Multimedia learning analytics feedback in simulation-based training: A brief review

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Abstract

Learning analytics has gained significant attention in recent years, particularly in the healthcare field. This area of research offers valuable insights to educators, students, and researchers to enhance the quality of education. One area of focus in learning analytics is how stakeholders provide feedback to each other during training in operating theatres. With the availability of diverse multimedia elements, such as text, images, and spoken language, as data, employing effective feedback methods can bring substantial benefits to teachers, students, and researchers. This study synthesizes various approaches that apply multimedia to provide feedback in teaching, comparing and exploring their potential application in simulation-based medical training. The feasibility of input data, the effectiveness of feedback on recipients, and the AI method of generating or synthesizing feedback using existing data efficiency are also discussed in line with ethical standards. Finally, a multimedia feedback framework is proposed, which utilizes diverse multimedia formats and can be effectively implemented in various real-world scenarios.

CCS Concepts: • **Applied computing** → *Computer-assisted instruction.*

Keywords: Learning analytics, Simulation-based learning, Multimedia feedback

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1 Introduction

Simulation-based training is widely employed in medical education worldwide and brings adequate clinical skill to medical students [1]. This methodology offers a structured learning environment with specialized equipment, facilities, and surgical mannequins. Simulation-based training enhances students' knowledge and skills, preventing potential medical errors during surgical procedures, and various ways to organize it are available, including simulation interviews, augmented reality in virtual environments, 3D anatomical models, and virtual operating room simulations [2]. In contrast, current research often relies on basic methods such as paper-based materials, evaluation forms, or single-source media to collect data and provide feedback, thus minimizing the quantity of collected data and the effectiveness of the feedback [3].

On the other hand, the advancement of artificial intelligence (AI), machine learning, and deep learning have demonstrated high potential across various interdisciplinary domains, such as finance and cryptography, [4, 5] and learning analytics [6]. Among these domains, education has emerged as a prominent area of research and exploration[7]. This transformation has revolutionized traditional teaching and learning methods and enabled multimedia data collection. Consequently, numerous theoretical concepts have been translated into practical applications, addressing critical learning perspectives such as error notification, auto-grading, and real-time intervention [8–10]. These developments showcase the immense potential of this research field in enhancing educational practices.

Another crucial aspect to consider is the feedback loop between teachers and students, which provides valuable insights into their respective fields of study or work [11]. The provision of constructive feedback creates opportunities for students and teachers to improve themselves and the overall learning system continually. In learning analytics, researchers have introduced methods for delivering feedback to end-users, taking into account the specific research context and data availability, which has the potential to enhance the learning process directly [12]. Therefore, the primary objective of this paper is to survey various feedback mechanisms from diverse perspectives within a classroom environment to explore the underlying motivations behind these methods, and the benefits feedback recipients can derive from them. By thoroughly addressing this issue, it is possible to identify a suitable approach for developing an end-to-end framework for learning analytics, thus strongly contributing to resolving practical challenges.

Overall, this paper aims to answer the following questions:

1. How are various multimedia elements applied in providing feedback to teachers, students, and researchers through different methods such as interactions, textual reports, or dashboard designs?
2. In the particular context of simulation-based medical learning analytics, how can we ensure feedback has been taken effectively and efficiently on board?

This paper surveys multiple methods of providing feedback in education, leading to a discussion of how these methods can be utilized in the context of simulation-based medical learning analytics to facilitate feedback and assessments.

This paper is published at AIQAM24, the 1st ACM Workshop in AI-powered Question & Answering System [13]. It aims to bring valuable insight into how can student gains benefit from the multimedia answer to the learning analytics question given in the simulation-based training.

2 Background

This section describes two research directions: learning analytics and giving feedback in education.

2.1 Learning analytics

Learning analytics (LA) involves applying modern technology to enhance the teaching and learning process [14]. Its primary objective is to analyze and understand learning behaviors in various contexts, providing suggestions and predictions to stakeholders regarding engagement, improvement, and satisfaction. With the diversity of learning subjects, LA collects data from multiple multimedia sources, including voice, camera, note-taking, and software logging, and explores different system setups for implementing learning analytics [15]. This field leverages artificial intelligence and machine learning techniques such as picture, video, audio processing and outlier detection to bridge the gap between theory and real-world applications [16].

