

Evaluation of ChatGPT Usability as A Code Generation Tool

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Abstract—With the rapid advance of machine learning (ML) technology, large language models (LLMs) are increasingly explored as an intelligent tool to generate program code from natural language specifications. However, existing evaluations of LLMs have focused on their capabilities in comparison with humans. It is desirable to evaluate their usability when deciding on whether to use a LLM in software production. This paper proposes a user centric method. It includes metadata in the test cases of a benchmark to describe their usages, conducts testing in a multi-attempt process that mimic the uses of LLMs, measures LLM generated solutions on a set of quality attributes that reflect usability, and evaluates the performance based on user experiences in the uses of LLMs as a tool. The paper reports an application of the method in the evaluation of ChatGPT usability as a code generation tool for the R programming language. Our experiments demonstrated that ChatGPT is highly useful for generating R program code although it may fail on hard programming tasks. The user experiences are good with overall average number of attempts being 1.61 and the average time of completion being 47.02 seconds. Our experiments also found that the weakest aspect of usability is conciseness, which has a score of 3.80 out of 5. Our experiment also shows that it is hard for human developers to learn from experiences to improve the skill of using ChatGPT to generate code.

Index Terms—Machine learning; Large language models; ChatGPT; Code generation; Performance evaluation; Usability; R programming language.

I. INTRODUCTION

The past few years have seen a rapid growth of machine learning (ML) techniques in the development of large language models (LLMs). The most advanced LLMs like ChatGPT¹ and Gemini² have demonstrated their impressive performance in completing natural language processing (NLP) tasks [1]. Although their primary goal is for NLP, they have also shown the capable of performing various programming tasks with input in natural language and/or partially completed program code, because some of them have included program codes in their training dataset in addition to large volumes of natural language texts. Typical examples of such LLMs include OpenAI's GPT-3.5 underlying ChatGPT and Google's LaMDA model underlying Bard. Another approach to achieve the capability of performing coding tasks is through fine tuning of a pretrained LLM with program code datasets to

build special purpose intelligent programming tools. Well-known examples of such systems include the Codex model underlying GitHub's Copilot. Many ML models have also been purposely built for various programming tasks. For example, AlphaCode [2], InCoder [3], StarCoder [4], PolyCoder [5], Replit's Ghostwrite³ and Tabnine⁴ have been developed for code completion, code generation, code comment summary generation, and debugging (code correction) tasks. ChatUnitTest [6], TestPilot [7], etc. are for the generation of test codes; see [8] for a survey. It is widely believed that it is becoming practical to automatically generate program code from natural language inputs; see, for example, [9]–[11].

However, a research question remains whether such ML based intelligent programming tools are useful for software development. Existing testing and evaluation of LLMs have focused on their capability in comparison with human intelligence. The evaluation results hardly represent LLM's usability from a user's point of view as a software development tool. Meanwhile, evaluations of LLMs reveal that LLMs like ChatGPT “*is still far from achieving the ability to reliably solve many challenging tasks.*” [12], [13] Moreover, they seriously suffer from the so-called hallucination problem, i.e., producing plausible sounding but incorrect or nonsensical answers [14].

Therefore, it is highly desirable to systematically test and evaluate LLMs' usability as an intelligent tool for generating program code. In this paper, we propose a user centric approach to the testing and evaluation of LLM's usability as code generation tools. Its applicability is demonstrated in a case study on testing and evaluation of ChatGPT's usability for generating program code in the R language from natural language input of functional specifications.

The paper is organized as follows. Section II reviews related works and discusses the problems associated with the existing methods of testing and evaluation of LLMs' capability of coding. Section III presents the proposed user centric methodology. Section IV is devoted to the experiment results and the main findings. Section V concludes the paper with a summary, an analysis of the potential threats to the validity and generalizability of the experiment results, and a discussion of the directions for future work.

¹<https://openai.com/chatgpt>

²<https://deepmind.google/technologies/gemini>

³<https://replit.com/>

⁴<https://www.tabnine.com/>

II. RELATED WORK

Evaluation of ML model’s performance is indispensable to ML research and application. A great amount of work has been reported in the literature. Here we focus on related work at two levels: the evaluations of LLMs in general and the evaluations of LLMs’ capability of code generation from natural language functional specifications.

A. 2.1 General Evaluation of LLMs

The announcement of a new ML model or the proposal of a new ML technique commonly accompanied by a report on the evaluation of its performance. Such evaluations typically use common datasets to compare ML models to demonstrate one model’s superiority over others. This evaluation method is called *benchmarking*, and the datasets are called *benchmark datasets*, or shortly *benchmarks*.

For example, the recent launch of Gemini [1] reports the performances of two versions of the ML model, i.e. Gemini-Ultra and Gemini-Pro, on many tasks of multi-modal language processing, which include multi-task language understanding, general reasoning, mathematical reasoning, and program code generation. It is compared with many front runners of LLMs, such as GPT-4, GPT-3.5, Palm 2-L, Inflection-2, Grok 1 and LLAMA-2. Table I lists some commonly used text datasets to benchmark LLMs on natural language text processing tasks. They are also used by Gemini team [1].

TABLE I
COMMONLY USES BENCHMARKS FOR NLP.

Name	Dataset
MMLU [15]	Multichoice questions in 57 professional and academic subjects.
GSM8K [16]	Graduate school math questions.
MATH [17]	Mathematics problems across 5 difficulty levels and 7 subdisciplines.
BIG-Bench-Hard [18]	Hard Big-Bench tasks written as CoT problems.
HumanEval [19]	Python coding tasks.
Natural2Code [1]	Python code generation problems.
DROP [20]	Reading comprehension and arithmetic problems.
HellaSwag [21]	Common sense multiple-choice questions.
WMT23 [22]	Machine translation problems.

Independent evaluations of LLMs also follow the same paradigm of benchmarking. For example, Laskar et al. [13] evaluated ChatGPT on 140 tasks including code generation using the HumanEval and MBPP datasets [23].

It is worth noting that the evaluation of LLMs has all focused on their capability of performing tasks in comparison with human intelligence rather than their usability as a tool.

B. Evaluation of LLMs on Code Generation

As discussed in the previous subsection, the capability of code generation is included in many of the general evaluation of LLMs. Much more work on the evaluation of LLMs’ capability of code generation has also been reported in the literature with the development of intelligent coding tools. Several datasets have been constructed and corresponding evaluation methods advanced.

The APPS dataset developed by Hendrycks et al. in 2021 [24] is perhaps the first benchmark for code generation from natural language input as functional specification. Earlier works have been reported in the literature for other coding tasks. For example, in year 2019, Kulal et al. evaluated the SPoC model, which generates code from pseudocode written in natural language [25]. In year 2020, Lachaux et al. evaluated a ML model for code translation [26].

Strictly speaking, Kulal et al.’s SPoC model does not belong to code generation from natural language functional specifications. The input to SPoC consists of a pseudocode and a set of test cases. However, they set two important milestones on the method of evaluating ML model’s performance on coding tasks. One is how to check the correctness of the generated code and the other is a metric to measure the performance of the ML model. These have become the common practice now.

How to check the correctness of generated code automatically is an important issue. In the evaluations of NLP capabilities, the common approach is matching output with reference solutions either exactly or fuzzily, for example, using the ROUGE and BLEU metrics. However, for code generation, ROUGE and BLEU cannot capture the semantics of code. For example, Hendrycks et al. compared BLEU score with testing correctness [24]. They found that “*BLEU increases as problem sources become more difficult, even though models actually perform worse on harder problems. Moreover, worse models can have similar or higher BLEU scores*” [24]. Chen et al. also pointed out that similarity metrics like BLEU score may not be a reliable indicator of functional correctness [19]. They also provided evidence that functionally inequivalent codes often have high BLEU scores. Ren et al. revised the BLEU metric and proposed CodeBLEU [27] to address the problem that the BLEU metric does not take the features of programming language syntax into consideration. However, the heart of the problem is that a coding problem can have many functionally equivalent solutions that are syntactically dissimilar to each other. In [31], Lai et al. used a much-relaxed form of similarity metric called surface-form constraints as a supplement to test correctness criterion discussed below. A surface-form constraint that requires the presence/absence of certain specific APIs and/or the keywords to occur in the solution code.

