Can Large Language Models Provide Feedback to Students? A Case Study on ChatGPT

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***Abstract*—Educational feedback has been widely acknowledged as an effective approach to improving student learning. However, scaling effective practices can be laborious and costly, which motivated researchers to work on automated feedback systems (AFS). Inspired by the recent advancements in the pre-trained language models (e.g., ChatGPT), we posit that such models might advance the existing knowledge of textual feedback generation in AFS because of their capability to offer natural-sounding and detailed responses. Therefore, we aimed to investigate the feasibility of using ChatGPT to provide students with feedback to help them learn better. Specifically, we first examined the readability of ChatGPT-generated feedback. Then, we measured the agreement between ChatGPT and the instructor when assessing students' assignments according to the marking rubric. Finally, we used a well-known theoretical feedback framework to further investigate the effectiveness of the feedback generated by ChatGPT. Our results show that i) ChatGPT is capable of generating more detailed feedback that fluently and coherently summarizes students' performance than human instructors; ii) ChatGPT achieved high agreement with the instructor when assessing the topic of students' assignments; and iii) ChatGPT could provide feedback on the process of students completing the task, which benefits students developing learning skills.**

***Index Terms*—Feedback Generation; Automated Feedback; Large Language Model; Feedback Effectiveness**

I. Introduction

It is widely acknowledged that quality feedback in education can be a significant lever to enhance the learning experience and student achievements [1]–[3]. However, due to limited teaching resources, providing timely and constructive feedback for a large cohort of students has become a challenging task [4], [5]. A potential solution lies in the use of automated feedback systems (AFS).

To facilitate the provision of feedback, various automated feedback systems have been developed for tackling different educational tasks from generating code explanations for novice programming [6], [7] to responding to forum posts for supporting learners in Massive Open Online Courses [8]. For instance, Marwan et al. [6] applied an adaptive immediate feedback system to provide real-time feedback for high-school programmers. Integrating this system into the programming environment enhanced students' engagement in learning computer science courses and thus improved their task performance. Nevertheless, few AFS have been tailored to open-ended writing tasks such as essay assignments and project proposals which are becoming more common in higher education but usually take instructors a significant amount of time to give comprehensive feedback [9].

The latest breakthroughs in the realm of Generative Pre-trained Transformer (GPT) models can be seen as a catalyst for the development of AFS [8], [10]. A recent variant of the GPT model developed by OpenAI, i.e., ChatGPT, has become extraordinarily popular since its launch in November 2022. Compared to its predecessors, the significant step forward with ChatGPT hinges on the extra human-guided fine-tuning for the conversational context. This specific training allows ChatGPT to generate more natural-sounding and context-specific responses. Therefore, we posit that ChatGPT holds the potential to advance the existing knowledge of textual feedback generation for open-ended writing tasks.

In this paper, we aimed to explore the feasibility of using ChatGPT for generating textual feedback for student assignment. The chosen assignment is a writing assignment in which students proposed a data science project that they needed to accomplish at an Australian university. Our study is guided by the following Research Questions:

- **RQ 1** To what extent is the feedback generated by ChatGPT readable?
- **RQ 2** To what extent does the ChatGPT-generated feedback agree with instructor-generated feedback when assessing students' performance?
- **RQ 3** To what extent does the ChatGPT-generated feedback contain effective feedback components to guide student learning?

To answer the above research questions, we first examined the readability of the generated feedback, which is a common metric for measuring the quality of the machine-generated text. Then, we measured the agreement between ChatGPT and human instructors when assessing an assignment according to the marking rubric. Finally, to further investigate the effectiveness of the feedback generated by ChatGPT, we used a well-known theoretical feedback model proposed by [11] to analyse and compare the presence of effective feedback components in the feedback generated by ChatGPT and human instructors.

Through extensive analyses, we contribute to the research on deploying ChatGPT in feedback provision for open-ended tasks in higher education with the following main findings:

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(i) ChatGPT can generate more detailed feedback that more fluently and coherently summarizes students' performance than the instructor; (ii) ChatGPT achieved a high level of agreement with human instructors in assessing the topic of student assignment out of the five aspects specified in the marking rubric; and (iii) ChatGPT could provide feedback on the process of students completing the task, e.g., suggesting learning strategies in feedback, in addition to feedback on task level that indicates how well students performed.

