WIP: Assessing the Effectiveness of ChatGPT in Preparatory Testing Activities

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***Abstract*—This innovative practice WIP paper describes a research study that explores the integration of ChatGPT into the software testing curriculum and evaluates its effectiveness compared to human-generated testing artifacts. In a Capstone Project course, students were tasked with generating preparatory testing artifacts using ChatGPT prompts, which they had previously created manually. Their understanding and the effectiveness of the Artificial Intelligence generated artifacts were assessed through targeted questions. The results, drawn from this in-class assignment at a North American community college indicate that while ChatGPT can automate many testing preparation tasks, it cannot fully replace human expertise. However, students already familiar with Information Technology at the postgraduate level, found the integration of ChatGPT into their workflow to be straightforward. The study suggests that AI can be gradually introduced into software testing education to keep pace with technological advancements.**

***Index Terms*—Software Testing Education, ChatGPT, Blackbox Testing, Product Testing, Higher Education**

I. INTRODUCTION

Software testing plays a critical role in delivering quality products to end users. The software that is not tested properly can exhibit unwanted critical bugs after moving to production which can cause a loss of goodwill, profit margin, and business [1], etc. To make this testing process efficient, researchers and practitioners are seeking innovative practices that can be applied in real-world applications.

Often organizations use third-party software or software as a service where source code is not accessible, leading the testers creating testing-related artifacts solely based on the specifications provided in the documentation. However, without examining the source code, software testers often face the challenge of ensuring proper requirements coverage incorporating both functional and non-functional aspects.

Software testing educators are progressively adopting innovative tools and techniques to enhance the learning experience and equip students more effectively for real-world challenges. They need teaching students effective ways of producing these testing entities. Traditional teaching methods often struggle to keep pace with the rapid advancements in software testing practices and technologies [2]. The software testing program curriculum should be updated to include the latest trends in modern technologies including Artificial Intelligence (AI), which can automate software testing processes, making them faster and more efficient. This integration will enable students to stay current with external developments in the testing field and contribute effectively to organizations after graduation [3].

Large Language Models (LLM) are a subset of AI and represent one of the latest inventions in deep learning and natural language processing (NLP) where the models are trained with vast amounts of data. ChatGPT is one of the LLM tools released by OpenAI [4] that allows users to use prompts with human-like language and receive the response on the provided prompts. Due to its simplicity, and human-like understanding of concepts, ChatGPT is showing promise in the various sectors of the Software Engineering domain including automation of software testing [5], [6].

This work-in-progress paper investigates the effectiveness of ChatGPT in preparatory testing activities without needing access to the application's source code. In addition, this study shows how software testing postgraduate students can use critical thinking skills to leverage LLM tools to generate preparatory testing artifacts while recognizing the challenges of relying on the generated content.

II. BACKGROUND AND LITERATURE SURVEY

Several researchers compared the performance of different LLM tools including GPT-3.5 [7] and GPT-4 [8] and found ChatGPT-4 outperformed ChatGPT-3.5 [9]. In this study, ChatGPT-3.5 was used because of its free availability, and open-source tools are often preferred in educational settings due to being economical and creating room for innovation [10]. ChatGPT-3.5 can ask and answer follow-up questions, admit mistakes, challenge incorrect premises, and reject inappropriate requests using reinforcement learning from human feedback.

In the software testing paradigm, LLM tools have been experimented with for unit test generation [11], test case generation from bug reports [12], GUI testing [13], code understanding [14], and program repair [15], etc. Wang et al. [16] conducted a review of the utilization of LLMs in software testing and identified test case preparation and program repair to be the most representative of software testing tasks.

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TABLE I
LIST OF QUESTIONS USED IN THIS ASSIGNMENT

Question Number	Question Description	Options provided
1	In which areas did ChatGPT work the best compared to you working as a group in generating the questions manually?	a) Test Cases b) Test Scripts c) Use Cases d) RTM
2	Which aspect of ChatGPT-assisted testing did you find most beneficial?	a) Test case generation speed b) Test case coverage c) Test case accuracy d) Ease of use d) Other (please specify)

Due to its popularity, and potential benefits in practical applications, the utilization of ChatGPT in the education domain is becoming inevitable. Mordan et al. [17] integrated LLM into higher education. Other researchers have incorporated ChatGPT into Software Engineering [18] and Computing Education [19], etc.