Each domain within learning analytics has its specific requirements in terms of expert knowledge and equipment. For example, class analytics focuses on monitoring student progress and engagement [17], while sports training analytics delves into a detailed analysis of athletic actions [10]. However, it is crucial to handle and utilize data in a careful and ethical manner, ensuring the approval and privacy of individuals who contribute to the datasets [18].

2.2 Feedback in education

Feedback in education refers to the activities through which teachers and students exchange information about the similarities and differences observed in the classroom and the objectives of the learning process, thereby playing a crucial role in both learning assessment and the learning cycle [19], as it helps stakeholders continuously discover the insight, understand the perspectives of the other party, and make appropriate adjustments. Effective feedback facilitates a closer relationship between teachers and students, enabling them to achieve the goals of learning analytics more easily.

In addition to ensuring accuracy and clarity in content, good feedback needs to be considered in various aspects such as word count, timing, and delivery method [20]. Moreover, effective feedback serves as an answer to the question of what stakeholders can change in the entire learning system [21].

In medical training, actively participating in discussions and providing feedback allows students to receive diverse opinions, enhancing meta-cognitive awareness of various aspects of the lesson [22]. This approach enables learners to provide feedback to each other, increasing the quantity of feedback received by each individual and facilitating peer-to-peer perspectives from individuals with similar levels of expertise. Understanding these insights is beneficial for evaluating the entire training session, but it also requires practitioner honesty and active engagement throughout the process [23].

3 Methods of giving feedback

In this section, this paper synthesizes feedback across various types of multimedia, categorizing them based on their similarities in form and application, mostly considered in research published within the last 12 years.

3.1 Interactive feedback

Giving interactive feedback in the form of verbal instruction provides immediate input from the teacher to the student following a simulation, making it particularly valuable for scenarios involving practical training or skill-based activities. For instance, during patient-simulation training sessions [24], the instructor assumes the role of a simulated patient and interacts with students, offering direct feedback at the conclusion of the session. Verbal feedback is prompt and adaptable to the specific situation, but it can also overwhelm students as they need to process a large amount of information, including technical terms [25, 26].

It is essential to consider that delivering feedback directly can potentially cause discomfort for students if the situation does not meet expectations [27]. Thus, it is crucial to avoid such situations. To address these concerns, discreet wearable devices like haptic vibrations or in-ear headphones have been found to offer support to students [8]. Haptic devices can be applied in specific skill training requiring in-time reflection [28], such as using a racket or bat, while in-ear headphones provide audio guidance for general tasks like following an instruction. This approach allows recipients to receive information and make immediate adjustments to their actions quickly, even as fast as verbal feedback [8], leading to the need for in-action feedback, which should be more real-time and subtle. However, learners may forget this guidance easily if they do not have a systematic recording and/or less practicing time.

3.2 Structured or semi-structured report

Structured or semi-structured reports like form and table feedback provide information on the use of figures for stakeholders, especially class administrator and researchers. There are many ways to provide feedback by forms: the questionnaire for the text answer [29], multiple choices [30] or the combined method with the scale H-shape [29]. The responses in the form can be well-organized into proper information about the idea and opinion, and therefore, the comparison is much easier. Moreover, feedback grouped by tables brings crossover information that can be used to compare several objects at the same time. Not only students and tutors but the researchers and class management can gain benefits from these forms. However, a clear form or table feedback may require much effort in writing and gathering questions for different kinds of learners, from the tutor, especially their intuition about the way they want to illustrate their question and answer [31].

Form and table feedback play a crucial role in providing stakeholders, particularly class management and researchers, with valuable statistical insights. Various methods can be employed when working with forms for feedback, including text-based questionnaires [29], multiple-choice options [30], or a combined approach incorporating the H-shape scale [29]. These forms facilitate the organized collection of information pertaining to ideas and opinions, making comparisons and analyses much more accessible.

Table feedback, on the other hand, allows for the simultaneous comparison of multiple objects, presenting cross-sectional information that can be applied to assess and evaluate various aspects. While score sheets and school schedules are commonly used examples of table feedback for students, tables can serve as a valuable tool for statistical analysis of factors such as satisfaction and evaluation [31, 32].

