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Feedback Generation Through Artificial Intelligence

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Abstract
Feedback is an essential part of the educational assessment that improves student learning. As education changes with the advancement of technology, educational assessment has also adapted to the advent of Artificial Intelligence (AI). Despite the increasing use of online assessments during the last decade, a limited number of studies have discussed the feedback generation process as implemented through AI. To address this gap, we propose a conceptual paper to organize and discuss the application of AI in the feedback generation and delivery processes. Among different branches of AI, Natural Language Processing (NLP), Educational Data Mining (EDM), and Learning Analytics (LA) play the most critical roles in the feedback generation process. The process begins with analyzing students' data from educational assessments to build a predictive machine learning model with additional features such as students' interaction with course material using EDM methods to predict students' learning outcomes. Written feedback can be generated from a model with NLP-based algorithms before being delivered, along with non-verbal feedback via a LA dashboard or a digital score report. Also, ethical recommendations for using AI for feedback generation are discussed. This paper contributes to understanding the feedback generation process to serve as a venue for the future development of digital feedback.

Keywords: feedback, artificial intelligence, learning analytics, educational data mining, assessment

Introduction

At all levels of education, feedback is an integral part of students' learning process because it informs students about improving their performance by updating their current knowledge and actively changing their corresponding behavior (Boud & Molloy, 2013; Hounsell, 2007). Feedback is used for both formative and summative purposes in a learning process; formative feedback informs students about their improvement opportunities, while summative feedback is used as an indicator of learners' success (Barana et al., 2019). This paper focuses on formative feedback as a part of the continual learning process.

The immense technological advancements over the last decade have introduced new ways of learning by allowing feedback delivery to take its digital form that allows for enhanced capability such as real-time access and personalization (Bulut et al., 2019; Ryan et al., 2019). Many of the mentioned functions were done through Artificial Intelligence (AI), which uses computers to perform tasks that usually require human intelligence (Jimenez & Boser, 2021). Among different branches of AI, the areas that pertain to the digital feedback generation process the most are natural language processing (NLP), educational data mining (EDM), and learning analytics (LA) (Gardner et al., 2021; Zhang et al., 2019).

Despite the mentioned technology, few studies have discussed the overview of how AI is specifically used in the feedback generation process, and the existing literature primarily focuses on the specific application of each branch rather than considering the AI area as a whole. To address this gap, we propose a theoretical paper to organize and discuss the application of AI, namely EDM, NLP, and LA, which are used in the digital feedback generation and delivery processes. This paper could contribute to understanding how AI is used in the feedback generation and delivery process as a venue for further development of feedback technology in the digital learning environment.

Feedback Process in Education

The underlying mechanism of feedback in stimulating students' learning process and improving their understanding of course materials is the usage of iterative learning activity, where students use the received feedback to update their understanding of the task and, therefore, their following action (Carless, 2019; Hounsell, 2007). To facilitate students' learning process, the feedback should be clear, specific, relevant to students' performance, and provided promptly for students to digest and put into practice (Bulut et al., 2020; Hounsell, 2007).

High-quality feedback not only informs students at the task level that concerns how well the task is performed (i.e., correct vs. incorrect) but also provides lasting influences at a deeper level, such as the process level that concerns the strategy to accomplish the task (i.e., how to do the task well) or self-regulated learning level that concerns students' motivation to direct themselves in their learning (Hattie & Timperley, 2007). To achieve that end, teachers need to make the feedback relatable and context-relevant to encourage them to engage in self-reflection during the feedback formulation and delivering process (Carless, 2019; Pengel et al., 2021). The teachers can craft high-quality feedback by themselves, but the burden of this task could be drastically lightened with the assistance of AI.

Feedback Generation with Artificial Intelligence

The Application of AI for Feedback Purposes

The field of AI consists of different branches such as deep learning or robotics, but the branches that play pivotal roles in the feedback generation process are NLP, EDM, and LA, as discussed above (Gardner et al., 2021; Holmes et al., 2019). NLP is a branch of AI that concerns the interactions of computer and human language through the understanding, manipulation, and generation of textual data (Moreno & Redondo, 2016). EDM is another AI branch that concerns leveraging large-scale educational data to extract hidden knowledge such as student clusters or learning outcome prediction (Hussain et al., 2018). LA, similarly to EDM, is also a branch of AI that concerns the usage of large-scale educational data to gain insights that would inform educators in their practice and students in their learning development (Larusson & White, 2014). The main difference between EDM and LA is that LA focuses on improving the effectiveness of teaching and learning through resource optimization (e.g., time, money, learning activity record) while EDM focuses on the improvement of the automation process via algorithms (Chen et al., 2020).

Despite their differences, these three AI branches can be used together as a single process to produce results that are more innovative than any single application. Instead of completely replacing teachers' role in the feedback generation and delivery processes, the application of AI for feedback purposes allows teachers to work more efficiently by enabling them to work with a large amount of student data and to provide automated feedback to a large number of students through the usage of predictive and natural language generation models (Bamiah et al., 2018). Also, feedback provided via LA dashboards can improve students' learning experience when compared to traditional feedback reports (Wang & Han, 2021).