Before the applications are ready for test execution, several activities are undertaken to enhance the efficiency of each step in the Software Testing Life Cycle (STLC) [20]. The Requirements Traceability Matrix (RTM) links requirements to test cases to track testing progress and measure coverage. Madan et al. [21] showed the importance of RTM in testing web applications, and researchers worked on generating test cases from RTM [22], and use case specification [23]–[25]. As considerable effort is required to generate test cases and test scripts [26], automating these steps would significantly reduce the total testing time required for a project.

III. METHODOLOGY

In this study, we analyzed a subset of student responses from an assignment in the Capstone Project course of the postgraduate certificate program in Software and Information Systems Testing at Fanshawe College, Canada. This is a second-semester course of a two-semester program followed by a co-op term. Students are expected to have a two to three-year college Diploma or a Degree in Business or Information Technology or an acceptable combination of related work experience and post-secondary education to be enrolled into this program. ’Test Methodologies’, ’Applied Project Management’, and ’Systems Design and Analysis’ are the prerequisite courses for this Capstone Project course.

This course covers all aspects of testing a real-world web application. Students are expected to develop various testing-related artifacts over a 15-week duration semester. They need to develop use cases, RTM, test cases, and test scripts for a provided web-based Travel Application in groups of 4-5 people. The students are evaluated based on their performance in these deliverables. In week 9, after manually completing all these activities, students are given an individual exercise to generate the same artifacts using ChatGPT. They then compare how manually generated test artifacts differ from those generated by ChatGPT. This was a mandatory assignment, and a total of 61 students incorporating two different sections submitted their work, and they were evaluated based on their comparative analysis. The assignment was graded on problem-solving and critical thinking skills measured with 8 different criteria consisting of depth of analysis, clarity of explanation, overall understanding and insights, identification of missing aspects, identification of inapplicable test cases, explanation of feasibility issues, justification of findings, and overall understanding and insights. Out of 61 submissions, 26 students scored at least 90%, and their responses were utilized in this study. From the original 11 questions, 2 were selected for this study and are shown in Table I, as they were directly applicable to students’ experience in generating testing preparatory artifacts compared to manual artifact generation.

The students were given flexibility in providing application information within the prompt, allowing them to learn how to tailor prompts to achieve the best outcome. This approach helped students understand that the non-deterministic nature of LLM tools may not always yield the expected outcome.

IV. RESULTS

A few students prompted ChatGPT to generate preparatory testing artifacts without providing additional context. As a result, ChatGPT returned limited information and produced only a small number of test cases and artifacts. The students then applied their critical thinking skills to refine their prompts and obtain the desired artifacts of the TravelApplication.

A. ChatGPT prompts by authors and responses received

This section shows a few examples of ChatGPT prompts used to generate preparatory testing artifacts. Fig. 1 shows a snapshot of the prompt engineering applied by authors to share detailed specifications in the prompt to get the required artifacts. In addition to what has been shown in this figure, the prompt included further descriptions of the modules in the existing and proposed versions, along with details about the technology used in the TravelApplication. The Fig. 2 demonstrates one of the ChatGPT-generated use cases with detailed information.

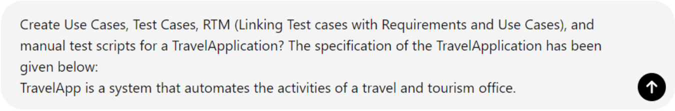
Create Use Cases, Test Cases, RTM (Linking Test cases with Requirements and Use Cases), and manual test scripts for a TravelApplication? The specification of the TravelApplication has been given below:
TravelApp is a system that automates the activities of a travel and tourism office.

Fig. 1. Prompts for generating testing artifacts for a TravelApplication.

Fig. 3 shows the generated RTM from the given prompt, presented in tabular format as instructed. Fig. 4 illustrates how additional information was needed to obtain both functional and non-functional test cases.

