors (i.e., failures), and 116 non-implementation errors. Except for the non-implementation errors, we performed an empirical analysis of 675 runtime and logic errors, ensuring that three out of four managers reviewed each error.

Based on our analysis results, we established a taxonomy comprising 19 categories for runtime errors and 10 categories for logic errors that can occur during HLI processes in multi-class code generation tasks. Each category is defined by a combination of its symptoms, such as `TypeError`, `LogicError`, and its root causes. Furthermore, we identified 25 independent root causes, excluding four overlapping root causes that were found in both the runtime and logic error categories within HLI processes.

Table 6. Taxonomy of Runtime Errors Identified in Our Experiment

Runtime Error	Error Name	Frequency	Explanation
TypeError	[T-1] Inconsistent Data Structure Handling	16	The initialization and usage of data structures are inconsistent (e.g., Initiating List, Treating Dictionary)
	[T-2] Wrong Output Format	7	Returned output format is hallucinated due to the lack of context (List expected, but Dictionary developed)
	[T-3] No dependency with other classes	16	A class contains List or Dictionary object named with dependent Classes, not the Class objects
AttributeError	[A-1] Missing Attribute	22	Attributes required in certain Classes are omitted.
	[A-2] Wrong Parameter Type in Function Call	24	Different types of parameters are used in calling dependent functions
	[A-3] Immutable Attribute Setting	70	Attributes have been defined as Immutable, while they should be Mutable.
	[A-4] Existing Attribute Overlapped	22	Some of the existing Attributes are removed in fixing specific Classes
	[A-5] Parameter Order Mixed	19	In fixing a specific function, the parameter order of the function is unexpectedly changed.
	[A-6] Condition Checking Order Issue	4	String processing is executed before checking whether the input type is String
ValueError	[V-1] Wrong Regex Condition	66	Case sensitivity, Strip, and other conditions of Regex on Email address are not correctly developed.
	[V-2] Wrong AND, OR Condition	30	String parsing and checking should be AND conditions, but the strip() is ignored or checked with OR conditions. Vice versa.
	[V-3] Hallucinated Conditions and Unexpected Error Raised	26	Insufficient context given to GPT, GPT generates the functions with hallucinated conditions.
	[V-4] Hallucinated Attributes Generated	1	GPT generates hallucinated attributes that are not requested to include by Users.
	[V-5] Wrong Boundary Setting	45	Wrong boundary conditions for float, integer variable have been implemented.
	[V-6] Missing Conditions	17	Required conditions are omitted in the implementation.
	[V-7] Wrong Return Type	14	Expected to return specific data structure (e.g., List), but actually return object in different format. (e.g., Dictionary)
KeyError	[K-1] Wrong Key Type	18	Dictionary key type is developed wrongly. (e.g., Expected: Numeric ID key, Code: String Name key)
	[K-2] Wrong Key ID Starting Number	3	0-based ID numbering is expected, but IDs starting from 1 have been applied.
	[K-3] Wrong Return Type	10	Return Boolean is expected, but Return Integer, especially zero that is considered False, has been implemented.

Table 6 and 7 describe the taxonomy of runtime and logic errors analyzed in this study, respectively. The Name column presents the plain-language description of identified errors, the Frequency indicates the number of detected errors in our experiment, and the last column explains how the root causes induce the particular errors. We explain these errors and their root causes based on the origins of faults from Users, Models, and Models during Debugging.

User-Originated Errors. There are 11 categories of runtime and logic errors that primarily arise from the user's provision of insufficient context, mistakes, or misunderstandings regarding the content of the design document. For instance, the [T-1] errors in Table 6 occur when participants copied and pasted only certain parts of the code, specifically omitting the initialization of new objects, from the responses generated by the GPT in the WebUI. This led to conflicts between the original initialization of list objects and the usage of new objects in the final code. Other error types, such as [A-3] and [L-10], stem from users' misunderstandings of the design document as follows: In the Cognitive Verifier pattern, GPTs inquired about the "Immutability" of attributes within specific classes, but participants provided incorrect responses. Additionally, in the case of [L-10] errors, one participant mistakenly defined the acceptable string conditions as "1 or 50" instead of the correct range of "1 to 50."

