Implementing Cloud-Based Feedback to Facilitate Scalable Psychomotor Skills Acquisition

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Abstract

Personalized feedback in psychomotor training often involves the use of sophisticated Machine Learning (ML)-based algorithms, requiring the utilization of cloud-based computational power for efficiency and scalability. By incorporating a cloud-based feedback system, learners may receive individualized feedback on their psychomotor performance in real-time or as summative analysis, allowing them to develop their abilities more efficiently. The integration of a cloud-based feedback mechanism into immersive learning environments is explored to improve the acquisition of psychomotor abilities. The essential components of the feedback system are discussed in this article, including data collection, analysis, and dissemination, as well as the obstacles and issues related to its implementation.

Keywords

multimodal learning analytics, immersive feedback generation, cloud infrastructuring, machine learning as a service, psychomotor learning, big data, MILKI-PSY

1. Introduction

The development and mastery of psychomotor abilities is essential in a variety of fields, including athletic training, healthcare, vocational education and in human-robot interaction. Immersive Learning Environments (ILEs) have emerged as effective platforms for facilitating psychomotor learning by providing learners with safe environments to practice and refine their skills. However, to optimize the learning experience, it is essential to implement a blend of real-time [1] and summative [2] feedback mechanisms. While real-time feedback is generally considered more impactful [3], a strategic balance between the two can optimally support learner growth and proficiency acquisition. Cloud-based feedback platforms provide advantages in this area through analyzing and transmitting personalized feedback to multiple learners, outperforming local systems. This contribution investigates the use of a cloud-based feedback mechanism for ILEs to improve the acquisition of psychomotor abilities. Leveraging cloud technologies allows for the scalable delivery of personalized feedback, leading to enhanced skill development and improved learning outcomes for a broad range of learners.

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2. Related Work

2.1. Immersive Learning Environments (ILEs)

Immersive technologies, such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), integrate real and simulated environments to generate innovative artificial experiences [4] and are gaining prominence in the field of education [5] because they engage learners in a genuine experience allow them to visualize abstract concepts [6]. Furthermore, they assist students in developing specific skills that are more difficult to acquire using traditional educational resources [7], and they have been shown to increase participation [8] and engagement [9]. Immersive Learning (IL) serves as an educational method that explores the educational benefits of non-mediated artificial experiences, involving the active construction and adaptation of cognitive, affective, and psychomotor models [10]. The technological affordances used in ILEs help to induce feelings of presence *(being there)*, co-presence *(being there together)*, and identity formation *(connecting the visual representation to the self)*, allowing participants to feel fully immersed and connected to a virtual environment [11, 12]. ILEs have been widely acknowledged for their ability to improve learning across a wide range of areas, such as STEM (science, technology, engineering, and mathematics) [13], language Education [14], medical education [6] or other domains [15, 16]. An example framework to support the understanding of the usage of immersive technology affordances in learning environments is the cognitive-affective model of immersive learning (CAMIL) [17], which is based on cognitive and affective factors such as interests, motivation, self-efficacy, cognitive load, and self-regulation.

2.2. Feedback in Immersive Psychomotor Learning

Psychomotor skills involve the interplay between motor skills and cognitive abilities for performing physical activities such as catching a ball or playing an instrument [18]. In psychomotor learning, teachers play a vital role by providing explanations, demonstrations, and evaluations of skills. Their presence enables the identification and correction of movement errors, leading to improved performance. Additionally, they have a positive impact on promoting human physical health [19]. However, the traditional methods of teaching these abilities based on repetition and teacher feedback [20] are often being complemented with immersive learning environments [21, 22] to provide scalable and engaging feedback. Two communication channels *(visual and auditory)* of the five human senses *(visual [23], auditory [24], gustatory [25], olfactory [26], and haptic [27])* have received the majority of the focus in multisensory feedback systems, potentially hindering the efficiency of learning [28]. Receiving timely feedback allows learners to gather information about their execution of movements and apply it effectively for immediate adjustments [1]. Instructional Design Methods (IDMs) or mechanisms for providing feedback in an ILE include point of view video, ghost track, contextual information, 3D models and animation, and interactive virtual objects [29]. These methods can enhance the learning experience by directing the trainee's attention, providing expert perspectives, and visualizing expert movements.

2.3. Cloud-Based Feedback Systems for Learning

A hands-on experience improves learners' practical abilities, but difficulties such as the scalability of such courses, teaching big groups, providing feedback, and evaluating learning gains, provide substantial challenges [30]. Leveraging cloud computing capabilities can help overcome local processing limitations [31], providing access to extensive computational resources that are frequently necessary for the high-demand Artificial Intelligence (AI) algorithms utilized in generating feedback during psychomotor learning. The utilization of cloud-based virtual learning environments has demonstrated promise in reducing the growing disparity in academic ability between rural and urban learners, enabling rural students to be more competitive academically [32]. By leveraging a cloud-based learning environment, instructors can extend the reflective activities of learners, overcoming constraints of face-to-face conversations and fostering reflective skill development [33]. This can be achieved by facilitating infrastructure for scalable feedback [34, 35], hosting of collaborative ILE sessions [36], provisioning of cloud-based media elements [37], and enabling of long-term persistence of educational materials [38]. Cloud-based feedback mechanisms can offer diverse learning opportunities in ILEs [39] by generating personalized and interactive instructions [40], provisioning of formative and summative feedback [41], or enabling peer-based feedback [42]. To enable scalable transmission, storage, and analysis, distributed communication systems like Apache Kafka [43] are used to effectively manage the heterogeneous data of multimodal sensor applications. Different modalities are processed using data fusion strategies such as early fusion, late fusion, and cross-modality fusion [44]. Time series databases, like InfluxDB, are designed to handle and analyze large volumes of time series data, such as sensor readings [45].