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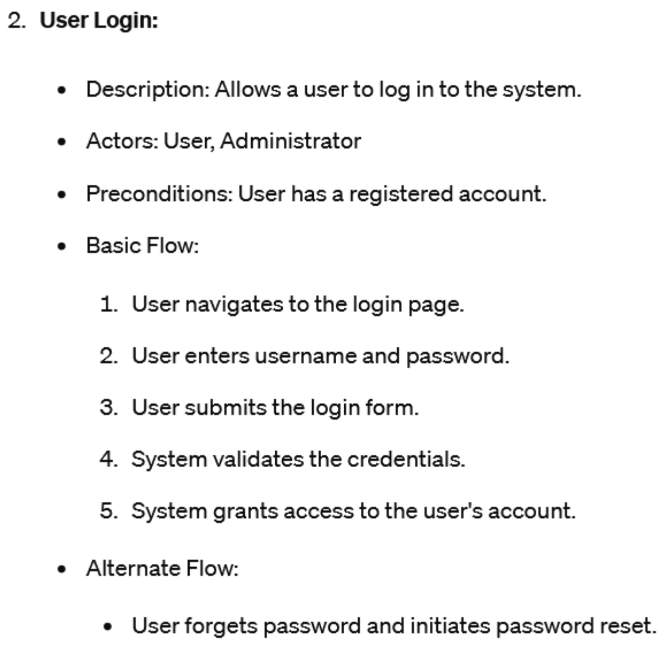
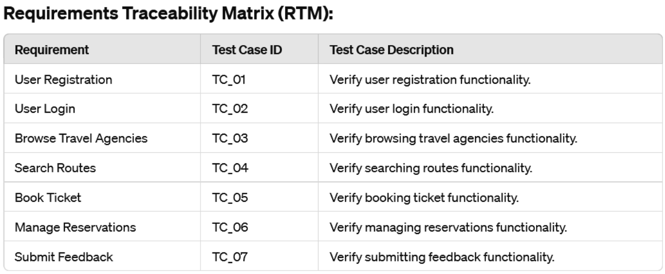


2. **User Login:**
   - Description: Allows a user to log in to the system.
   - Actors: User, Administrator
   - Preconditions: User has a registered account.
   - Basic Flow:
     1. User navigates to the login page.
     2. User enters username and password.
     3. User submits the login form.
     4. System validates the credentials.
     5. System grants access to the user's account.
   - Alternate Flow:
     - User forgets password and initiates password reset.

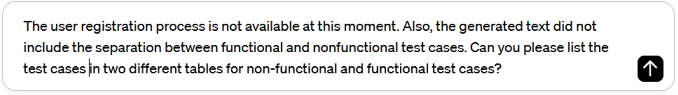
Fig. 2. A ChatGPT-generated use case for login feature of the TravelApplication.



Requirements Traceability Matrix (RTM):

Requirement	Test Case ID	Test Case Description
User Registration	TC_01	Verify user registration functionality.
User Login	TC_02	Verify user login functionality.
Browse Travel Agencies	TC_03	Verify browsing travel agencies functionality.
Search Routes	TC_04	Verify searching routes functionality.
Book Ticket	TC_05	Verify booking ticket functionality.
Manage Reservations	TC_06	Verify managing reservations functionality.
Submit Feedback	TC_07	Verify submitting feedback functionality.

Fig. 3. RTM generated by ChatGPT for the TravelApplication.



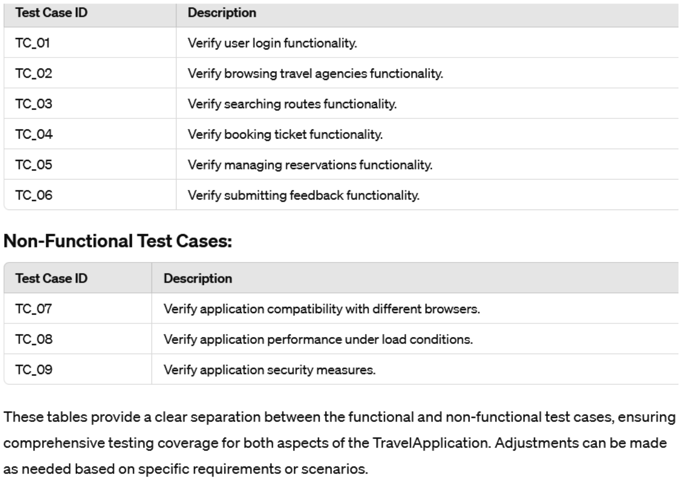
The user registration process is not available at this moment. Also, the generated text did not include the separation between functional and nonfunctional test cases. Can you please list the test cases in two different tables for non-functional and functional test cases?

Fig. 4. Additional prompt for generating functional and nonfunctional test cases in a tabular format for the same TravelApplication

Fig. 5 shows the functional and non-functional test cases generated by ChatGPT. Due to the generic nature of the prompt, only a minimal number of non-functional test cases were produced. To generate a more comprehensive set, the prompt can be refined to specifically mention non-functional aspects like performance, load, stress, usability, maintainability, etc.