Table 7. Taxonomy of Logic Errors (i.e., Failures) Identified in Our Experiment

	Error Name	Frequency	Explanation
	[L-1] Wrong Return Type	10	Expected to return Boolean, but return Integer, especially 0 that is considered False.
	[L-2] Rounding Issue	4	Too strict rounding strategy on floating values, which is not required.
	[L-3] String Cleaning before Validation	2	String values are preprocessed and cleaned before the validation.
	[L-4] Existing Condition Overlapped	12	Existing conditions are omitted by refining codes for satisfying different test cases
Logic Error (i.e., Failure)	[L-5] Existing Function Name Overlapped	14	Existing function names are overlapped by random function names during debugging phase
	[L-6] Expected to Raise Error, but No Error Raised	58	Wrong conditions failed to handle exceptional inputs
	[L-7] Missing Conditions	61	Conditions for checking ranges of numbers or string exceptions are omitted in implementation
	[L-8] No dependency with other classes	66	One class contains List/Dictionary named with dependent Classes, not the Class objects
	[L-9] Function Location Error in Debugging Multiple Classes	15	Move one function from the originally located class to another class, and Generate a new function that works similarly with different names in the original class
	[L-10] Wrong Boundary Setting	13	Wrong boundary for integer variable was set

While we found that these minor user-side faults result in fatal errors, most user-originated errors are caused by GPTs' hallucinations when faced with incomplete context while developing functions and classes. There are eight types of errors associated with this issue, categorized as [T-2,3], [A-5], [V-3,5], and [L-1,6,7], all of which arise from insufficient information provided by the users. For instance, [T-2] errors occur when participants fail to specify the output data structure required for specific functions. The hallucination due to a lack of context also occurs when unclear descriptions of conditions within various functions are given. Another example is the multi-class dependency error [T-3], which occurred when participants did not include the definitions or code for dependent classes, such as Product or ShoppingCart, in their prompts when requesting the development of another class, like EcommerceApp. However, we found that GPTs have already developed dependent classes within the same chat session. This indicates that although GPTs have generated classes with the same names previously, they have weaknesses in handling multi-class dependencies intelligently, resulting in the implementation of List or Dictionary attributes with the same names as previously developed classes.

In our analysis of insufficient context errors, we identified another pattern: participants with a higher score of Algorithm Solving Experience (defined as a score greater than 75) typically created context manually during the initial development phase, rather than copying and pasting directly from the design description. Although some participants copied and pasted context from the provided document during the debugging phase, the GPTs struggled to identify the appropriate fixes for code that already contained hallucinated structures. This indicates that relying solely on manual context formulation may lead to hallucinations due to insufficient information about the functions and classes involved.

While minor mistakes and misunderstandings of context from users can lead to a significant number of errors, it is advisable for GPT users to provide sufficient context when developing target functions or classes, especially for multi-class dependencies. Manual context formulation is not recommended without copying and pasting the original specification, as it increases the risk of hallucinations on missing details.

Model-Originated Errors. The other 18 categories of errors arise from the misbehavior of GPTs, despite users providing the appropriate context in their requests. Among these 18 types, 13 error patterns occurred during the initial implementation phase, as listed in Table 6 as [A-1,2], [V-1,2,4,6], and [K-1,2], and in Table 7 as [L-2,3,8].

AttributeErrors: [A-1,2] primarily result from missing required attributes or the incorrect use of parameter types in specific functions when they are called. For example, the `_init_()` method in the `Order` class is defined to accept a parameter `ItemList: List`, but GPT-generated code incorrectly calls the method with a parameter of another class, `ShoppingCart`, instead of the expected `List`. Another attribute-related cause of `ValueError`, noted as [V-4], appears in the following scenario: A participant requests the development of a `Product` class with adequate context, but GPT unexpectedly inquires about stock management, which was not included in the request. When the participant clarifies that stock management should not be considered, GPT still generates this attribute in the class and introduces stock-related conditions, resulting in value errors.

Most of the root causes of the `ValueError` stem from issues in developing incorrect conditions from GPTs. Specifically, 66 `ValueErrors` are caused by the incorrect regex condition settings in [V-1], while 30 `ValueErrors` arise from improper combinations of AND and OR in a single if statement in [V-2]. Additionally, cases in [V-6] reveal missing conditions from the required sets. Many of these errors are related to string processing functions, such as `String.strip()` and `String.lower()`. These functions are often implemented in an OR relationship within a conditional statement when they should be combined with an AND.