II. Related Work

A. Effective feedback design

Since feedback is gaining increasing recognition in learning and teaching systems, scholars have been working on developing theoretical models that explain how feedback affects learning and what principles contribute to effective feedback design. For example, Nicol and Macfarlane-Dick [12] identified seven principles of good feedback practice from the research literature on formative assessment, which support self-regulation from the cognitive, behavioural and motivational aspects. However, these principles are considered too general and unsuitable for analysing textual feedback [13].

Hattie and Timperley [11] proposed a feedback model, which has been adopted widely in previous research to analyse textual feedback [13]–[15]. This feedback model [11] categorized effective feedback into four-level focuses, i.e., *task* focus (FT), *process* focus (FP), *self-regulatory* focus (FR), and *self* focus (FS). In particular, feedback on *task* normally contains corrective information that indicates how well a task is performed (e.g., "*The interpretation of this machine learning model is incorrect.*"). Feedback on *process* is primarily aimed at suggesting strategies for completing the task (e.g., "*This page may make more sense if you use the strategies we talked about earlier.*"). Feedback at the *self-regulatory* level addresses how students monitor their learning (e.g., "*You already know the key features of the opening of an argument. Check to see whether you have incorporated them in your first paragraph.*"), and feedback at the *self* level is about personal evaluations (e.g., "*You are a great student.*", "*Well done!*") [11]. These four levels can effectively enhance student learning by answering questions regarding the learning goals, the current performance, and the next movement to the desired goal. Thus, our study used it to assess the effectiveness of feedback.

B. Automated Feedback Generation

Many existing AFSs generate feedback based on pre-defined rules by domain experts [16]–[19]. For instance, OnTask [17] is a rule-based AFS, where instructors can offer feedback on student learning behaviors at scale by setting up conditional rules about students' learning activities such as lesson attendance and academic performance. Although these systems can alleviate some of the pressure on teachers, they are not ideal for open-ended assignments (e.g., students' proposal reports) whose answers vary widely and thus a vast set of expert-design rules need to be defined.

Recent advancements in artificial intelligence have attracted researchers' interest in using pre-trained language models such as BART [20] and GPT-based models [8], [10] to generate textual feedback for more complex tasks. For example, Jia et al. [20] designed Insta-Reviewer based on BART for automatically generating instant feedback on students' reports that documented coding tasks for an engineering course. To enhance students' engagement in learning, Li and Xing [8] employed GPT-2 to generate post replies on MOOC discussion forums. Despite these studies presenting the feasibility of pre-trained language models on feedback generation, none of them has attempted to generate elaborated feedback on open-ended tasks such as students' project proposals. This kind of assignment is common in higher education yet instructors often struggle to deliver comprehensive feedback on it [9].

We posit that ChatGPT, a variant of GPT-based models, might advance the existing knowledge on textual feedback generation for complex tasks. The adoption of self-attention mechanisms enables ChatGPT to handle long-range dependencies, and the fine-tuning on a large amount of conversational data allows it to generate coherent and contextually relevant answers. For instance, Aydin and Karaarslan [21] applied ChatGPT in the task of academic literature writing and evaluated ChatGPT according to the matching rate by the plagiarism tool. Results showed that ChatGPT gained a low matching rate when generating the literature review. Given the promising impact of ChatGPT in text generation, it is worthwhile to investigate the potential values of ChatGPT in generating elaborated feedback in educational settings as a precedent.

III. Method

A. Dataset

Our study obtained ethics approval from ANONYMOUS University under project number [BLINDED]. We retrieved the dataset from a postgraduate course teaching introductory data science skills. In this course, students were required to propose a data science project relevant to a business scenario and submit a project proposal for academic performance assessment. The proposal should include two sections, i.e., Project Description and Business Model which is an analysis of the business or application areas the project sits in. Instructors evaluated the submitted proposal and provided textual feedback for each student according to the following five aspects specified in the marking rubric: i) clear description of the goals of the project (**Goal**); ii) appropriateness of the topic to data science (**Topic**); iii) clear description of the business benefits (**Benefit**); iv) novelty/creativity (**Novelty**), and v) overall clarity of the report (**Clarity**).