B. Students' findings from their assignment

The student responses to the provided questions were analyzed afterward. Fig. 6 shows the students' responses to the question of which aspect of ChatGPT-assisted testing was most beneficial. Out of the 26 responses, fourteen students found that 'Test Case Generation Speed' was the most important aspect whereas four students considered the most benefit of ChatGPT-assisted testing is observed in the criteria of 'Ease of Use'. Three students referred to 'test case coverage' as the area where the most benefit is observed compared to manual test artifact generation. Two students selected the 'Test case generation speed and ease of use', two students picked 'Test Generation Speed and Test Case Coverage' and one student selected the 'Test Case Accuracy and Test Case' option as the best outcome of utilizing ChatGPT based test artifacts generation. Only one student selected 'Test Case Accuracy' as the most advantageous option. It was found that several students noted that the generated test cases were not always accurate, requiring them to tailor the prompts by providing additional context to obtain updated results.



Test Case ID	Description
TC_01	Verify user login functionality.
TC_02	Verify browsing travel agencies functionality.
TC_03	Verify searching routes functionality.
TC_04	Verify booking ticket functionality.
TC_05	Verify managing reservations functionality.
TC_06	Verify submitting feedback functionality.

Non-Functional Test Cases:

Test Case ID	Description
TC_07	Verify application compatibility with different browsers.
TC_08	Verify application performance under load conditions.
TC_09	Verify application security measures.

These tables provide a clear separation between the functional and non-functional test cases, ensuring comprehensive testing coverage for both aspects of the TravelApplication. Adjustments can be made as needed based on specific requirements or scenarios.

Fig. 5. List of Functional and Non-Functional Test Cases

Fig. 7 shows which artifact among RTM, use cases, test cases, and test scripts was most effective according to the students and presents the results of this evaluation. Most students found use cases to be the most helpful artifacts because they included all the pre-conditions, basic flows, and alternate flows. These alternate flows were sometimes missed in manual use case generation. RTM was the next preferred artifact as the ChatGPT-generated responses demonstrated that each requirement was successfully linked to a specific test case. The students noted that some of the groups had inadvertently omitted non-functional test cases from their manually created testing artifacts whereas these test cases were included in the ChatGPT-generated test cases. However, not all the ChatGPT-generated test cases apply to this application, which revealed ambiguities in the provided test specifications. Only three students found that the generated test scripts were helpful compared to others. As the application behaviors were not clearly defined in the specifications, the generated step-by-step instructions did not always match the actual requirements. Only those students who effectively tailored their requirements by providing more details in the ChatGPT prompt were able to achieve good results with their test script generation. Finally,

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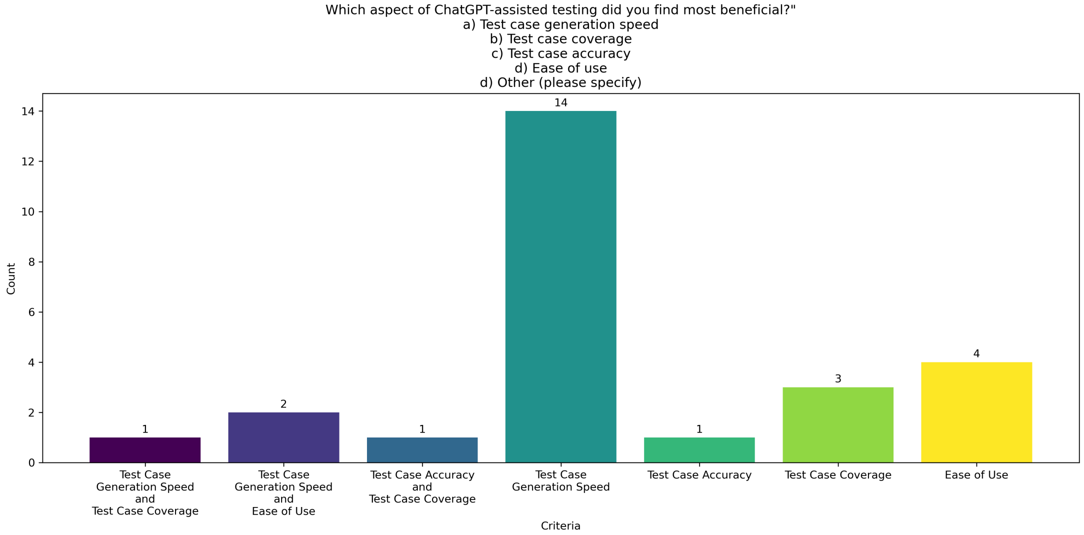