An interesting root cause of the missing condition errors arises from the use of the *Alternative Approach* pattern. We found that when GPTs generate three different answers based on the prompt pattern, the in-depth context information given by the users is only applied to the first answer. In contrast, the two subsequent answers often contain hallucinated conditions appearing to be developed without the concrete conditions. However, in all these cases, GPTs tend to recommend the second or third answer, which contains these hallucinated conditions, highlighting the persuasive strengths of its structure. Participants in our experiment generally followed these suggestions.

Similarly, `KeyErrors` are mainly caused by (1) improper implementation of the `Key` type in a `Dictionary` about the specified requirements, and (2) counting IDs starting from 1 instead of 0.

In `LogicErrors`, we found that these error types of [L-2,3] are caused by similar root causes to other `RuntimeErrors`, except for the [L-8] error. For example, in the first project-level task, this error returns the main class, `EcommerceApp`, with no or partial connection to other preceding classes, such as `Product` and `Order`. Instead, GPTs generated `List` or `Dictionary` objects with the same name and save corresponding information in those ad-hoc objects. The key distinction between these errors and those categorized as User-originated errors is that, in this case, relevant information about the classes was provided in the request. Nevertheless, GPTs were unable to develop the multi-class dependency correctly. Our empirical inference suggests that the primary cause of these errors was related to the context window size. Errors occurred when participants copied and pasted the entire content of the design document while asking for the development of the `EcommerceApp`. Because the `EcommerceApp` uses all four other classes, the coverage of information used by the participants may not be incorrect. Still, they appended too many redundant details of the comprising functions in each class. These findings further clarify the superior performance of the *Few-Shot* pattern, which includes well-abstracted information for one of the dependent classes in its example content.

Even with the proper context, GPTs still have the uncertainty of producing erroneous code. This uncertainty increases when users request multiple solutions for optimized decision-making or when they get excessive and redundant details. It is essential to clearly describe the necessary context and allocate sufficient time for thorough debugging processes to minimize uncertainties.

Errors Occurred in Debugging Phase. The remaining five categories of errors are described in Table 6 as [A-4,5] and in Table 7 as [L-4,5,9]. These errors are all caused by the GPTs in generating patches of existing code. For example, the [A-4,5] errors arose from the unexpected removal of attributes in fixing and the change of parameter orders in specific function calls, respectively. Similarly, [L-4,5] errors have root causes of (1) omission of certain conditions in corresponding functions and (2) name changes of functions. These errors share a common point in that the newly added error parts are not directly relevant to the actual fixing locations.

The [L-9] error presents a multi-class dependency issue in fixing logic related to multiple classes. In this error, the `add_to_cart()` function, located initially in the `ShoppingCart` class, is moved to another `User` class, followed by adding a fixed logic in a new function called `add_items()` in the `ShoppingCart` class. This indicates that the uncertainty in GPTs can lead to confusion about the multi-class dependencies and induce side-effect errors.

During the debugging phase, GPT users should be aware of the risk of code overlap with the original code, particularly in multi-class fixing scenarios, where the side-effect errors need to be carefully reviewed.

5.5 Threats to Validity

Internal Validity. Some screen recordings or GPT chat logs are unavailable for certain participants. For instance, one participant who joined via their Ubuntu environment could not use the screen recording tool we prepared. Consequently, we concentrated on examining GPT chat logs for the three participants who could not provide a screen recording. However, the communication logs from OpenAI lack time stamps, so we inferred the approximate timeline for the code generation and fixing phases based on their prompt logs. Additionally, some issues exist in GPT logs due to OpenAI's logging limitations. When we have restricted access to request and answer logs, we primarily use the screen recording files. Additionally, to ensure serious engagement from participants in our experiments, we distributed the rewards: 50 USD for 90 minutes of participation after reviewing all the submitted files.

External Validity. Since our experiment was conducted online and offline, we prepared printed and PDF versions of the design documents for the Project-level tasks. We observed that some participants primarily focused on understanding the printed material and formulating prompts, while others copied content from the PDF files. Our analysis revealed that using printed or PDF materials does not impact the experiment results. Instead, a deeper understanding of the problem and its requirements appears more significant. We found that most participants who merely copied the PDF materials without comprehending them did not achieve first and second quartile productivity in our experiment.