3. Cloud-Based Feedback Mechanism for Immersive Psychomotor Learning

In Immersive Learning Environments, the collection of sensor-based data plays a crucial role in accurately recording and assessing learner behavior to enhance their learning experience with accurate feedback. The proposed cloud-based feedback generation system, illustrated in Fig. 1, incorporates a comprehensive framework that efficiently collects sensor data from learners **(1)** through the utilization of a Unity-based frontend template. The gathered sensor data spans multiple modalities and can be used for movement tracking and other psychomotor performance metrics. This collected data is then transmitted to the backend **(2)** via a distributed messaging channel. The backend of the Cloud-supported feedback generation platform manages learner sessions and conducts learning analytics. Raw sensor data collected from learners is transmitted to the backend, where it is stored in a time series database (3) and analyzed to identify areas for improvement. Based on the information stored in the database, the Machine Learning (ML)-based Feedback Generation component (4) can analyze learner data and generate personalized feedback tailored to the unique context of the learners. Insights derived from the collected sensor data allow the system to identify patterns, trends, and potential areas of focus for personalized feedback. Currently, the feedback generating decision interface is enabled using a mocked *Wizard-of-Oz* method, allowing us to gather insights from the collected sensor data and observe patterns, trends, and potential areas of focus for giving individualized feedback. The analyzed information is subsequently sent to the frontend (5), enabling the delivery of targeted feedback instructions to learners (6) through one of the reusable IDMs provided by the frontend template (see Section 2.2).

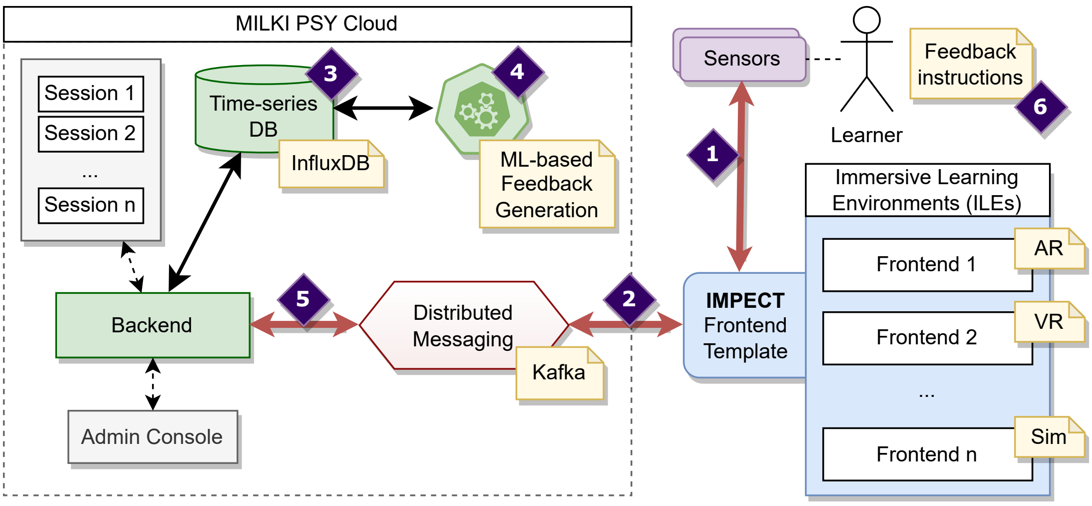

Figure 1: Proposed Cloud-based Feedback System in ILEs for Psychomotor Learning

Our cloud-based platform provides a scalable and high-performance infrastructure to offer feedback in ILEs, independent of the user count or complexity of the learning activities. The design and architecture of our infrastructure have been designed to accommodate various requirements of diverse use cases of ILEs, encompassing AR, VR, and simulated environments.

4. Conclusions and Future Work

This work explores the potential for a cloud-based feedback system in ILEs to increase the development of psychomotor skills, which could enhance skill development and learning outcomes. The cloud-based feedback generation system has been implemented successfully; however, an in-depth evaluation remains necessary to determine its performance and efficacy. Our approach attempts to address the drawbacks of conventional teaching techniques by utilizing cloud computing to give feedback that is personalized for a large number of students. This research contributes to the field of Immersive Learning and inspires further exploration of cloud-based solutions for more engaging and effective ILEs.

Future work For future work, we plan to address a few crucial areas to further improve our cloud-based feedback mechanism. One of the most significant additions is the integration of an ML-based Feedback Generation component, which will automatically evaluate the learner data stored in the database and produce individualized feedback particularly adapted to the individual context of the learners. Following this, we will evaluate scalability in large-scale deployments to ensure the system's efficacy and efficiency while serving a sizable user base.

To assure the validity and integrity of the obtained data for proper feedback creation, we will also investigate the accuracy and reliability of the sensors. Another key part is reviewing long-term assessment and skill advancement, with the goal of providing learners with continual feedback and insights into their skill improvement over time. Reducing feedback latency is crucial in ILEs to enhance learning results. Minimizing delay in feedback delivery allows for improved students' feeling of presence and immersion in the learning process. Future research will focus on optimizing feedback generation and transmission speed to provide instantaneous, tailored feedback in psychomotor training within ILEs. Minimizing feedback latency for learner actions is crucial in ILEs, which further prompts research on end-to-end latency-aware feedback generation algorithms. This could include investigating edge computing approaches and establishing an optimal threshold for partitioning client-side and server-side responsibilities to minimize feedback latency. Furthermore, we intend to focus on enhancing the security and privacy features of our system to ensure comprehensive data protection in ILEs, including federated learning, advanced encryption, and robust data handling procedures.

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