Leveraging Generative AI and Human Collaboration in Peer-Feedback

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Peer feedback is an important practice frequently employed in education. However, it is often challenging for students to provide well-structured and standardized feedback. With the development of conversational generative AI, such tools can be leveraged to support the peer feedback process. However, it is unclear the impact of such human-AI collaboration on the peer feedback process, especially the learning and perception of the feedback provider and receiver. In this work, we present a review of existing literature as well as a study design to investigate this question.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**.

Additional Key Words and Phrases: generative AI, peer feedback, ai-mediated communication

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1 INTRODUCTION

The ability to provide effective feedback is a crucial skill in education and beyond. However, research has shown that students often struggle with providing constructive feedback to their peers [16]. Well-structured and comprehensive feedback is essential for the receiver to learn from the feedback [15]. The lack of feedback skills can hinder the development of both the provider and the receiver of feedback. In recent years, artificial intelligence (AI) has been employed as a tool to provide automatic feedback to students [12]. With the development of conversational generative AI such as ChatGPT, these AI tools have demonstrated considerable advance in providing human-like structured responses. Generative AIs show promise in being integrated as a tool to provide feedback in a structured and coherent manner, offering students a standardized content and grounds for starting the feedback process. This can potentially lead to improved feedback quality, more engagement and greater confidence in providing feedback to others. For instance, AI can provide the initial feedback on a piece of student's work, the feedback provider can use such feedback as a starting ground, editing and improving on the AI generated feedback.

Despite the promises provided by conversational generative AI, it is important to note that AI-generated feedback is not a substitute for human feedback and human involvement is still necessary. Providing feedback itself is a valuable skill as students providing the feedback can learn

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as much from this process as the receiver of the feedback [16]. Therefore, a hybrid model that leverages the collaboration between human and AI-generated feedback may be the most effective approach.

Furthermore, prior research has illustrated the importance of understanding trust in AI-generated content as well as in Human-AI collaboration [17]. While AI-generated feedback can help standardize the feedback content, feedback can be an especially vulnerable process for the students. The inclusion of AI-generated content in this process could potentially have significant impact on the perception of such feedback. It raises an important question of how such information can be integrated to the students so it is perceived as helpful and constructive.

We therefore propose the following research question: how does human collaboration with generative AI affect peer feedback? More specifically, we want to investigate the following three questions:

1. How does Human-AI collaboration affect peer feedback quality?
2. How does Human-AI collaboration affect feedback provider's learning?
3. How does Human-AI collaboration in peer-feedback affect perceptions of feedback quality, usefulness, and receptivity?

2 BACKGROUND

2.1 Peer feedback and intelligent systems in education

Feedback is an essential element in education research. Feedback provides a means for obtaining external evaluation of their learning [7]. Good feedback not only stimulates students to reflect on their actions, but also provides directions for them to further grow. However, there is a high demand for feedback yet limited ways it can be provided especially from an authoritative figure. To address this gap, a variety of intelligent tools have been developed and used in educational settings. For instance, AI-based tools have also been used to assist students in correcting and improving their works [10, 12].

On the other hand, peers are also frequently employed as an important feedback provider [14]. The students can use the feedback and assessment provided by the peers as a guide to evaluate and reflect on their work [2]. At the same time, peer-based feedback provides less stress to the students compared to feedback provided by an authoritative figure and contributes to creating a collaborative learning environment [3, 13].

Even though feedback is valuable, the quality of feedback is especially important. For instance, simply pointing out something as good or bad is not enough to provide information for the student to benefit from the feedback [15]. Past research has suggested that some of the challenges that students face when providing peer feedback is the lack of structure [16]. Students frequently are not able to provide feedback in a systematic and standardized way, resulting in varying quality and different perception of usefulness from their partners [16]. Generative conversational AI can provide valuable resources to fill this gap. Based on our initial experience with such interfaces, the responses from generative conversational AI like ChatGPT are adaptable, conversational, efficient, human-like. There is a high potential for such tools to serve as a guide to provide feedback that is well structured and standardized, serving as a good scaffolding for students to learn from and improve upon, while teaching the student good methods to organize their thoughts and language. Weisz et al. [18] in their work pointed out the potential of using responses generated by AI as scaffolding to build upon.

However, despite the promises of AI in augmenting feedback, the involvement of human should still be considered essential in this process. Most importantly, prior research pointed out that not only the process of receiving peer feedback but also providing the feedback by reviewing and reflecting on other students' work has positive impact on the student's learning [5]. A study comparing the performance of undergraduate students who either provided or received written peer feedback in the context of a writing task found that both providing and receiving feedback led to similar improvements of writing performance [9]. This highlights the role of AI in this process should be supplemental, instead of a complete replacement.