Construction Validity. Our study defined productivity by considering the accuracy of outcomes, task-solving efficiency, and subjective evaluations of development satisfaction. However, traditional productivity measures also consider maintenance, security, and reusability [4, 21, 30, 36]. We anticipate that this future analysis will provide insights into which GPTs or prompting strategies are likely to produce high-complexity, vulnerable, or duplicated code.

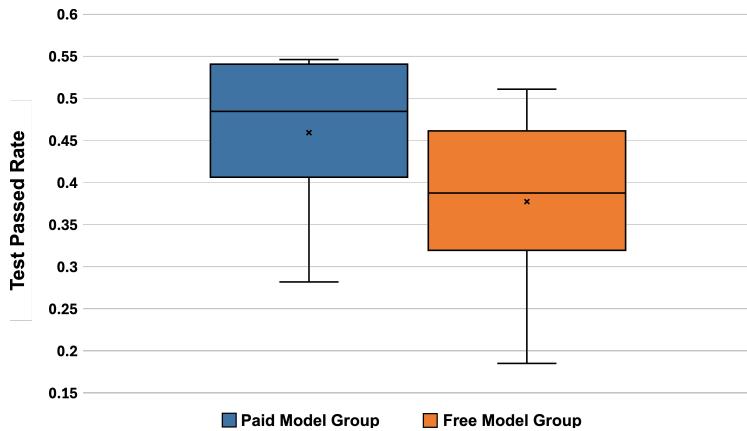


Fig. 8. TPR Comparison with Paid and Free GPT Groups

Conclusion Validity. In our analysis, we recruited 36 participants to encompass various user backgrounds and experiences. While we aimed to diversify these backgrounds and gather representative data from each experimental perspective, we could not cover all combinations of the features for each participant and concentrated on GPT models due to the user's familiarity. Especially, this combinatorial coverage is essential for detailed correlation and impact analysis of the features. Nevertheless, our study considered various factors of user experiences in the statistical and empirical analysis of human GPT interaction processes.

Additionally, we conducted a statistical analysis for 36 participants, which is a relatively small sample size. To address the statistical risks related to the sample size, we employed a systematically designed statistical analysis process. We only utilized non-parametric statistical methods that are recognized for their effectiveness in analyzing small sample sizes through ranking and frequency-based analysis. Additionally, we evaluated the effect size and posthoc power or stability values of the outcomes, incorporating only those with power or stability values above 80, which is a commonly accepted threshold for the power values. Finally, we manually examined all the data and empirically assessed the statistical findings.

6 Discussion

General Discourse: Better Model vs Better Prompting. In LLM applications, there is an ongoing debate about whether to focus on improving the models themselves or on developing more effective prompting strategies to enhance performance. The investigation of our experiment results revealed that while both aspects are synergistic, the prompting strategies should be emphasized more in the code generation task.

Fig. 8 illustrates the code generation productivity results, TPR values, for the Paid and Free GPT groups among 24 participants in the project-level task. On average, the Paid group achieved a productivity level that is 12.2% higher than that of the Free group. However, statistical analysis using the Wilcoxon-Rank-Sum test yielded a p-value greater than 0.05, indicating that there is no significant difference in distribution between the two groups. In contrast, we observed that different prompting strategies generated substantial differences within both the Paid and Free GPT groups. For example, the Few-Shot prompting pattern outperformed all other patterns within the Free GPT group, although it had a power value of only 0.56. In the Paid group, the Spearman's correlation test [37] revealed that the time distribution

feature significantly affects the TPR values, with a p-value of 0.004 and a power of 0.84. These results indicate that there exists a statistically different distribution of productivity by different features in the same GPT group.

Based on the investigation outcomes through RQs and the analysis results of the Paid and Free groups, our findings suggest that the prompting strategies, involving context curation methods, strategic processes, and prompting patterns, can significantly impact code generation productivity. Additionally, the Paid GPTs, referring to better models, may add a synergistic benefit to the prompting strategies.