The benefits of utilizing forms and tables for feedback extend beyond students and teachers, encompassing researchers and class management. These tools empower stakeholders to make data-driven decisions and gain valuable insights. Nonetheless, it is essential to note that creating clear and effective forms or tables for feedback requires substantial effort in terms of question formulation and gathering information suitable for different students. The intuition of teachers is essential in effectively structuring and presenting questions and answers [31]. In short, form and table can be powerful tools to aggregate the data for further implementation.

3.3 Text-based report

A wall-of-text report is the most established method to provide feedback to students and tutors, and recent researchers have shown a way to apply prompts and a large language model (LLM) to make this process more convenient [33–35]. The topic of the text report is various, discussing many aspects of learning analytics. For example, writing a student diary is a basic method to collect feedback from students on class content, but it needs ethical approval from individuals [29]. Following the huge advance of LLM models such as GPT-4 [36], huge potential can be seen to set up experiments for transfer learning that focus directly on the specific type of learning. In this paper [37], LLM models generate reports for individual behavior analysis, but they can be applied widely to any other kind of training. As everything can be represented by text, stakeholders can get all the information, but it is not limited to student identity and behavior, class context and situations, and the summary of teaching elements without any missing information. Furthermore, studies have been conducted on using automated content extraction methods to extract the main points from lengthy full-text feedback, as it can be time-consuming to read and summarize [38].

3.4 Graphic-based feedback visualization on dashboard

A learning analytics dashboard (LAD) utilizes various types of media, including graphs, charts, and maps, to present information visually engagingly, offering valuable insights to supervisors and students [39, 40]. These visual elements enhance comprehension and provide a more intuitive understanding than traditional text-based reports. By leveraging these tools, teachers and students can explore and grasp the concepts of learning, reorganize their knowledge structures, make informed decisions, and foster a deeper sense of engagement with the other class members and study material. However, research recommends that these visualizations be focused on pedagogic purposes to avoid distraction [40].

Graphs and charts are widely used in LADs to track student's progress throughout the learning process, making them suitable for any task that involves a series of actions or comparisons [41]. Supervisors can gain insights into specific skill gaps or visualize students' satisfaction levels upon class completion. These visual representations enable supervisors to identify areas where students may require additional support or intervention.

Maps and flow diagrams are instrumental in supporting students' organization of thoughts and logical concepts that guide their actions. Traditional approaches like the Japanese network tree concept map [42] showcasing individual activities demonstrate their effectiveness in various learning contexts, offering valuable descriptions, predictions, and suggestions. In contrast to direct feedback methods like haptic guidance, which are suitable for discrete tasks, visual feedback excels in describing sequential actions such as body movements or positional changes.

By incorporating graphs, charts, maps, and other visual elements, a learning analytics dashboard provides a rich and comprehensive visual representation of data, enabling supervisors and students to gain deeper insights into the learning process [43]. This visual approach with multimedia facilitates better decision-making, enhances engagement, and encourages a more profound understanding of the subject matter.

4 Discussion

This section discusses the application of various feedback methods in simulation-based training, considering their efficiency for stakeholders and the specific conditions in which they demonstrate advantages. Additionally, it presents a brief proposal for a multimedia-based feedback delivery method.

4.1 Comparison of feedback types

To facilitate systematic research on feedback methods, this paper will categorize several reviewed approaches based on the mechanism of actor involvement in the feedback process. Table 1 can serve as a reference for researching and designing a semi-automatic feedback system that incorporates the evaluation of human actors.

Table 1. Classification table for the actor mechanism

	Human-based	**AI-method**	**Device-based**
Structured report	[19, 32]	[32]	
Graphics-based report	[8]	[41]	
Text-based	[19]	[33, 37]	
Alert	[25]	[44]	[45]
Haptic signal	[10]		[8]

4.2 Feedback in simulation-based training

As mentioned above, one potential feedback method is interaction on-time feedback, such as verbal or vibrator signals, recorded by the system and provided to students upon completing an operation. However, obtaining ethical approval to collect this type of data from students is crucial, and they must spend time to become familiar with the learning equipment [46]. The frequency of guidance commands and signals can be considered a means of facilitating students' seamless interaction with the simulation. However, more profound research, such as voice processing, poses challenges due to the subjectivity of teaching experts, the presence of various noise sources in the operation room, and the use of scientific vocabulary [47].