An alternative to the uses of similarity metrics is to test the correctness of generated code. Borrowing the ideas of test-driving software development methodology, Kulal et al. proposed “pass test cases” as the correctness criterion to emphasize the importance of functional correctness over text similarity. Each code generation problem is therefore associated with a set of test cases. Du et al. further requires that the set of test cases to be highly adequate and uses test coverages of the reference solutions as measures of the quality of the dataset [28]. In [29], Liu et al. pointed out that the existing benchmark and the approach to evaluating code generation capability suffers from two problems. First, the test cases included in the task as the standard of correctness are insufficient to be a reliable criterion of correctness. Second,

the natural language specifications of the tasks are often not precise and complete enough for LLM to process. Their solution to the problems is to generate test cases automatically and check the correctness of LLM output code against the output from the ground-truth solutions.

The second milestone that Kuala et al. set is now known as the *pass@k* metric. Kulal et al. asked the SPoC model to produce 100 solutions and considered the task of code generation is successfully completed if one of these solutions is correct in the terms of passing all test cases. This led to the *pass@k* performance metrics, i.e., probability of completing tasks in k trials. However, *pass@k* tends to produce large variance [19]. The problem is addressed by Chen et al. in the evaluation of Codex [19]. They asked the model to produce a large number n of solutions on each problem, where $n = 200$, and counted the number c of solutions that pass the correctness test. They used n and c to calculate an unbiased estimator of the *pass@k* metric for $k < n$.

The APPS dataset was extracted from open-access websites where software developers share coding problems with each other, including Codewars, AtCoder, Kattis, and Codeforces. Problems that were posed as natural language specifications of what should be coded are manually polished and refined. Duplications were removed using tf-idf features with SVD dimensionality reduction and cosine similarity. Each problem is associated with test cases for checking correctness and ground-truth solutions written by humans. The dataset contains 10,000 problems, with 131,777 test cases and 232,421 ground-truth solutions. The dataset is split into three subsets according to the difficulty levels: Introductory (3,639 problems), Interview (5,000 problems), and Competition (1,361 problems).

Hendrycks et al. used APPS to evaluate several GPT models. They used two performance metrics: test case coverage and strict accuracy. The former is the average proportions of test cases on which the model passes the test. The latter is the ratio of the problems that the model passes all test cases. They calculated the overall performance of GPT models using *pass@1* and *pass@5*.

In the evaluation of Codex, Chen et al. constructed the dataset HumanEval [19]. Codex is a LLM that empowers GitHub Copilot for code generation. It is obtained by fine tuning the GPT model using data publicly available from GitHub. The HumanEval dataset contains 164 handwritten problems. Each problem contains:

- a signature, which defines the syntax format of the function to be generated.
- a docstring, which is a text in natural language that describes the function of the code to be generated.
- several unit tests, which is used to check the correctness of the code generated.

Chen et al. also used “pass all test cases” as the correctness criterion. In other words, a coding solution is regarded as satisfactory only if it passes all the test cases. The signature element of a problem in the HumanEval dataset enables the solution to be executed automatically on test cases to check the correctness of the generated code. It limits the format of

the code to be generated. Thus, the dataset can only be applied to generate code at method level. The dataset has an average of 7.7 tests per problem.

Du et al.’s ClassEval dataset [28] is a benchmark for generating code at class level while APPS and HumanEval are all benchmarks for code generation at standalone function or method level. Similar to APPS and HumanEval, each coding task in ClassEval comprises three elements: a description for the target class, a set of test cases for verifying the correctness of the generated code, and a canonical solution that acts as a reference solution. The description of the target class is a class skeleton with signatures of the methods of the class annotated with natural language texts to specify the functional requirements of the target class and methods and to describe the meanings of the parameters. The ClassEval dataset contains 100 problems to generate 100 classes with 412 methods. The data are manually curated from real-world projects and existing data from HumanEval and MBPP. An important feature of ClassEval is that they emphasized the adequacy of the test cases for the problem to facilitate reliable correctness checking of the generated code. On average, ClassEval’s test suites are of 98.2% branch coverage and 99.75 statement coverage.

Yu et al.’s benchmark CoderEval [30] aims to provide a wider range of code generation tasks. They classify code generation tasks into six levels: self-contained, slib runnable, plib runnable, class runnable, file runnable, and project runnable. According to Yu et al., APPS and HumanEval are at the first two levels. The dataset contains 230 tasks for Java and 230 for Python code generation in total.

Lai et al.’s DS-1000 is a code generation benchmark specialized in Python code for data science problems [31]. It contains 1000 coding problems collected from Stack Overflow to reflect natural or real-world coding problems. The problems are also manually modified to create executable context, add reference solutions and additional test cases, and rewrite LLM unreadable data such as figures, etc. Their evaluation of LMMs employed test correctness as well as surface-form constraints that require the presence/absence of certain specific APIs as the keywords.

C. Analysis of Existing Work

A common feature of existing work on the evaluation of LLMs is that one figure is used to represent a LLM’s performance on one type of tasks such as mathematical reasoning, text comprehension, and code generation, etc. The figure is calculated from testing the ML model on a benchmark dataset using one metric. The most important advantage of the approach is that it offers a means of relatively objective comparison of different ML techniques and models. Such benchmarking has played a significant role in the research on ML techniques as pointed out by Martínez-Plumed et al. [32].

However, the evaluations of LLMs have not reflected their usability from users’ point of view. For example, ChatGPT is popular to many users while its evaluation scores seem poor [33]. Codex only achieved a score of 28.8% on *pass@100* [19]

while many users have highly appraised its coding capability. While human testers are in favour of ChatGPT’s output on text summary tasks over other state of art ML models, its evaluation result figure based on ROUGE metric shows the other way [13]. For the following reasons, such evaluation results may not reflect the usability of the models in real usage scenarios.

First, to be a true reflection of the performance of a ML model in a specific real usage, the dataset used in the evaluation must have the same distribution as the users’ input profile. From the constructions of existing datasets, it is hard to see how these datasets represent user input profiles.

Second, the users of a ML model may have different usage scenarios. The input profiles in different use scenarios have different distributions. For example, a senior software developer may have more complicated code generation tasks while junior programmers usually have less difficult coding tasks. A front-end developer may be more likely to produce GUI program code, while a back-end developer would have more tasks to write database related code, and a data analyst would need to generate more statistics code. Therefore, their input profile will have different distributions. Consequently, one ML model having a high performance for one user may perform poorly from another user’s point of view if their usages are very different. Even if a dataset that well represents the overall usage of the LLM for the average distribution of input profiles by all users, the figure obtained from such a benchmark will not reflect the usability for a specific type of users. It is desirable to know the performances of the LLM for different types of users in different scenarios. Moreover, for many natural language processing tasks, such as to write poems and to engage in dialogues with a human user, there is no objective correctness criterion. A solution that is good enough for one user could be far from satisfactory from another user’s point of view. The evaluation of ML models on such types of tasks is inevitably subjective. Using one decimal number to represent the performance of a ML model can hardly represent all users’ assessment.

The above problems also occur in the evaluations of LLM’s capability of code generation. However, there are also a few issues specific to code generation.