After removing the student records without feedback, we finally obtained 103 students' proposal reports and the associated instructor-generated feedback. Note that we removed the personally identifiable information of students both in reports and feedback for the protection of privacy. Table I shows the basic statistics of the length of instructor-generated feedback.

TABLE I
STATISTICS FOR FEEDBACK LENGTH COUNTED BY THE NUMBER OF WORDS.

Feedback	Min	Median	Max	Mean	Std
Instructor	6	51	143	57.34	30.60
ChatGPT	102	160	270	166.44	34.81

TABLE II
AGREEMENT SCORES AND COHEN'S κ BETWEEN TWO ANNOTATORS.

Categories	Agreement score		Cohen's κ	
Five aspects	**Instructor**	**ChatGPT**	**Instructor**	**ChatGPT**
Goal	1.00	0.98	1.00	0.87
Topic	0.98	0.98	0.93	0.85
Benefit	0.99	0.95	0.98	0.83
Novelty	0.98	0.88	0.98	0.81
Clarity	0.97	0.92	0.94	0.82
Four levels				
Task	1.00	1.00	All[1]	All[1]
Process	0.95	0.92	0.85	0.84
Regulation	0.96	1.00	0.81	None[2]
Self	0.98	1.00	0.95	None[2]

[1] All feedback contained comments in this category.
[2] No feedback contained comments in this category.

B. Feedback Generation by ChatGPT

ChatGPT is released for free use by OpenAI and can be accessed by visiting https://chat.openai.com/ [21]. ChatGPT is able to generate responses from seeing a prompt describing the task (i.e., an instruction or a query written in natural language by a user for the ChatGPT model to execute). In the current study, the task for ChatGPT was to generate text feedback on students' proposal reports in terms of five assessment aspects. Thus, we designed the prompt for ChatGPT as follows, "*Please give feedback on the following text in terms of clear description of the goals of the project, appropriateness of the topic to data science, clear description of the business benefits, novelty/creativity and overall clarity of the report. <INSERT THE TEXT OF A REPORT>*". For each student, we inserted the text of their proposal report into the prompt and submitted it to ChatGPT to obtain generated feedback. The statistics of the length of feedback generated by ChatGPT are shown in Table I.

C. Evaluation Methods

To answer RQ1, we adopted a widely-used measure, i.e., readability [20], [22] to examine the quality of the machine-generated text. In line with the process of evaluating readability in the work [20], we invited three experts, and each of them was asked to score each piece of feedback either by ChatGPT or the instructor using a five-point scale where: (i) 0 denotes *Incomprehensible*; (ii) 1 *Not fluent and incoherent*; (iii) 2 *Somewhat fluent but incoherent*; (iv) 3 *Fluent but somewhat incoherent* and (v) 4 *Fluent and coherent*. As the evaluation for text readability varied from one individual human expert to another one, we calculated the average score of the three experts as the final metric of readability for each piece of feedback.

To answer RQ2, we measured how ChatGPT-generated feedback agreed with instructor feedback when it served as assessment information about student performance. As indicated in [11], the role of feedback is to reduce discrepancies between students' current performance and a desired goal. In a feedback process, when students accomplish the set goal, the instructor may affirm students' effort in the feedback. When students perform undesirably, the instructor may indicate the areas that they should further improve. In this paper, we use "Polarity" to denote whether the feedback is given to affirm students' effort ("Positive") or indicate the areas that they should further improve ("Negative"). If a feedback generator was unable to give feedback that accurately indicated how well students' performance was – i.e., positive feedback on poor performance or negative feedback on good performance – the generated feedback may have inadvertently misled the student and negatively impacted learning. Hence, we needed to investigate to what extent ChatGPT-generated feedback agreed with instructor feedback in terms of feedback polarity.