HLI Features on Different Roles in SE Process. In the SE process, several roles exist, including Architecture Designer, Software Engineer, and Tester [26]. Our study aimed to examine the one-to-one interactions of human engineers with GPT assistants for code generation. Therefore, we defined a set of 15 features that are known to impact and are expected to affect the code generation productivity during the HLI processes. We believe this research scope can be expanded to include multi-role and multi-participant experiments to assess the GPTs' effectiveness in a more scalable environment with multilateral aspects. For instance, after fine-tuning GPT agents for various roles in SE processes, one or more roles can be substituted with human participants with specific experience. In this case, a different HLI feature space, including experience on specific roles (e.g., architecture designer) or combined sets of multiple prompting patterns for different roles, can be defined and assessed throughout the experiment. We believe our project-level task design and a set of HLI features for code generation productivity can serve as a foundation for designing the multi-role user study, covering different roles in the SE process.

7 Conclusion

Our study designed and conducted an experimental analysis of the most productive prompting strategies for interacting with GPT assistants in multi-level code generation tasks. This research has contributed to the LLM-driven software engineering field by (1) introducing a novel benchmark for project-level tasks (i.e., multi-class), considering several dependency features, (2) comparatively identifying the most impactful features in the HLI process, as well as providing practical guidelines for the primary features to enhance productivity, and (3) proposing a taxonomy of 29 runtime and logic errors, followed by their in-depth root causes and mitigation plans to minimize uncertainties of GPTs in debugging phase and multi-class requests.

Our findings pave the way for exploring more productive interactions between engineers, particularly students and early-career practitioners, and GPTs in project-level code generation tasks. For software engineers, these results emphasize the value of explicitly integrating requirement details and spending focused effort on code fixing after initial implementation. Team managers may focus on streamlining development process workflows and improving team efficiency, especially in large-scale projects. Researchers can utilize our project-level benchmarks and the error taxonomy to refine or propose new prompting paradigms that address the uncertainty and dependency issues more accurately or efficiently.

We expect to conduct several future studies based on the results and artifacts from this experiment. First, we can engage in multi-role and multi-participant experiments to gain insights into collective best practices and knowledge-sharing by extending the suggested feature space in the HLI processes, such as combining multiple prompting patterns and models for different sub-tasks (e.g., code generation and explanation). Lastly, a domain-specific exploration of concrete case scenarios, including machine-learning codes or specific quality attributes (e.g., security or maintenance), may reveal how prompts should be structured for the cases.

Appendix

Class: EcommerceApp
Description: Manages the e-commerce application, coordinating user registration, product listing, and orders. Includes methods for registering users, adding products, managing the shopping cart, processing checkouts, and tracking orders.

```
Methods:  
...  
5. checkout(username: str, address: str, payment_method: str) -> int  
    • Processes the checkout for the user's current cart and generates an order.  
    • Parameters:  
        ✓ username: The username of the user checking out. ...  
    • Returns: int. The order ID if the checkout is successful, -1 otherwise.  
    • Raises: ValueError if the username, address, or payment method is invalid.  
    • In-depth Conditions: The Address length must be exactly 100 characters. ...  
    • Example Inputs/Outputs:  
app = EcommerceApp()  
app.register('johndoe', 'password123!', 'johndoe@example.com')  
app.add_product('Laptop', '999.99', 'A high-performance laptop')  
app.add_to_cart('johndoe', 0, 2)  
order_id = app.checkout('johndoe', '123 Main St.', 'credit_card')  
print(order_id) # Output: Some integer representing the order ID  
...  
6. ...
```

(a) Example Design Description for `checkout()` function in `EcommerceApp` Class

HW1 INSTRUCTION - HW1 -Few-Shop-

When you are done, provide the technically correct answer code that can solve the task based on the Reference and Examples below. You must recall that the two examples illustrate the exact I/O format you must imitate.

Question
 Please generate a Python function "check_out()" by thoroughly investigating the attached reference context information.

Reference Context
(Manual Formulation on the Reference)

In this challenge, we will be required to focus on the condition statements, In-depth Conditions, and using previously developed classes: ShoppingCart and Order.