First, the quality attributes evaluated in the existing work are mostly focused on correctness of the code. There is a wide range of other important quality attributes because code generation is only a part of the software engineering process. Other quality attributes, like readability, well structuredness, logic clarity, etc., are important for software maintenance, evolution and reuse. They should also be assessed. Such quality attributes are also particularly important for intelligent interactive coding environments based on reinforcement learning such as Yang et al.’s recent work on InterCode [34].

Second, a piece of code generated by a LLM is often classified in a binary way, i.e., the code is either correct or incorrect. In the real uses of LLMs for code generation, developers mostly use the generated codes as bases for further manual revision [9]–[11]. An incorrect code can also be

useful if it can be easily revised into a good solution to the problem. It is desirable to evaluate the performance taking into consideration how close are the generated codes to the required results and how easy to make such changes to get a satisfactory solution.

Moreover, the evaluation is a process of “one attempt per test case”. That is, on each test case, the LLM is invoked with one input, no matter whether it is a one-shot or multiple shot query [35], or multi-solution/multi-chances query (i.e. to generate many solutions on the same input) and the $\text{pass}@k$ metric is used for $k \geq 1$. However, in the real uses of LLMs as a code generation tool, the developers make many attempts to modify their inputs until they are satisfied with the output or give up after many attempts. It is desirable to evaluate LLMs’ performance on how many such attempts one could expect until a good solution is generated.

Finally, in the context of using ChatGPT as a code generation tool, natural language input is the human-computer interface. It is widely recognized as a great feature of ChatGPT over other means of invoking LLMs for completing coding tasks. For example, for code completion, incomplete code is the input. For debugging or code correction, incorrect code and error messages are the input. For code comment and summary generation, the code is the input. However, formulating a natural language input has been proven a non-trivial task. This raises an open question on the learnability of using LLM models. That is, how easy will the users learn formulating effective natural language inputs through the experiences of using a LLM like ChatGPT? Such evaluation is missing in the existing work on evaluation of LLMs.

III. METHODOLOGY

In this section, we propose a user centric approach to address the above problems.

The general principle of the approach is that, first, the test dataset should be constructed according to the use scenario. Second, the process of testing the ML model on each test case should be resemble how the users use it. Moreover, the outputs from the ML model should be evaluated on quality attributes that reflect the usability of the output from the users’ point of view. Finally, the performance metrics should represent user’s experience with using the ML model. By doing so, we put the user at the center of the evaluation, thus the name of user centric evaluation.

We will first outline the key ideas of the method in subsection III-A. We will then delineate the method with the evaluation of ChatGPT on its usability of generating R program code.

A. Main Ideas

Our new methodology consists of the following new features.

1) Multi-attempt testing process: In the testing of a LLM, we require the testers to try their best to complete the specified task with as few attempts as possible. Each attempt consists of formulating the best text inputs to invoke the LLM and then

inspecting the solution generated by the LLM. If the output from the LLM is unsatisfactory, a second attempt is made. The process continues until either the number of attempts reached the maximum of k , or a satisfactory solution is obtained. This leads to two performance metrics: *average number of attempts*, denoted by $\#\text{attempt}_k$, and *average time used to complete the test tasks*, or *average completion time* for short. They reflect the user experiences in the use of the LLM. The testing process better matches the process that a user typically uses a LLM to generate code than the single attempt approach and the corresponding performance metric $\text{pass}@k$.

It is worth noting that being user centric, whether a solution is satisfactory should be judged by the user. In our experiment, a guideline is given to the tester that a solution should be judged as satisfactory if it is correct when compared with the standard reference solution, or it is very close to the reference solution. A functionally incorrect solution may well be regarded as satisfactory if a minor editing of the machine generated solution will work. For this reason, when the number of attempts reached the maximum threshold, the test should not be considered as a complete failure. Instead, the quality of the result at the final attempt should also be assessed.

2) *Metadata to describe test case's usage:* Our methodology to the evaluation of ChatGPT's usability as a code generation tool is a scenario-based testing approach. Conceptually, scenario-based testing is to test a software on a series of subsets of test sets that each subset represents a specific scenario of using the system. Evaluating a ML model's performance on each subset separately can provide the detailed performance information for different usages of the system. As reported in [36], this will also enable us to identify the strength and weakness of the model in different usage scenarios, thus providing directions for future improvement of the model. However, scenario combinations may cause duplicated running of test cases. To support efficient scenario-based testing and evaluating a ML model, we propose to use metadata associated with each data item in the dataset to describe the usage scenarios that the data item represents. This can eliminate the need for duplicated execution of test cases. This paper will demonstrate this by combining the scenarios that the task is of different difficult levels with scenarios to generate different types of codes.

3) *A set of quality attributes on usability:* Based on the assumption that the code generated by a LLM will be examined and possibly revised by the human user, we propose a set of quality attributes on the usability of the solution generated by the LLM. These quality attributes are not only on the generated program code but also on the generated texts that explain the code. They reflect various aspects of how close the output of LLM is to the perfect solution, how easy to revise it to a usable solution, and how good the output is in the context of code maintenance, debugging, evolution and reuse. These attributes include accuracy, readability, structuredness, logic clarity, depth of explanations, completeness, and coverage of parameters, etc. Although such attributes heavily rely on the tester's subject assessment, they better reflect users' true

opinions on the usability of the tool. To complement such subjective metrics, we also measure the time taken to complete the task and the number of attempts the tester made to finish the task. These are objective measurements.

4) *Multi-scored metrics:* For each quality metric, the output from the LLM is assessed on the scale from 1 to 5, where 1 is the poorest and 5 the best. Each score value between 1 and 5 is clearly defined for each quality attribute to minimize the impact of subjectiveness in the assessment. It also reflects the fact that, even if a generated code is imperfect, it could still be useful after manual revision.

5) *A sequential multi-stage process to evaluate learnability:* To study the learnability of LLMs, each tester engages in a linear sequence of experiments on disjoint subsets of the test dataset, which are drawn at random from a given dataset. The performance of the system is evaluated statistically on each subset separately and compared to understand the trend of performance improvement. This enables us to study the learnability of the LLM.

In the remainder of the section, we delineate the proposed method with the evaluation of ChatGPT on its usability of generating R program code. We will present the research question addressed, the design of the experiment, the construction of our benchmark dataset and the performance evaluation criteria applied. The results of the experiment will be presented in Section IV.

B. Research Questions and Experiment Design

Our goal is to evaluate ChatGPT's usability as a tool of generating program code in R language. The following are the specific research questions.

- RQ0: How good is the usability of ChatGPT as a R program code generation tool? Here, usability is measured in terms of (a) the quality of the generated code as measured on various usability attributes, (b) the user's experiences in using ChatGPT as measured by the average number of attempts, and the average completion time.
- RQ1: How good is the usability of ChatGPT when it is used to solve coding problems of different levels of difficulty?
- RQ2: How good is the usability of ChatGPT when it is used to generate different types of program code?
- RQ3: How easy to learn the uses of ChatGPT as a code generation tool?

To answer these research questions, we first constructed a benchmark. Then, five disjoint test subsets T_0, T_1, \dots, T_4 were drawn at random from the benchmark. These test sets are of equal size, which consists of 20 test cases. Since these test sets are drawn at random, each of them contains various types of questions and various levels of difficulty, and from different sources.

The experiments are conducted with the same subject (i.e., a human tester) who is a master degree student studying on a data analytics program but has no experiences in the use of ChatGPT before the experiment. The testing of ChatGPT is performed sequentially from T_0 to T_4 .

In the experiment, each test case is a task to be completed by the tester by using ChatGPT. The tester is required to formulate a query to invoke ChatGPT with the coding question. The output from ChatGPT is recorded and checked. If the output from ChatGPT is not satisfactory in terms of the correctness of the generated code, a further prompt is submitted to ChatGPT. This is repeated until a satisfactory output is obtained or it is terminated after 10 cycles of input/output. Each cycle is called an *attempt*. The time used to complete the task on each test case and the number of cycles engaged with ChatGPT were also recorded. The final output is then assessed on a set of quality criteria presented in the next subsection.