Two experts were recruited to identify the feedback polarity. As each piece of feedback from either instructor or ChatGPT was generated by assessing the students' reports based on five aspects (i.e., Goal, Topic, Benefit, Novelty and Clarity), we identified the polarity of feedback for each of these aspects. Specifically, if feedback was given to affirm a student's effort on a specific aspect, then the expert marked it with "Positive", whereas if feedback was given to indicate that the student needs to improve on a specific aspect, the expert marked it with "Negative". If the feedback did not contain any comments on a specific aspect, then the expert marked it with "None". For each piece of instructor or ChatGPT feedback, we obtained five labels, and each of them indicates the feedback polarity (i.e., "Positive", "Negative" or "None") on each of the five assessment aspects. To measure the ability of ChatGPT to generate feedback on each assessment aspect with accurate polarity, we calculated precision and recall, two commonly-used metrics for multi-class prediction tasks, by regarding three feedback polarities as three classes, the labels of instructor feedback as the ground truth, and labels of ChatGPT feedback as predicted classes, as the purpose of this study is to evaluate the feasibility of using ChatGPT to support human educators in feedback provision. For example, supposing that ChatGPT gave positive feedback on the aspect of "Topic" to 4 reports in total, while only 2 of them obtained positive feedback from the instructor on the same aspect, then the precision was 2/4 (0.50). Supposing that the instructor gave positive feedback on the aspect of "Topic" to 6 reports in total, the recall was calculated as 2/6 (0.33).

For answering RQ3, we used a well-known theoretical framework for feedback proposed by Hattie and Timperley [11] to analyse the presence of effective feedback components in the feedback generated by ChatGPT and instructors. We recruited two experts to annotate both instructor and ChatGPT feedback using the four-level feedback model proposed in [11]. After a pre-training session about annotation rules, each expert annotated 206 pieces of feedback in our dataset including 103

TABLE III
STATISTICS FOR FEEDBACK READABILITY.

Feedback	Min	Median	Max	Mean	Std
Instructor	2.33	3.33	4	3.21	0.52
ChatGPT	2.67	3.67	4	3.76	0.28

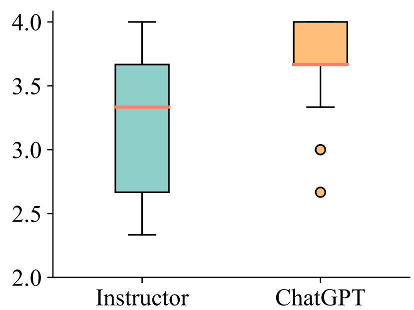

Fig. 1. The distribution of feedback readability.

instructor feedback and 103 ChatGPT-generated feedback.

In two annotation tasks for answering RQ2 and RQ3, we calculated the agreement score and Cohen's κ between two experts separately for instructor feedback and ChatGPT-generated feedback. The results are shown in Table II. The inconsistency between the two experts was resolved by the third expert.

IV. RESULTS

A. Results on RQ1

Scores of readability between ChatGPT and instructor feedback are reported in Table III. We can see that feedback generated by ChatGPT was significantly more readable than instructor feedback ($p < 0.001$, examined by paired t-test). Fig. 1 shows the distribution of readability scores for the feedback provided by instructors and ChatGPT. The distribution indicates that the majority of readability scores on ChatGPT feedback was rated between 3.75 to 4.0, whereas most instructor feedback (over 75%) was below the readability score of 3.75 with a higher standard deviation than ChatGPT. By scrutinizing the content of instructor and ChatGPT feedback, we found that feedback generated by ChatGPT usually contained a brief summary of students' works and the evaluation feedback followed by an explanation of how this feedback was given, while feedback from the instructor consisted mostly of simple expressions about the evaluation of student performance. We extracted the following examples from our dataset for reference.

- **Instructor:** "*Good choice of topic. Not a novel idea. Clear and well-structured report.*"
- **ChatGPT:** "*Overall, the text provides a clear description of the goals of the project, which is to implement a data-driven approach...The topic of using data science for talent scouting is appropriate and relevant, as the popularity and commercial success of the game...*"

TABLE IV
THE DISTRIBUTION OF INSTRUCTOR AND CHATGPT-GENERATED FEEDBACK WITH DIFFERENT POLARITY ON EACH ASSESSMENT ASPECT. AND THE PRECISION AND RECALL FOR THE TASK THAT CHATGPT GENERATES FEEDBACK WITH THE SAME POLARITY AS INSTRUCTOR FEEDBACK.

