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Developing a Multimodal Learning Analytics Approach for Collaborative Learning and Metacognitive Strategies in Virtual Learning Environments for Primary Science Education

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Abstract: The growing use of virtual learning environments (VLEs) in primary education offers new opportunities for enhancing student learning. However, understanding and analysing student behaviour in these environments is still challenging, especially in collaborative science education. This research aims to develop and evaluate a multimodal learning analytics (MMLA) approach tailored for primary science education. The study will focus on four key questions: understanding the current state of learning analytics (LA) in VLEs, identifying which data types in MMLA most effectively contribute to insights into student learning behaviours, creating an MMLA approach to support collaborative problem solving (CPS) and metacognitive strategies in VLEs, and improving the visualization of MMLA results for educators and students. To achieve these goals, the research will use a series of studies that collect and analyse multimodal data, including eye-tracking, behaviour logs, and dialogue text. Machine learning and deep learning techniques will be applied to identify critical data types, and these insights will inform the creation of an MMLA approach specifically designed to support CPS and metacognitive strategies. A user-centred design will guide the creation of a visualisation dashboard. This research is expected to contribute to theory by expanding the application of the MMLA approach, critically reflecting on the potential to innovate CPS and metacognitive strategies within VLEs and improving data analysis and dashboard design, and to practice by enhancing tools for primary science education.

Keywords: Multimodal learning analytics, virtual learning environments, collaborative problem solving, metacognitive strategies, primary science education

1. Research motivation

With the rapid development of educational technology, using virtual learning environments (VLEs) in primary education has become increasingly widespread. VLEs are digital platforms that provide students with an interactive space for learning, offering resources, discussions, and educational content. Unlike general online learning, which often focuses on content delivery through static websites or video lectures, VLEs create a more immersive and interactive experience by incorporating elements such as simulations, collaborative tools, and real-time feedback (Maher & Buchanan, 2021). VLEs offer flexible and personalised learning pathways for students while providing educators with rich data for in-depth learning analytics (LA). However, despite these advantages, effectively analysing and understanding student behaviour within VLEs remains a significant research challenge (Wang, Lu, & Harter, 2021). In primary science education, collaborative learning is essential for developing students' scientific literacy and problem-solving skills. Multimodal learning analytics (MMLA) provides a new approach by integrating various data sources, offering a more comprehensive understanding and support for collaborative learning processes (Chango et al., 2022).

Therefore, this research aims to develop and evaluate a multimodal learning analytics approach specifically tailored for enhancing collaborative learning in primary science education within VLEs.

2. Related work

2.1 Learning analytics in virtual learning environments

Research on LA in VLEs has become a significant focus within educational technology. VLEs, as interactive platforms, allow for collecting rich data on student behaviours, which can be analysed to provide valuable insights. These insights support personalised teaching and optimise learning pathways by offering real-time feedback and adaptation to students' needs (Ramaswami, Susnjak, & Mathrani, 2022). However, most of this research is concentrated in higher education, particularly in the contexts of remote and blended learning environments, with relatively little focus on primary education (Gupta, Garg, & Kumar, 2022). Furthermore, many LA studies in VLEs fail to sufficiently integrate learning theories, which affects their effectiveness in educational practice (Farrell, Alani, & Mikroyannidis, 2024; Giannakos & Cukurova, 2023). These limitations highlight the need to further explore the application of LA within VLEs in primary education, especially in science education.

2.2 The transition to multimodal learning analytics in VLEs

While traditional LA in VLEs primarily relies on data such as clickstreams, time spent on tasks, and quiz scores, these forms of data may not fully capture the complexities of student learning behaviours, particularly in collaborative and interactive settings such as primary science education. This is where MMLA comes into play. MMLA expands upon traditional LA by integrating data from multiple sources—such as eye-tracking, facial expressions, and text analysis—allowing for a more holistic view of student interactions and learning processes within VLEs (Chango et al., 2022). By capturing a richer array of behavioural and cognitive indicators, MMLA holds the potential to address some of the limitations of traditional LA, particularly in environments that require deeper insights into student collaboration and metacognition. However, existing MMLA research often fails to adequately consider learners' needs, resulting in systems that are less effective in supporting student reflection and decision-making (Wang et al., 2023). This suggests a need to develop more adaptable MMLA methods that better support collaborative learning in primary science education, a critical area of focus for this research.

2.3 Visualising learning analytics results in VLEs

Despite the significant potential of dashboards to display LA results in education, their design often needs to be revised, especially in VLEs. Research indicates that many dashboards do not adequately consider user needs, making it difficult for users to derive meaningful insights, thus limiting their practical application (Jayashanka, Hettiarachchi, & Hewagamage, 2022). Moreover, dashboards are often overly complex and lack user-friendliness, which presents challenges for educators in interpreting and using these data effectively (Ramaswami, Susnjak, & Mathrani, 2022). Therefore, improving the usability and relevance of dashboard designs to better support educational decision-making for teachers and students is a pressing issue.