Statistical analysis is conducted on the union T of these test sets, i.e., $T = T_0 \cup T_1 \cup \dots \cup T_4$, for the overall performance of ChatGPT to answer research question RQ0. The test set T is then split into subsets according to difficulty level and types of program code to answer research questions RQ1 and RQ2 using the metadata associated with the test cases without re-executing them. To answer research question RQ3, the tendency of performances changes is analyzed separately on the disjoint subsets T_0, T_1, \dots, T_4 .

C. Construction of Dataset

As far as we know, there is no existing dataset available for generating R program codes. Being a special purpose language targeting data analysis and statistics, R contains many special features. General datasets of code generation and for other languages cannot provide a fair evaluation. Therefore, we constructed a dataset specifically for the generation of R program code.

1) *Source of Data*: The data are gathered from exercise questions of accredited R programming textbooks, which covers a wide range of topics, including uses of various language facilities and libraries, numerical calculations, data structural manipulations and transformations, data visualization and statistical analysis, etc. The questions are of different difficulty levels. The questions are well presented as they are from well written textbooks. These books are primarily used in the IT industry to educate and train professional programmers who have no experience of programming in the R language. We have collected all questions from six textbooks given in references [37]–[42]. They are referred to as B1 to B6, respectively, in the sequel.

Each test case in the benchmark contains the exercise question as the programming task and the answer provided by the textbook as the reference solution of the task.

2) *Metadata*: In addition to the question and the reference solution, we also contain the following metadata to each question in order to support scenario-based testing.

(a) **Difficulty Levels**. For each programming task in the benchmark, a difficulty level is assigned manually according to the following criterion.

- *Easy*: when the program code to be generated consists of a small number of lines of code that is essentially a simple invocation of a library function.

- *Medium*: when the program code to be generated has about 10 lines of code that is beyond a simple invocation of predefined functions. However, it does not involve complicated data structure and algorithms.
- *Hard*: when the program code to be generated is more complicated than ten lines and requires more complex data structures and algorithms.

(b) **Types of Questions**. For each question in the benchmark, a type is assigned according to the type of code to be generated. We classify coding questions into the following types.

- *Numerical*: The task is to generate a numerical calculation program for a given calculation formula or equation.
- *Statistical*: The task is to generate a program that performs statistical analysis of a dataset, such as a code to do linear regression.
- *Structural*: The task is to change the structure of data, for example, to remove or add a feature from/to the elements of a dataset.
- *Programming*: The task is to use a particular language facility in problem solving, such as to use a loop statement, input/output statement, etc.
- *Visualization*: The task is to generate a code to visualize a dataset, such as to create a plotting graph, etc.
- *Exploratory*: The task is to generate code that performs exploratory analysis of a given dataset.

(c) **Sources of the data**. The source of a question is also provided as a metadata of the test case. Since our questions are all from textbooks, the metadata contains the title of the book, the year of publication and the chapter of the book where the original question is in. This metadata is potentially useful to analyze how well a LLM deals with new programming tasks and uses new libraries and facilities of the R programming language, although it is not used in the experiments reported in this paper.

The data are represented in JSON format. Figure 1 shows the structure of the JSON representation of test cases. An example is given in Figure 2.

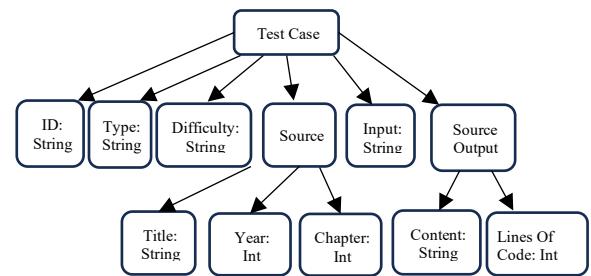


Fig. 1. Structure of JSON Representation of Test Cases.

The dataset contains 351 test cases in total. Table 1 shows the statistical characteristics of the dataset. Each row of the table gives the number of test cases of a specific feature given in the first column from different sources in column B1 to B6

```

{
  "ID": "TTH20",
  "Type": "Numeric",
  "Difficulty": "Hard",
  "Source": {
    "Title": "R for Everyone: Advanced Analytics and Graphics, 2nd Edition",
    "Year": "2017",
    "Chapter": "13",
    "Input": "What is the R Code that creates a list containing the elements shown below, named 'theList', creates a new list labelled 'theList3', this is identical list to 'theList', then creates a new factor variable 'E', which is composed of a vector of 'A, B, C' and has an argument that specifies that the factor has ordered levels? Then, what is the R Code used to check the class of 'E' within 'theList3'?",
    "Element A": "A 3x3 matrix with values from 1 to 9.",
    "Element B": "A vector containing values from 1 to 5.",
    "Element C": "A 2x2 matrix with values from 1 to 4.",
    "Element D": "A single numeric value, 2."
  },
  "Source Output": {
    "Result": "TTH20_Source_Output.png",
    "Source Number of Lines": 5
  }
}

```

Fig. 2. Example of test case represented in the JSON format.

and the total number in the column Total. The final row shows the total number of test cases from each source.

TABLE II
STATISTICAL CHARACTERISTICS OF THE DATASET

Feature	B1	B2	B3	B4	B5	B6	Total
Easy	26	32	19	12	27	14	130
Medium	29	36	15	11	25	10	126
Hard	25	28	10	10	13	9	95
Numerical	10	14	8	9	13	8	62
Statistical	12	15	6	4	17	6	60
Structural	16	17	10	5	9	9	66
Programming	20	22	12	8	7	4	73
Visualization	16	18	8	4	15	4	65
Exploratory	6	10	8	3	4	2	33
Total	80	96	44	33	65	33	351

D. Quality Attributes and Evaluation Criteria

The solution produced by ChatGPT is assessed on the following criteria.

(1) **Accuracy:** The correctness and accuracy of the LLM model's response in comparison with the standard answer to the programming question. It is assessed through executing the code produced by ChatGPT and the standard answer to the coding question. Their outputs are compared to see if the generated code gives correct output.

(2) **Completeness:** the completeness of the solution that covers the requirements of the programming question. It is assessed by comparing the functionality of the code generated against the coding problem.

(3) **Structuredness:** the structure of the code generated and formatted. It is assessed by inspection of the code on how well the code is structured and organized.

(4) **Conciseness:** The conciseness of the code produced by ChatGPT without compromising functionality. This is assessed by review of the code in comparison with the standard

answer. Typically, the generated code and standard answer are compared on the number of lines of code.

(5) **Logic clarity:** the coherence, soundness, and clarity of the generated code. This is examined and assessed via review of the code to identify inconsistencies or logic errors.

(6) **Parameter Coverage:** how well the parameters provided in the coding question are used or covered in the solution produced by the LLM model. Here, “parameter” refers to the coding elements given in the question like dataset name, variable name, data values, function names, library code names, etc. This is assessed by inspection of the code to measure if all coding elements in the question were used and appropriately incorporated in the solution.

(7) **Readability:** the easiness for human readers to read and understand the produced solution. This is assessed by a human tester to read the produced solution and attempt to understand it, where a solution typically includes pieces of code together with natural language explanations.

(8) **Depth of Explanation:** the quality of the textual explanation produced together with the code. This is assessed by reviewing the text produced by the language model accompanying the code and provides explanation of the generated code. It focuses on how well the text explains the code in a comprehensible and understandable way and to elucidate the rationale behind the code.

For each criterion, the performance of the LLM model is scored in the scale from 1 to 5, where 1 is the worst and 5 is the best. Table III gives the criteria to assess the logic clarity of the generated solution. The criteria for other quality attributes can be found in Appendix A.