The Feedback Generation Process Through the Three AI Branches

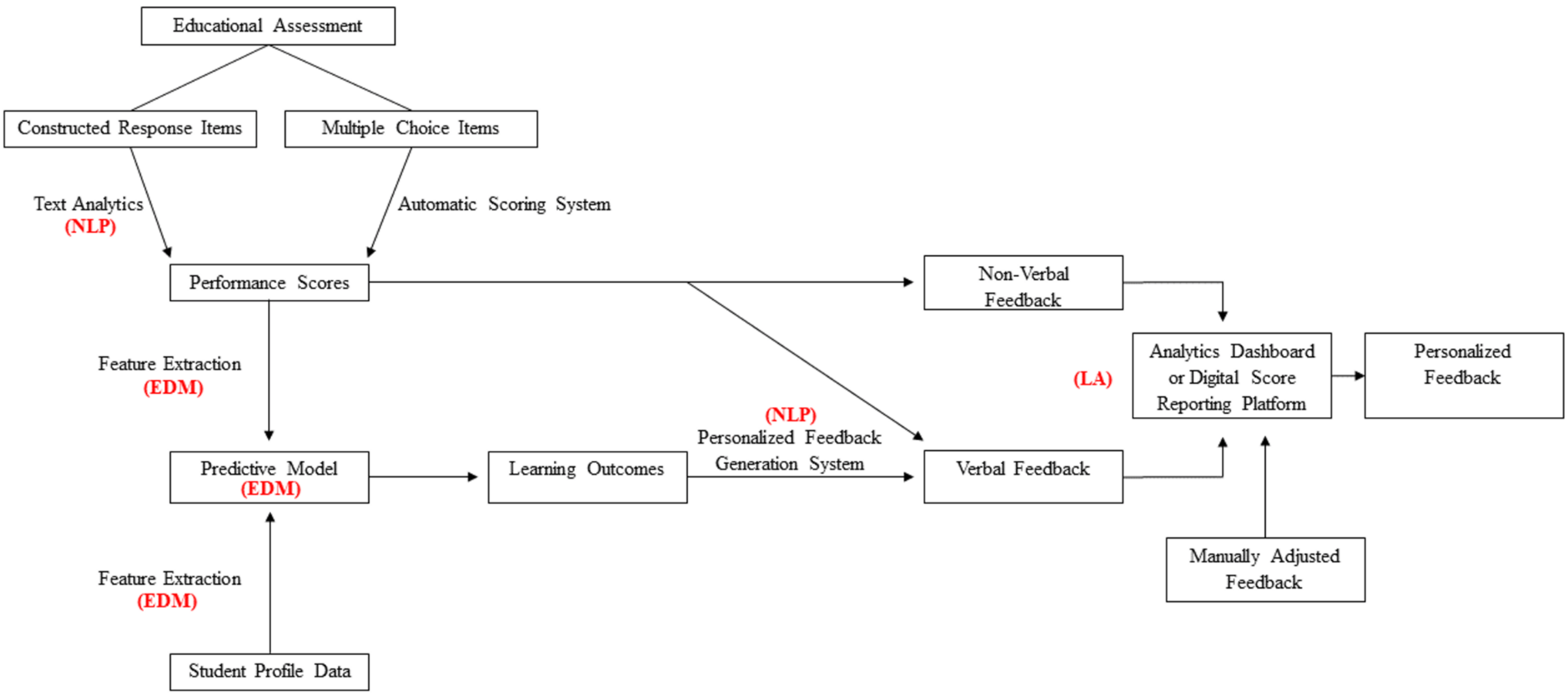
Figure 1 represents the process of feedback generation via AI. The three AI branches (i.e., NLP, EDM, and LA) work together at each point of the process, from raw data processing to delivering personalized feedback as an end-product. In the digital feedback generation pipeline, raw data from students' assessments, such as the results of quizzes, homework assignments, and formative assessments, are analyzed to develop a predictive model using a machine learning algorithm (Liu et al., 2020). Data from assessments with multiple-choice items can be analyzed with the automatic scoring system and constructed response data can be analyzed with text analytics for key themes or other linguistic elements (Kuwana et al., 2018; Moreno & Redondo, 2016). Then, students' performance data can be combined with their profile data (e.g., interaction with course materials, students' course history) as additional features. The usage of EDM methods allows numerical profiles such as log data, previous grades, or learning-related constructs (e.g., motivation, behavior) to be processed into features of a predictive model (Elatia et al., 2016). Textual data such as students' verbal responses to surveys can also be converted into features with NLP techniques such as word frequency with the Bag-of-Words model or weighted term frequency with the Term Frequency-Inverse Document Frequency (TF-IDF) statistics (Ahuja et al., 2019).