On the other hand, an effective way to address the challenge of expert domain terms is by applying a well-trained, large language model that focuses on medical terminology [26]. This approach involves generating detailed and comprehensive reports for each operation session, providing thorough explanations. Nonetheless, researchers must carefully review the length of the reports to ensure the quality of feedback for both students and teachers [48]. Students can contribute to the full-text feedback by submitting their lesson notes and highlighting key observations from discussions during the class review.

In addition, incorporating multimedia content that reflects the classroom situations, such as operation positions or action timelines, can be a valuable resource for describing the learning process [37]. Since simulation-based classes require students to adapt to scripted situations, decision-making mind maps can also be utilized to support students in making informed choices during their learning journey. Stakeholders, including teachers and researchers, can gain significant insights from these multimedia dashboards, enabling them to compare the actions of different student groups facing similar problem sets and draw conclusions about the efficacy of these learning materials in guiding students through their lessons [49]. However, the use of generative AI (Gen-AI) [3] should be carefully evaluated for accuracy before providing such images to individuals.

While research on feedback methods continues to advance [50], it is essential to recognize that real-world classrooms present unique challenges that require a deep understanding and practical experience within their specific contexts. Therefore, this paper aims to provide a framework for how researchers can effectively implement learning analytics in one particular learning condition, emphasizing the significant potential of technology in the fields of education and healthcare. The proposal focuses on optimizing the feedback cycle for teachers and students in simulation-based medical training classes, utilizing multimedia data as input and output. The proposed iterative process involves the following steps, shown in Figure 1.

1. Identify the key questions for stakeholders in the class.
2. Collect input data from the operations and discussions by the camera, audio recording, or haptic devices.
3. Aggregate storage data with proper learning analytics tools to extract the critical points.
4. Employ LLM or Gen-AI techniques to generate approximate feedback for students and teachers.

5 Conclusion

In the realm of medical education, learning analytics presents a remarkable opportunity to bridge the gap between machine learning theory and practical challenges. By addressing the perspectives of all participants in the learning environment, it is promising to enhance the quality of learning for both instructors and learners. This study explores four multimedia-based methods for providing feedback and compares their usage in terms of factor involvement before proposing a solution to integrate them into a cohesive flow that adds value to the recipients. This serves as a foundational step towards developing a framework that incorporates multimodal data

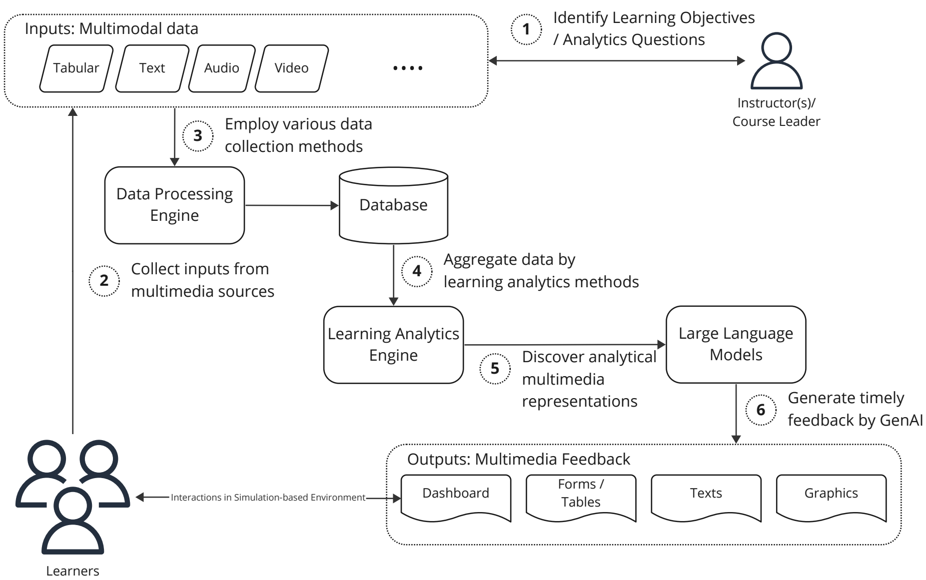

Figure 1. Proposal flow for applying AI into multimedia feedback

and employs automated processing to generate evaluations, ultimately improving teaching quality. In the pipeline, we plan to assess the effectiveness of the proposed framework in the context of real-world learning with simulation-based training scenarios.

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