TABLE III
ASSESSMENT CRITERIA FOR LOGIC CLARITY

Score	Criterion
1	The response lacks logic and has no clear flow of thought as demonstrated in the code.
2	The response demonstrates some flow of thought, but it contains many lines of code misplaced.
3	The response demonstrates a flow of thought, but some lines of code are misplaced.
4	The response demonstrates a clear logic flow of thought but could be improved by minor rearrangement of the code.
5	The response demonstrates a clear flow of thought, and the code is logically well ordered.

IV. EXPERIMENT RESULTS

This section reports the experiment results.

A. Overall Performance

To answer research question RQ0, the overall performance of ChatGPT on its capability of generating R language code is analysed on all test cases in the test set $T = T_0 \cup \dots \cup T_4$. The experiment results are shown in Figure 3 with the average performance scores on various quality criteria.

As the data shows, on average ChatGPT performed very well on all quality criteria except conciseness, which has an overall average score of 3.80 out of 5, i.e., 76%. The second

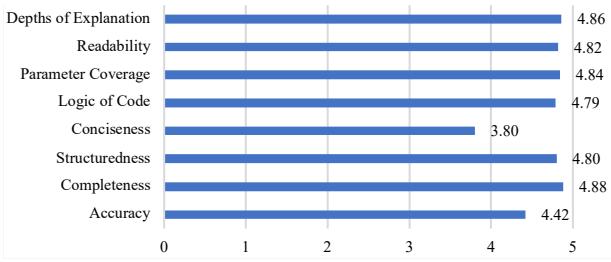


Fig. 3. Average Performance Scores on Quality Criteria.

weakest quality aspect is accuracy, which has an average score of 4.42 out of 5, i.e. 88.4%.

ChatGPT also performed very well on objective metrics, i.e. the number of attempts and the time to complete the task. Figure 4 shows the distribution of the numbers of attempts. The average number of attempts is only 1.61. Among 100 test cases, 72% is completed with one attempt, 14 with 2 attempts, 6 requires 3 attempts. On 98% of the test cases, ChatGPT successfully generates accurate results with less than or equal to 5 attempts. Only 2 test cases required more than 5 attempts, where one completed the task with 7 attempts, while on only one test case it failed to generate a satisfactory result after 10 attempts.

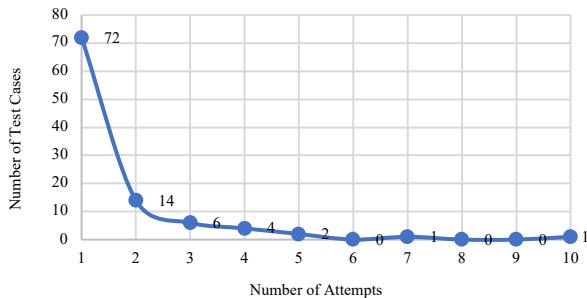


Fig. 4. Distribution of the Numbers of Attempts.

The time to complete the task is mostly spent on formulating text inputs as the queries to the ChatGPT and reviewing the output obtained from ChatGPT. ChatGPT responds to queries so fast that the time is negligible. Figure 5 shows the distribution of the time needed to complete the task of generating R code, where X-axis is the time required to complete the task of generating R code, Y-axis is the number of test cases. The average of completion time is only 47 seconds while the median is 31.50 seconds. It is worth noting that 90% of test cases can be completed within 100 seconds, while 98% of test cases were completed within two and half minutes. The two cases that required more than 5 attempts took more than 180 seconds, where one of them was given up after 10 attempts, which took 462 seconds, which is less than 8 minutes.

The objective metrics of performance confirmed our conclusion that ChatGPT's capability of code generation is satisfactory in general.

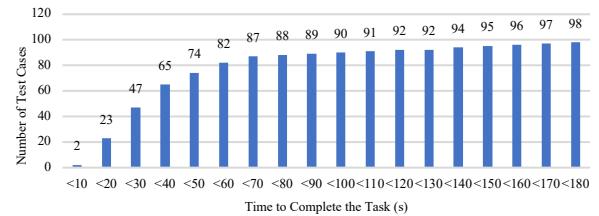


Fig. 5. Distribution of Completion Times (Seconds).

B. Types of Code to Generate

A detailed analysis of ChatGPT's performance on generating different types of R code reveals that it has the best performance on generating general programming type of code, while weakest in generating visualization and exploration type of code. The average total performance scores on different types of questions are depicted in Figure 6.

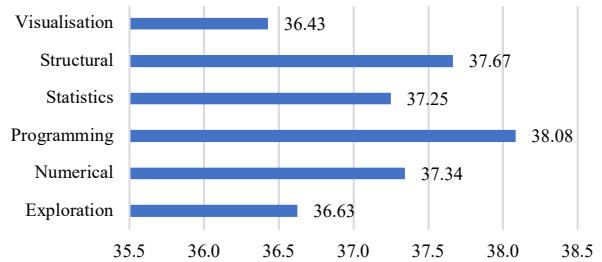


Fig. 6. Average Total Scores of Various Types of Questions.

The data shows that ChatGPT scored an average of 38.08 out of 40 (i.e. 95.2%) on general programming questions, 36.43 (91.1%) on visualization and 36.63 (91.6%) on exploration.

The observation that ChatGPT is weakest on the generation of visualization code is confirmed by the analysis on the objective metrics, i.e. the average number of attempts and the average time to complete tasks; see Figure 7 and 8.

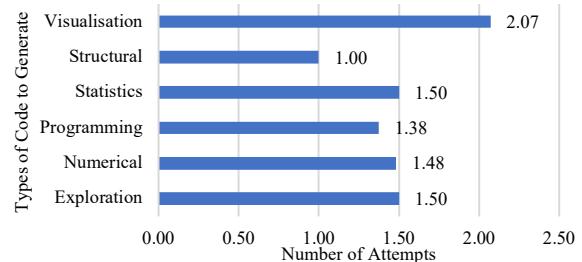


Fig. 7. Average Numbers of Attempts to Complete Tasks of Generating Various Types of Code.

The distributions of attempts and task completion times are shown in Figure 9 and 10, respectively.

Figure 11 shows the average scores of various quality attributes for generating visualization type of code. The data shows that conciseness is the weakest aspect of quality on generating visualization code, which scored 3.43 out of 5, i.e. 66.8%.

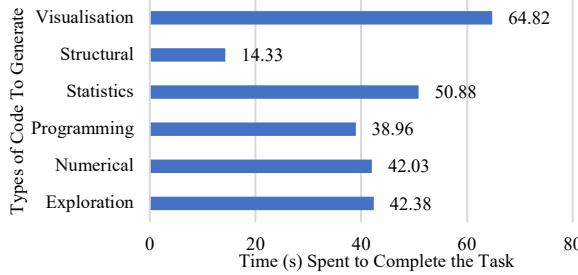


Fig. 8. Average Completion Times on Tasks of Generating Various Types of Code (Seconds).

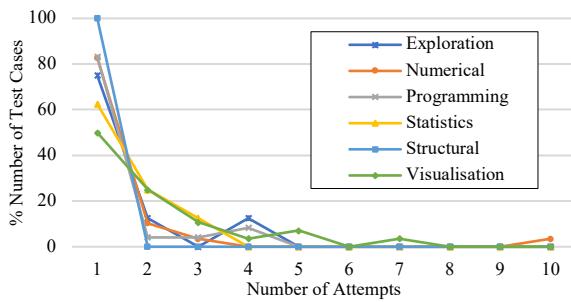


Fig. 9. Distributions of The Numbers (%) of Attempts to Complete Tasks of Generating Various Types of Code.