The extracted features can be integrated into the model to predict students' learning outcomes (e.g., final course grades, the probability of failing the course) with classification and/or regression methods such as logistic regression, linear regression, or a more sophisticated method such as Classification and Regression Tree (CART) (Shaun Baker & Salvador Inventado, 2014). Results from the final model can then be used along with students' performance data to generate written feedback through the personalized feedback generation system, which uses an NLP algorithm with functions such as a personalized bias mechanism to formulate feedback relevant to the student context in each learning domain; doing so could influence students up to the self-regulation level and therefore create sustainable improvements in student knowledge (Hattie & Timperley, 2007; Liu et al., 2020; Pengel et al., 2021).

Finally, the generated verbal feedback and non-verbal feedback (e.g., scores, tables, and graphs) can be delivered via a LA dashboard or a digital score report for a comprehensive and personalized understanding of student performance with the addition of innovative visualization such as bubble graphs or radar charts (Bulut et al., 2019; Roberts et al., 2017). In this phase, software programs such as OnTask can provide opportunities for teachers to manually inspect and adjust the feedback to account for students' creativity and original thoughts that may be overlooked by the system before pushing the feedback to go "live" (Tsai et al., 2021). The dashboard could also provide an early indication of potential difficulties that the students may face (e.g., a drop in performance in certain course topics) that could inform both teachers and students in their planning of future learning strategies with a lasting change (Jokhan et al., 2019; Roberts et al., 2017).

Figure 1

The Process of Feedback Generation through Artificial Intelligence



Ethical Recommendations for the Use of AI for Feedback Generation

The whole feedback generation process (see Figure 1) is driven by learners' data. However, there are times when data is collected without the users' awareness, which contradicts the general data protection regulation (GDPR) that protects individuals' rights to their personal data (Trade Commissioner Service, 2022). Furthermore, machine learning models used in the feedback generation may be subjected to the "black box" problem that obscures the model's mechanism and reduces the system's trustworthiness and credibility (McGovern et al., 2019). Given how the feedback generation system primarily relies on students' data and the capability of machine learning models, we are providing recommendations that practitioners or developers could consider respecting students' rights and upholding the system's trustworthiness.

First, researchers can focus on using models that are understandable by the audience at large such as logistic regression or decision trees instead of black box models such as neural networks (Khosravi et al., 2022; Wang et al., 2019). The explainability of predictive models can also be enhanced by using predictors that are malleable and rooted in pedagogy (e.g., students' time use in an online assessment) instead of non-academic predictors that may benefit the model but cannot be improved (e.g., race) (Hooshyar et al., 2019). Second, to promote ethical uses of NLP in a feedback generation system, researchers could develop the system with a user-centered co-design approach by involving students and teachers in the planning and development process of the system to identify and meet the needs of stakeholders (Sanders & Stappers, 2008). For example, AcaWriter–a writing analytic tool that provides feedback on students' writing tasks (e.g., essays), was designed to allow teachers to customize feedback to be context-relevant before letting the software deliver such feedback to students (Knight et al., 2020).

Discussion and Conclusion

This theoretical paper seeks to organize and discuss the application of NLP, EDM, and LA to the feedback generation process. Each AI branch plays pivotal roles throughout the process from transforming students' assessment data into both verbal and non-verbal feedback and display them as personalized feedback via a dashboard or a digital score reporting platform. However, there are still limitations that need to be addressed. First, the results regarding students' learning outcomes as the predictive model could exclude minor but meaningful differences between students, such as their context outside of the learning environment. If possible, the feedback should be supervised by teachers as an additional effort to ensure its relevance to students' context. Second, the feedback generation system explained in this paper is based on studies in the context of English as the primary language. To increase accessibility, teachers could consider localizing system into local languages such as Chinese (Wang & Han, 2021). Third, the feedback system discussed in this paper only focuses on the application in the higher education context. The educational level of the users (i.e., K-12 vs. higher education) should be considered in the application as the positive effect can change depending on the use of technology and the conceptualization of learning (Hew & Cheung, 2013).

There are three primary contributions of this paper. For theoretical contribution, this paper could contribute to understanding the application of AI in the feedback generation process as a venue for future study of feedback generation. Secondly, this paper could serve as an initial point of contact for researchers who are new to the field of feedback generation as related to AI as it covers the basics of the three branches and how it contributes to the process. For practical contribution, this paper could inform teachers about aspects of the feedback generation process and aid them in leveraging their capability to maximize the efficiency and effectiveness in their feedback delivery in classrooms. Future research could find a way to integrate a venue for students to provide feedback regarding the accuracy, applicability, and practicality of the provided feedback into the system for audit and transparency purposes. Feedback from students is helpful in both secondary and higher education in improving teachers' practice (Flodén, 2017; Mandouit, 2018).

Author's Contributions

The authors confirm their contributions to the paper as follows: manuscript conception and design: TW, OB; figure design: TW, OB; supervision: OB. All authors reviewed and approved the final version of the manuscript.

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Ethics Statement

This study did not require ethics approval because no data collection was involved in the writing of this manuscript.

Conflict of Interest

The authors do not declare any conflict of interest.

Data Availability Statement

No data was used in the writing of this manuscript.

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