2.2 Perception of trust and usefulness in AI-mediated collaboration

Recent research has suggested perception of AI, especially trust to be a crucial element for successful interaction between human and AI. Without trust, users may be reluctant to use AI-powered technologies, incorporating them into their current workflow [1, 18]. In order to develop trust in AI, there are several important factors. For instance, people need to understand how AI works, what data it uses, and how it makes decisions. This means making AI systems more explainable and interpretable, providing users with clear feedback on why a particular decision was made, and allowing them to provide feedback to improve the system's accuracy. At the same time, AI systems should work accurately and provide consistent results over time. For technical tasks such as computation, trust in AI tends to also be higher. Lastly, personalization also improves trust [6].

Even though a large body of research has focused on AI trust, these research has focused mainly on the trust between human and AI when the human is directly influenced by the AI. However, as previously described, AI has been incorporated as assistive technology, providing suggestions to certain tasks, or completing tasks specified by humans. These collaborations between humans and AI provide an important perspective into understanding the role of AI and how its advantages can be best leveraged.

This leads to a different type of trust. Past research has focused mainly on the trust of AI as a direct product. However, when AI is employed as part of the performance of a specific task, the product is consequently a mixture between AI and humans, and the contribution of the human can be obfuscated and difficult to quantify. There is limited research on the direct impact of AI involvement in a final product that is intended for a third party. Hancock et al. [8] in their work defined the term AI-mediated communication and pointed out potential benefits and drawbacks of interpersonal communications with AI-involvement. Various studies also examined when incorporated into interpersonal communications, the involvement of AI frequently decreases perceived authenticity of the message [6, 11].

Interestingly, Wu and Kelly [19] demonstrated that AI involvement in creating dating profiles decreased the trustworthiness of the creator, yet did not affect the perception of attractiveness of their profile, highlighting that even though affective dimensions such as trustworthiness and authenticity might be affected, the final product still can produce positive impact in cognitive dimensions. This study pointed out the potential of incorporating AI into tasks that are utilitarian and the potential positive impact it might have in producing a more polished product that can be well received on its utility.

In the context for peer feedback, this also raises an important question. The utilitarian nature of such AI-mediated responses can be even more evident in this context. As previously mentioned, for instance, one challenge that peers face when providing feedback is the lack of structure and standardization of the feedback [16]. These elements are about the utilitarian nature of the feedback, instead of whether the feedback feels authentic, in the affective dimension. Therefore, it is likely that the impact of AI-mediation would have a less pronounced impact on the perceived usefulness of the feedback. We believe that this is an important research question to understand in order to design feedback systems that can successfully incorporate AI without causing negative perceptions on the receiver.

Fig. 1. Pin-MI main interface. The pinning button is depicted on the bottom left corner.

3 PROPOSED WORK

In our prior work, we presented the design of a system Pin-MI, which integrated real-time annotation and peer feedback to help psychotherapy skill learning. In our work, our finding corresponded to prior research where learners, especially ones with less experience, tend to have trouble organizing their thoughts and providing feedback in a consistent manner [4]. In our design, two peers are connected to practice Motivational Interviewing (MI) skills in a conversation. During this process, with a click of a button, they can mark in real time moments where they feel they either performed MI skills well or poorly (Fig 1). After the session, the peers are first asked to independently reflect on these moments, and then provide feedback based on their reflections.

We believe generative AI can be integrated as a resource in this procedure. The conversation between the peers are transcribed in real time. The transcript of the marked moments can therefore be fed into an AI tool to generate feedback. During the self-reflection process, the peers can edit the AI-generated feedback and use them as a starting point to write their own feedback for their partner.

In order to evaluate the learning and perception of the feedback receiver on the AI-mediated content, we propose a between-subject study. Half of the participants will go through the feedback process in Pin-MI using the AI-generated tool, the other half going through the original feedback process. Participants will then be asked to rate the quality and usefulness of the feedback they receive, as well as their willingness to integrate the feedback into their future practice. The feedback generated by both groups will be compared in terms of their objective quality using a rubric.

4 CONCLUSION

In this position paper, we outlined the past research on peer feedback and intelligent systems in education, as well as problems and opportunities in AI-mediated collaboration. We focus on the research question of how human collaboration with generative AI affect peer feedback. We propose a design extension of a feedback system based on our prior work, and potential plan to study our research question.

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