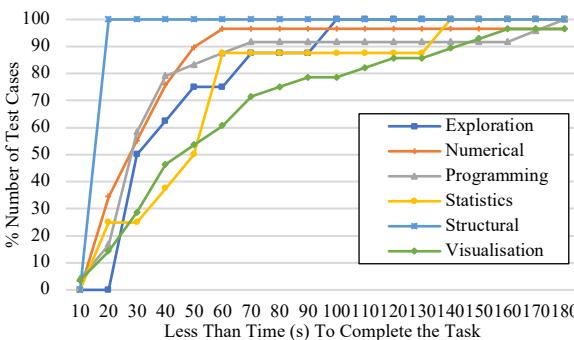


Fig. 10. Distribution of Task Completion Times on Tasks of Generating Various Types of Code.

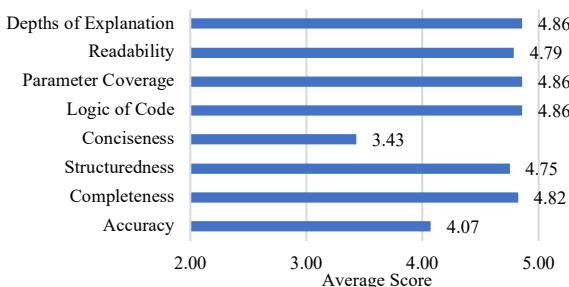


Fig. 11. Average Performance Scores on Visualization Questions in Various Quality Attributes.

C. Difficulty Levels

Will ChatGPT's usability decrease as the difficulty of the task increases? Yes. The experiment data shows clearly that the total quality scores on subjective quality criteria decrease as the level of difficulty increases, while the average number of attempts and the average amount of time required to complete code generation tasks increase as the difficulty level increases; see Figure 12.

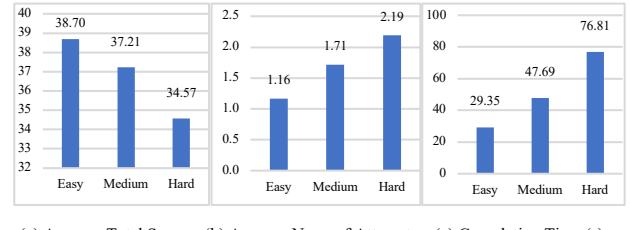


Fig. 12. Usability on Different Levels of Difficulty.

Moreover, when measuring usability on each individual quality criterion, the experiment data also clearly demonstrates the monotonicity of performance with difficulty level; see Figure 13.

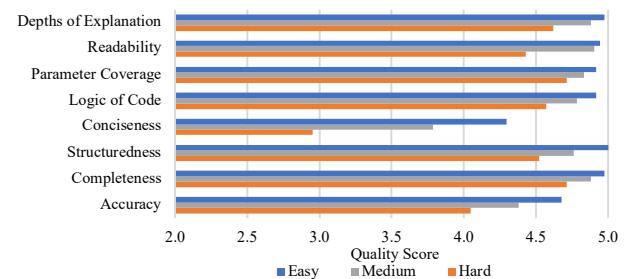


Fig. 13. Usability on Various Quality Criteria for Tasks of Different Difficulty Levels.

D. Learnability

The use of LLMs like ChatGPT to generate program code with natural language input is a process of interactions between the human user and the ML system. It has been widely recognized that the natural language input plays a significant part to the success of generating high quality outputs. This leads to a research question whether it is easy for the human user to learn how to make good input to the ML system. To answer this question, we conducted the testing and evaluation in a sequential process from test set T_0 to T_4 and analyzed the differences between the results.

Because the test cases in various test sets are drawn at random from a large dataset, the questions in different test sets have different levels of difficulty. In order to take this factor into consideration, we calculate the difficulty levels of the test sets using the following formula.

$$DL(T) = (1 \times E_T + 2 \times M_T + 3 \times H_T) / (E_T + M_T + H_T)$$

where $DL(T)$ denotes the difficulty level of a test set T , E_T , M_T and H_T are the numbers of easy, medium, and hard questions in test dataset T , respectively. Figure 14 shows the difficulty levels of the test sets.

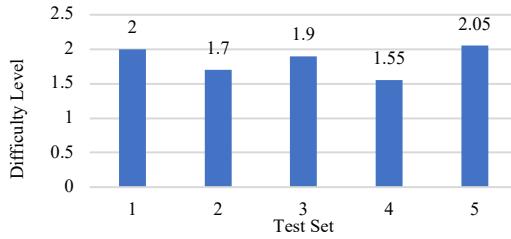


Fig. 14. Difficulty Levels of the Test Sets.

The quality scores of various test sets are then adjusted according to the difficulty levels; see Figure 15 and 16 for the results. From the data, we cannot observe any improvement in the quality when testing progresses from T_0 to T_4 ;

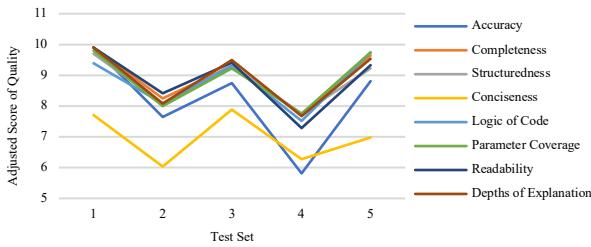


Fig. 15. Quality Scores of Test Sets On Various Quality Attributes After Adjusted by Difficulty Levels.

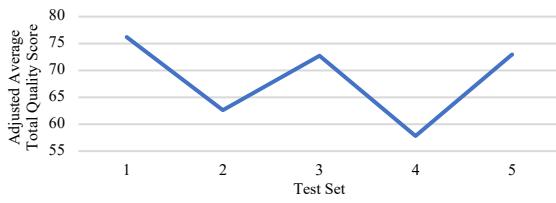


Fig. 16. Total Quality Scores of Test Sets After Adjusted By Difficulty Levels.

It is also observed that even the average numbers of attempts and the average completion times do not improve with the increases of experiences in using ChatGPT; see Figure 17 and 18.

Figure 19 contains three charts that show the performance changes over 5 test sets on various quality attributes for the easy, medium, and hard code generation tasks, respectively. None of these three charts shows an obvious quality improvement trend with the increase of experiences in using ChatGPT.

Figure 20 shows the changes in the average total quality scores on tasks of three different difficulty levels. It also shows a lack of improvement with the increase of experiences.

Therefore, we conclude that it is not easy to learn how to use ChatGPT to generate program code through experiences of using the ML model.

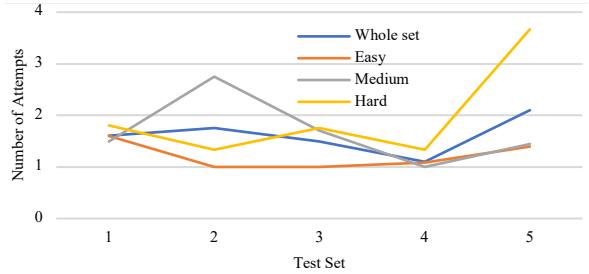


Fig. 17. Average Number of Attempts on Various Test Sets at Different Difficulty Levels.

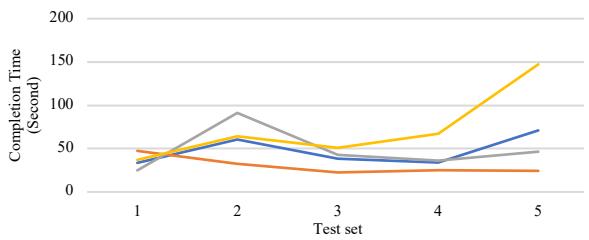


Fig. 18. Average Completion Time (Second) on Various Test Sets at Different Difficulty Levels.