Fig. 6. Effectiveness of Testing Artifacts Generation

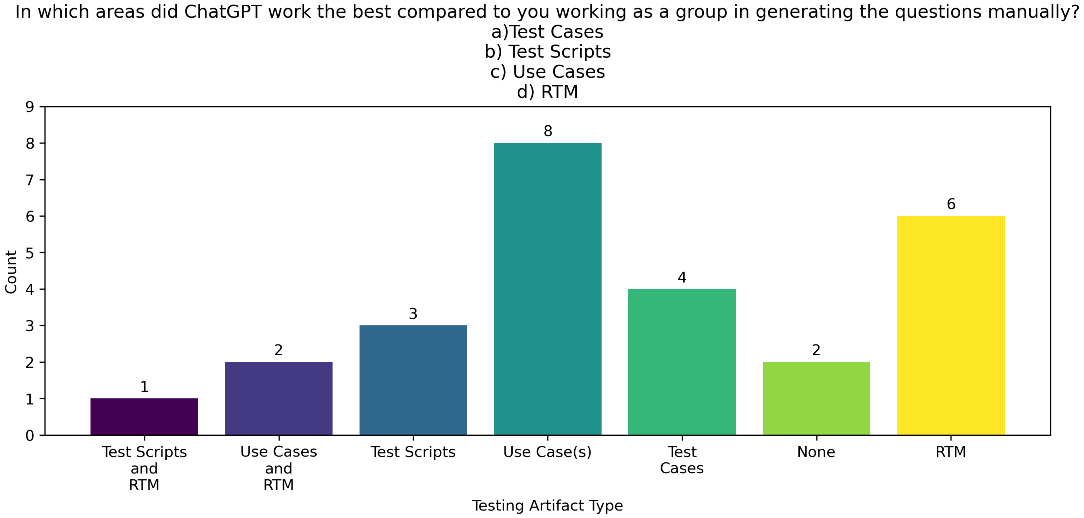

Fig. 7. Effectiveness of Testing Artifacts Generation

a few students combined the effectiveness of use cases, RTM, and test scripts, by grouping them as either ”use cases and RTM” or ”test scripts and RTM”. Two students found that the manually generated scripts were more effective than ChatGPT-generated artifacts shown as ’None’ in this bar diagram.

V. DISCUSSION AND LIMITATIONS

From students’ responses, it was observed that while ChatGPT automatically generated RTM, use cases, test cases, and test scripts based on the given prompts, not all the generated information was accurate or feasible to implement. ChatGPT has limitations such as the ’Software Under Test’ cannot be directly accessed through a web browser. Without providing sufficient context in the prompt, the ChatGPT cannot generate an ample number of feasible test artifacts. To successfully generate test artifacts, providing a clear chain of instructions is crucial. In addition, when teaching with proprietary applications, without taking precautions, ChatGPT may use the given information in prompt for training. As a result, caution should be taken so that sensitive information is not shared unwillingly. The educators can show students different ways of prompt engineering to lead them in the right direction before handling this exercise. Since this set of twenty-six students was already in the Information Technology domain in a post-graduate setting, it did not take time for them to familiarize themselves with test artifact generation using ChatGPT. Many of them have already utilized ChatGPT, but this exercise also made them aware that they cannot simply rely on ChatGPT without proper validation due to the risk of generating inaccurate information. Having prior knowledge of manual test artifact development can assist them with creating effective prompts.

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VI. CONCLUSION AND FUTURE DIRECTION

In this study, we explored how student assignments can be innovatively designed to compare their manually crafted testing artifacts with those generated by ChatGPT, providing a practical introduction to AI concepts within the testing domain. When integrating ChatGPT into the curriculum, guiding students to avoid the inclusion of sensitive information in their prompts and encouraging them to validate the generated content before accepting the outcome is important. This innovative approach gradually introduces students to the complexities and challenges of using ChatGPT in real-world scenarios.

For future research, further analysis of student responses could yield valuable insights, and experimenting with additional open-source tools could offer a deeper understanding of ChatGPT's effectiveness in testing education. This continued investigation can help identify the potential and limitations of LLM tools in software testing studies.

VII. ACKNOWLEDGEMENT

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