<Copy & Paste from Design Document>

- 3. check_out(username, str; address: str; payment_method: str) >> int
 - Processes the check_out for the user's current cart and generates an order.
 - Parameters:
 - username: str
 - address: str
 - payment: int
 - Returns int: The order ID if the check-out is successful, 1 otherwise.
 - Raises ValueError if the username, address, or payment method is invalid.
- **In-depth Conditions:** The Address length must be exactly 1 to 100 characters,

<Copy & Paste from Skeleton Code>

```
class EcommerceApp:
    def __init__(self):
        self.cart = ShoppingCart()
        self.orders = []

    def checkout(selfif, username: str, address: str, payment_method: str) >> int
        pass
        ...

```

Examples##

Example1
 Question: Please develop update_email(new_email, str) function that updates the user's email address in the User class. Parameters: new_email (str). The new email address, which must be in a valid email format. Leading or trailing spaces will be cut off.

```
def update_email(selfif, new_email: str):
    new_email = new_email.strip()
    if not re.match(r'^[A-Za-z0-9]+([.-_]?[A-Za-z0-9]+)*@[A-Za-z0-9]+\.[A-Za-z0-9]{2,}$', new_email):
        raise ValueError("Invalid email")
    else:
        self.email = new_email
```

Example2 ...

(b) Example Few-Shot prompt pattern used by a participant in generating the `checkout()` function

(c) Example response of generating checkout() function

Fig. 9. Example Code Generation Practice in Our Experiment

```
### Instruction ### <Reflection>
When I ask a question, explain the reasoning behind your answer by breaking down
the steps you took to arrive at it. Additionally, provide three different perspectives or
considerations that could affect the accuracy or relevance of your answer. Once I
evaluate those perspectives and give feedback, update your response accordingly to
provide a more refined and complete answer.

### Question ###
Failures diminished, good job. But there are still more failures. Please provide with the
newly fixed code. Suggest the code first other than any other explanations.

### Reference Context ###
<Manual Formulation on the Reference>
First, categorize the below failure logs by each function and class. Then, provide
solutions for each function in the classes considering the failed messages and the
corresponding test case codes.

<Copy & Paste from Test Logs>
=====
FAIL: test_checkout_address_with_special_characters
=====
Traceback (most recent call last): File "<ipython-input-31-b55f678e13f8>", line 929, in
test_checkout_address_with_special_characters self.assertEqual(app.checkout('johndoe',
'@123 Main St$1', 'credit_card'), -1)
AssertionError: -1 == -1
=====
...
<Copy & Paste from Skeleton Code>
def test_checkout_address_with_special_characters(self):
    app = EcommerceApp()
    app.register_user('johndoe', 'Password123!', 'johndoe@example.com')
    app.add_product('Laptop', 999.99, 'A high-performance laptop')
    app.add_to_cart('johndoe', 0, 2)
    self.assertEqual(app.checkout('johndoe', '@123 Main St$1', 'credit_card'), -1)
```

(a) Example Reflection pattern used by a participant in fixing the checkout() function

```
Here's the updated code with fixes for the remaining issues. I've made adjustments to resolve the errors
and failures in the relevant methods and tests.

python
=====
class EcommerceApp:
    def __init__(self):
        self.orders = []
        self.carts = {}

    def checkout(self, username, address, payment_method):
        if username not in self.carts or not self.carts[username].items:
            raise ValueError("Cannot checkout: Cart is empty or user does not exist.")
        order = Order(self.users.get(username), self.carts[username].view_cart(), address, payment_method)
        self.orders.append(order)
        self.carts[username] = ShoppingCart() # Clear the cart
        return len(self.orders) - 1
    def track_order(self, order_id):
        ...
Reasoning for changes:
...
4. EcommerceApp Class:
    * Handled errors in adding products to cart and checking out properly.

Let me know your evaluation of these changes!
... 
```

(b) Example response of fixing the checkout() function

Fig. 10. Example Debugging Practice in Our Experiment

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Data Availability Statement: The datasets utilized and generated during this experiment, along with the benchmark information, can be found in the Supplementary Material. Due to our research institution's strict intellectual property policy, this data is currently available for review purposes only. However, we intend to make all the data accessible as an open benchmark repository after the review process is complete. The sample Benchmark information is also included in the Supplementary Material. Please note that we cannot provide screen recording videos or GPT chat logs that contain personal information. Instead, we have included participants' survey responses and code outcomes with all the experiment files used in this research.

Conflict of Interest: All authors certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Clinical Trial Number: Not applicable.

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