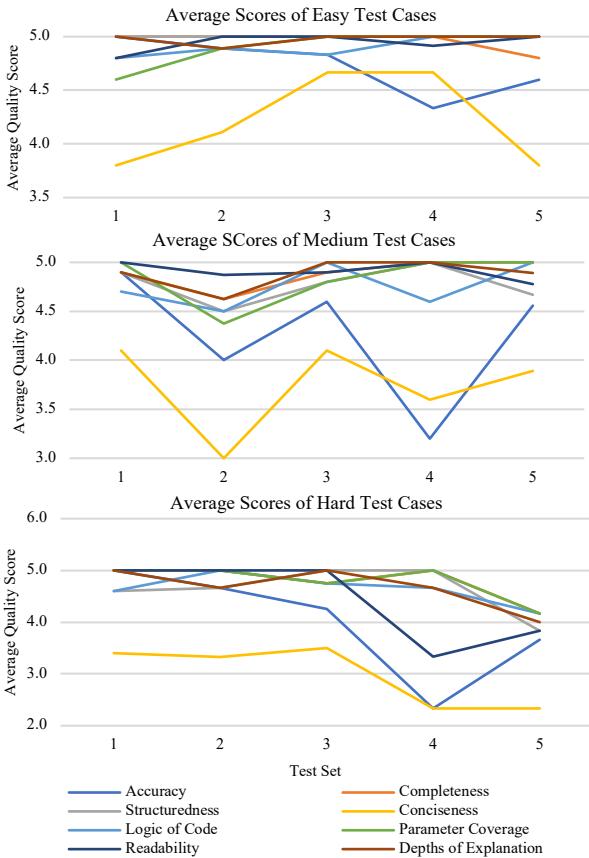


Fig. 19. Average Quality Scores on Tasks of Difficulty Levels at Different Difficulty Levels.

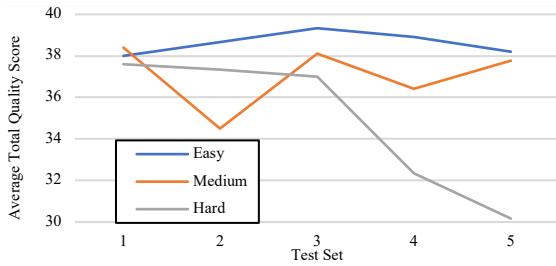


Fig. 20. Total Quality Scores of Test Sets at Different Difficulty Levels.

V. CONCLUSION

A. Summary and Comparison with Existing Works

Existing evaluations of LLM models are mostly conducted through benchmarking on standard test datasets. While this enables objective comparisons of LLMs, the results hardly reflect their usability from the user's perspective. This is particularly important when deciding on whether to use a LLM in a specific use scenario. The difficulty is that there is a wide range potential uses of LLMs, while testing and evaluating a LLM is expensive and difficult. This paper proposed a new method that aims at assessing and evaluating LLM's performance to reflect its usability in various use scenarios efficiently and effectively. The method consists of the following elements.

First, metadata that describe the usages of the test cases are assigned to each test case in the test dataset. This enables the flexibility of tailoring the dataset to generate subsets that represent various use scenarios, and to adjust the evaluation of the performances on different scenarios with existing test results without re-run test cases. It is different from existing datasets for evaluating code generation capability, which only contain the task (also called the problem to be solved in the literature), reference solution(s) to the problem, and a set of test data for checking the correctness of the machine generated solution.

Second, the testing on each test case takes a process that mimics the real use of the LLM. In particular, we proposed a multiple attempt process for testing LLMs. In this process, the tester tries to complete the testing task through a series of attempts until a satisfactory solution is obtained or gives up after a fixed number of maximal attempts. In each attempt, the tester formulates an input based on the previous results and the task to be completed, invokes the ML model, and then inspects the output to decide whether the solution is satisfactory. This contrasts with the single attempt process currently used by the existing work on evaluating code generation, in which a number of solutions are generated for the same input. Our process is closer to the real uses of LLMs.

Third, in our method, the quality of an output is measured by a set of metrics on usefulness from the users' perspective. This contrasts with existing evaluations of code generation, where the functional equivalence of a machine produced solution to the reference solution(s) are used as the sole judgement on the quality of the code generated. In the real uses of LLMs for code generation, a piece of code is considered as useful

even if it is not functionally correct. In many cases, a skeleton of code is acceptable even if it cannot be compiled. Our metrics focus on the usability of a solution via considering its readability, logic clarity, well-structuredness, etc. Thus, the method is closer to the real uses of LLMs.

Finally, we define two metrics on user experiences in the uses of the LLM: (1) $\#attempt_k$, i.e. the average number of attempts, and (2) the average amount of time taken to complete the test tasks. They differ from the $pass@k$ metric, which is currently used in evaluation of code generation capability. It is the probability of generating at least one correct solution when the LLM is asked to generate $k > 0$ solutions. In contrast, our metrics reflect the expected number of attempts that the user will make to find a satisfactory solution, and the expected time that a user will spend on to complete a code generation task. Thus, it better represents the user experiences in the use of the LLM.

Therefore, our proposed approach to the evaluation of LLMs capability of code generation can be characterized as user centric for its focus on user experiences in the uses of the LLM. This is reflected in all aspects of the testing and evaluation, including the information contained in the test dataset, the testing process, the measurement of solution quality and the performance metrics.

Our experiment results are consistent with the good user experiences and general opinions on ChatGPT. We have also identified the weakness as well as the strength of the LLM model. In particular, it is the first time that the learnability of using ChatGPT to complete code generation tasks is studied. Our experiment data show that skills of using ChatGPT for code generation would not come naturally through experiences.

B. Potential Threats to Validity and Future Work

The scale of our experiments is small in terms of the number of subjects involved in the testing process due to our resource limitation. This forms a potential threat to the validity and generalizability of the results on the performance of ChatGPT's code generation capability. However, the feasibility of the proposed testing method is not affected. The potential threat can be eliminated by repeated experiments with more subjects. This suggests that a topic for future work is to repeat the experiments with more subjects.

For some quality metrics like readability and logic clarity, the values of metrics assigned to each test case are subjective, which depends on the subject's knowledge, experience, and ability. This causes another potential threat to the validity of the results. Efforts have already been made to confine the threat by applying the metrics consistently according to the clear definitions of the metric values. Thus, the risk is minimized. Moreover, our experiment data show that the results obtained from such subjective judgements are consistent with objective metrics of the number of attempts and time to completion. Thus, the results should be trustable. For future research, we are working on using more objective metrics about the quality of program code developed in software engineering

research, like cyclomatic complexity, coupling and cohesion, code smell, etc., in complementary to the subjective metrics proposed and used in this paper. It is worth further research to find out if machine generated codes are of high quality on these attributes designed for traditional human written code, and whether such metrics can provide meaningful assessment of the usability of machine generated code.

A factor that has an impact on the experiment results is the criterion to determine whether a solution is satisfactory in the multi-attempt testing process. In principle, being user centric, it must be judged by the human users who engage in the testing. In our experiment, the guideline given to the tester is that the generated code is satisfactory if it is correct when compared with the reference solution or is close enough to the reference solution. In other words, a functionally incorrect solution may well be regarded as satisfactory if a minor editing of the machine generated solution will work. However, in practice, such reference solutions are usually unknown. Therefore, there is a gap between the judgements of satisfactoriness by the testers and the real users. This is a potential threat to the validity of the experiment results. It is desirable to give a more rigorous criterion to judge the satisfactoriness of solutions generated by machine. However, defining such a rigorous criterion is a non-trivial issue and worth further research. Study of metrics on the usefulness of machine generated solutions could be helpful.