Aspects	Polarity	Instructor	ChatGPT	Precision	Recall
Goal	Positive	5	95	0.04	0.80
	Negative	40	3	0.33	0.03
	None	58	5	0.40	0.03
Topic	Positive	86	95	0.84	0.93
	Negative	5	0	0.00	0.00
	None	12	8	0.13	0.08
Benefit	Positive	19	85	0.20	0.90
	Negative	59	5	0.60	0.05
	None	25	13	0.31	0.16
Novelty	Positive	31	52	0.35	0.58
	Negative	19	22	0.27	0.32
	None	53	29	0.59	0.32
Clarity	Positive	24	77	0.21	0.67
	Negative	11	17	0.29	0.46
	None	68	9	0.44	0.06

TABLE V
THE DISTRIBUTION OF FOUR LEVELS IN THE FEEDBACK PROVIDED BY THE INSTRUCTOR AND GENERATED BY CHATGPT.

Levels	Instructor		ChatGPT	
	Quantity	Frequency	Quantity	Frequency
Task	103	100%	103	100%
Process	82	80%	57	55%
Regulation	11	11%	0	0%
Self	25	24%	0	0%

B. Results on RQ2

The results for answering RQ2 are presented in Table IV. By observing the values of precision and recall metrics (introduced in Sec. III-C), we can see that among five assessment aspects, ChatGPT achieved the highest agreement score (precision: 0.84, recall: 0.93) in positive polarity for the aspect of "Topic". This observation can be supported by the fact that both the instructor and ChatGPT gave a majority of students positive feedback on the aspect of "Topic", i.e., 86 out of 103 positive feedback by the instructor and 95 out of 103 by ChatGPT, as shown in the number of feedback in positive polarity of "Topic" in Table IV. On the other four aspects, students mostly received either negative feedback or empty feedback (i.e., feedback that did not contain any comments on a specific aspect, which was denoted as None in Table IV) from the instructor, in comparison with ChatGPT which generated more positive feedback than the instructor. Although the recall scores of ChatGPT on positive polarity in the "Goal" and "Benefit" were also high, we can not draw a conclusion that ChatGPT agreed with the instructor as the precision on these levels was very low (0.04 on positive polarity in the "Goal" and 0.20 on positive polarity in the "Benefit"). In other words, for the aspect of "Goal", among 95 reports that ChatGPT gave positive feedback, only 4 percent of them also obtained positive feedback from the instructor, and for the aspect of "Benefit", among 85 reports that ChatGPT gave positive feedback, only 20 percent of them also obtained positive feedback from the instructor.

C. Results on RQ3

Table V indicates that task-level feedback appeared in every piece of feedback either provided by the instructor or generated by ChatGPT. What is surprising is that ChatGPT was able to generate process-focus feedback for over half of the reports. The proportion of feedback offered by the instructor at self-regulation and self levels was smaller compared to other levels, while feedback at self-regulation level and self level was not detected at all in the feedback generated by ChatGPT.

V. Discussion

Implications. It is worth noting that instructors in higher education struggle to consistently deliver feedback of quality that meets students' expectations due to time constraints [4], [23]. Our study showed ChatGPT's ability to generate more readable feedback with greater consistency, which provides support for deploying ChatGPT to help educators provide personalized feedback of consistently high quality for a larger scale of class in less time. The results of RQ2 indicated that ChatGPT could not offer a reliable assessment of student performance compared to the instructor. A possible explanation for this might be that we did not train ChatGPT by feeding examples including students' assignments of different quality and associated golden feedback that accurately evaluates their performance. In future research, prompt engineering should be done to ensure the reliability of ChatGPT in terms of assessing students' assignments, based on which we can further investigate the effectiveness of ChatGPT feedback in promoting student learning. Moreover, we surprisingly found that ChatGPT could generate a considerable number of process-focus feedback which is regarded as more effective than task-focus feedback for shaping students' task strategy [11]. This implies the promising values of ChatGPT in guiding students towards improving their tasks or even developing learning skills.

Limitations. *Firstly*, although the current study measured the overall agreement between the instructor's feedback and ChatGPT's feedback in terms of polarity on each assessment aspect, we have not tested their alignment on the same assignment, which is more critical to each individual student. Further studies should investigate to what extent ChatGPT can provide effective feedback relevant to the assignment that it comments on. *Secondly*, ChatGPT generating feedback in an unsupervised way could potentially influence the effectiveness of generated feedback in our study. In the future, we may consider conducting prompt engineering to obtain the desired feedback from ChatGPT according to the learning goal. *Lastly*, the analyses conducted in our study heavily rely on human annotation which is time-consuming. Therefore, automatic evaluations warrant further development for assessing the effectiveness of educational feedback.

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