Our dataset is constructed by extracting exercise questions from textbooks. An advantage is that the questions are well presented in terms of the clarity of the language and coverage of the programming language facilities and usages as well as the correctness of the reference solution. Thus, little manual editing and filtering of data is required while other datasets constructed by extracting data from open-source code repositories have required heavy workload on manual editing and cleaning of the data. It also minimizes the possibility of testing LLM on incorrect questions. Moreover, we have managed to construct a relatively large dataset with a small amount of human resource. A potential threat to the validity of the experiment is that questions from textbooks may not represent the coding tasks in the real uses of LLMs. It is worth further research on the validity of the dataset via studying the differences between real input from users and the data in our dataset.

We have included three types of metadata to our benchmark data: the type of code to be generated, the difficulty level of the task to be completed, and the source of the data. The first two represent two kinds of scenarios, which can be combined to form various specific usage scenarios as demonstrated in the experiments. Since the metadata are manually assigned to the data in the dataset, a potential threat to the validity of the experiment results can be caused by errors in the metadata. In the experiment, we have taken mitigation means to minimize the error rate by giving clear definitions of the values of metadata. For example, a coding task is assigned with “hard” as its difficulty level, if and only if “when the program code to be generated is more complicated than ten lines

and requires more complex data structures and algorithms.” In the literature, some datasets do classify the coding tasks into different difficulty levels. For example, APPS dataset has three subsets of data on three difficult levels: Introductory, Interview, and Competition. However, there is no definition of the criterion on how the tasks were classified [24]. Our approach enables metadata to be assigned systematically and consistently, thus the chances of human errors are reduced. As for future work, it is worth studying other types of metadata and other values of metadata, for example, difficulty levels could be more than three. Another topic for future work is how to check the correctness of metadata.

Addition to the above directions of further research that address the potential threats to the validity of the work and the generalizability of the results, there are also several other interesting topics for future work. For example, the user centric testing method proposed in this paper is expensive to conduct because of human users’ involvement in the testing process. It is worth further research to reduce the cost and to improve efficiency through testing tools and automation.

It is worth noting that evaluating LLM is inevitably subjective due to the nature of NLP. Instead of trying to avoid subjective assessment, we minimize the potential bias of the assessment by decomposing the overall subject opinions into a set of quality attributes that represent different aspects of subjective opinions and use multiple levels of scores to normalize the assessments. This approach to the evaluation of software quality has been well developed and widely applied in software engineering and HCI. How to further improve the methodological rigor of user centric evaluations of LLMs will be of great importance.

Finally, LLMs’ capability of generating program code is not only applicable to software development as our evaluation results show, but it is also potentially useful for other purposes such as education. For example, a student could learn coding with a LLM by raising questions in natural language and getting answers from the LLM with program codes and detailed explanations. Another possibility is to help students to understand example program code by inputting a piece of code to a LLM and getting an explanation of the code. Moreover, a student’s answer to an exercise or examination question could be input to a LLM for checking its correctness and producing a mark and feedback to the student. If a student’s answer on an exercise question is incorrect, the LLM could give the reasons why it is incorrect and delineate on how to correct it. It is worth further research to assess and evaluate the usability of LLM in such use scenarios.

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APPENDIX A. EVALUATION CRITERIA OF QUALITY ATTRIBUTES

This appendix gives the details of the evaluation criteria for each of the quality attributes.

(1) Accuracy: The correctness and accuracy of the LLM model’s response in comparison with the standard answer to the programming question. It is assessed through executing the code produced by ChatGPT and the standard answer to the coding question. Their outputs are compared to see if the generated code gives correct output. The scores are:

- 1: The response is completely wrong.
- 2: The response contains many errors.
- 3: The response is reasonably accurate, shows somewhat understanding of the question but it contains some errors.
- 4: The response is mostly accurate but it contains a small number of minor errors.
- 5: The response is clear, accurate, and solves the problem comprehensively without any error.

(2) Completeness: the completeness of the solution that covers the requirements of the programming question. It is assessed by comparing the functionality of the code generated against the coding problem. The scores are:

- 1: The response is incomplete and addresses the question inadequately.
- 2: The response has significant omissions.

- 3: The response covers the requirements well with some minor omissions.
- 4: The response covers almost all requirements adequately with a small number of omissions.
- 5: The response is thorough, comprehensive, and covers all requirements areas.

(3) Well structuredness: the structure of the code generated and formatted. It is assessed by inspection of the code on how well the code is structured and organized. The scores are:

- 1: Response is poorly organized and lacks proper structure.
- 2: Response is somewhat organized but there are issues with the structure.
- 3: Response is organized well, but there is a large room for improvement for clearer structure.
- 4: Response is well organized and provides a clear and logical structure, however there is some room for improvement.
- 5: Response is highly organized and has a clear and logical structure.

(4) Conciseness: The conciseness of the code produced by ChatGPT without compromising functionality. This is assessed by review of the code in comparison with the standard answer. Typically, the generated code and standard answer are compared on the number of lines of code. The scores are:

- 1: The response includes significant redundancies and has a larger number of lines of code in comparison with the code of the standard answer.
- 2: The response has noticeable redundancies and has a notably larger number of lines compared to standard answers.
- 3: The response is somewhat concise but can be further reduced.
- 4: The response is concise with minimal redundancies.
- 5: The response is highly concise, conveying the information efficiently, and matches the number of lines of code compared to the standard answer.

(5) Logic clarity: the coherence, soundness, and clarity of the generated code. This is examined and assessed via review of the code to identify inconsistencies or logic errors.

- 1: The response lacks logic and has no clear flow of thought as demonstrated in the code.
- 2: The response demonstrates some flow of thought, but it contains many lines of code misplaced.
- 3: The response demonstrates a flow of thought, but some lines of code are misplaced.
- 4: The response demonstrates a clear logic flow of thought but could be improved by minor rearrangement of the code.
- 5: The response demonstrates a clear flow of thought, and the code is logically well ordered.

(6) Parameter coverage: how well the parameters provided in the coding question are used or covered in the solution produced by the LLM model. Here, “parameter” refers to the coding elements given in the question like dataset name, variable name, data values, function names, library code names, etc. This is assessed by inspection of the code to measure if all coding elements in the question were used and appropriately incorporated in the solution.

- 1: The response does not use any of the parameters from the question.
- 2: The response uses a small proportion of parameters, however some key parameters are missed or incorrectly used.
- 3: The response uses some parameters correctly; however, some are not.
- 4: The response uses most of the parameters correctly except a small number of minor errors.
- 5: The response uses all parameters correctly.

(7) Readability: the easiness for human readers to read and understand the produced solution. This is assessed by a human tester to read the produced solution and attempt to understand it, where a solution typically includes pieces of code together with natural language explanations. The scores are:

- 1: The response is difficult to understand, with poor grammar, confusing language and awkward spacing, etc.
- 2: The response is somewhat readable but contains poor grammar, confusing language, and some awkward format, such as spacing.
- 3: The response is mostly readable, but it includes some grammar issues, confusing language and awkward spacing.
- 4: The response is generally well-written and easy to understand, with only minor grammar, language, and formatting issues.
- 5: The response is highly readable, language is clear and concise, grammar is correct, formatting is good.

(8) Depth of explanation: the quality of the textual explanation produced together with the code. This is assessed by reviewing the text produced by the language model accompanying the code and provides explanation of the generated code. It focuses on how well the text explains the code in a comprehensible and understandable way and to elucidate the rationale behind the code. The scores are:

- 1: The text part of the response is in lack of information and explanation of the code.
- 2: The text part of the response provides some basic information about the code, but many aspects are not fully explained.
- 3: The text part of the response provides the necessary information and explanation of the code; however, the explanation lacks depth.
- 4: The text part of the response provides sufficient explanations on most aspects of the code at a satisfactory level of detail and depth.
- 5: The text part of the response produces highly sufficient explanations that covers all aspects of the code with high clarity and depth.