3. Proposed research work and preliminary research questions

The research process is organised around four key research questions (RQs) and corresponding empirical studies (See figure 1):

The first research question investigates the current state of LA in VLEs. This has been addressed through a systematic literature review (currently under submission), which identified several gaps, including limited exploration of MMLA in VLEs, a lack of focus on K-12 education, insufficient use of theoretical frameworks, and the need for improved interpretability of LA results. These findings provide the insights into the subsequent empirical studies. The second research question focuses on determining which types of data in MMLA most effectively contribute to predicting and enhancing insights into student learning behaviours in collaborative science lessons within VLEs. The corresponding empirical study will investigate various multimodal data types, such as eye-tracking, dialogue text, and behaviour logs, to assess how well they help in understanding and interpreting student learning behaviours. The third research question seeks to develop an MMLA approach tailored to support collaborative problem-solving (CPS) and metacognitive strategies among primary students within VLEs. Building on insights from the previous question, the related empirical study will design and evaluate an MMLA approach specifically aimed at enhancing these educational strategies. Finally, the fourth research question addresses how to improve the interpretability of MMLA methods for both educators and students in VLEs. The empirical study associated with this question will focus on creating a visualisation dashboard that enhances the usability of MMLA results, ensuring the data is actionable for educational practice.

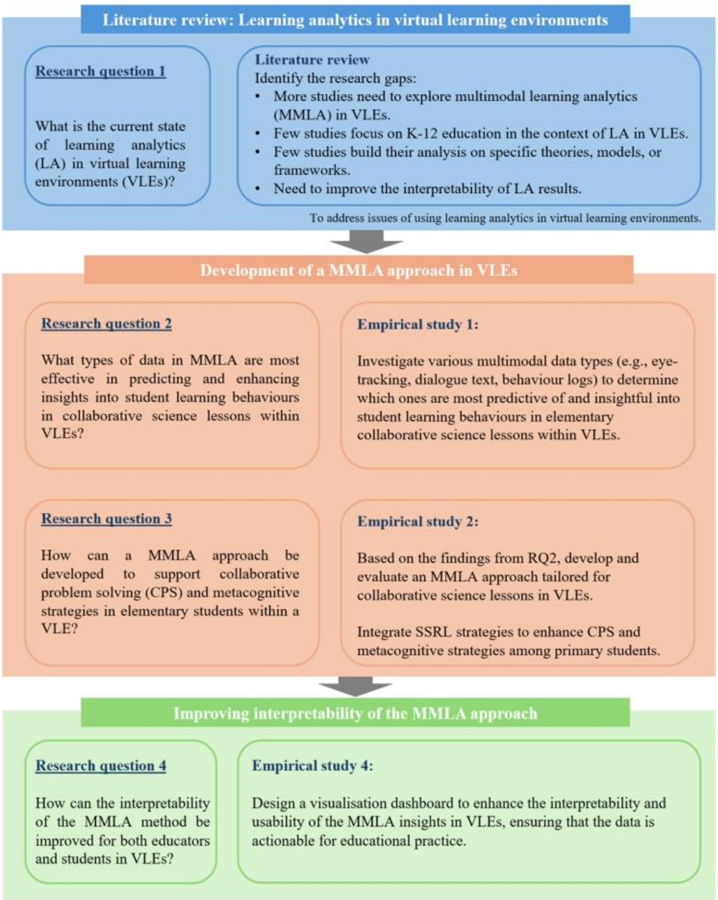

Figure 1. Research process.

4. Contributions of the proposed research

4.1 Theoretical contributions

This research will contribute to the theoretical foundations of MMLA by developing and optimising methods for integrating and analysing multimodal data within VLEs. By identifying key data types that provide deeper insights into student learning behaviours, the study will enhance the theoretical understanding of how CPS and metacognitive strategies can be effectively supported in primary science education. Additionally, the research will innovate by creating and assessing new analytical tools and dashboard designs. These tools will improve the interpretability and usability of MMLA results, supporting educators and students in making data-driven decisions.

4.2 Practical contributions

The findings of this research will be directly applied to primary science education, optimising MMLA methods to enhance collaborative learning and the development of metacognitive skills. The study will also produce practical analytical tools and dashboards that support educational practice and foster further innovations in educational technology.

5. Proposed research methodology

The first study will involve collecting multimodal data such as eye-tracking, behaviour logs, and dialogue text within VLEs. Machine learning techniques like random forests and support vector machines, alongside deep learning methods such as convolutional and recurrent neural networks, will be applied to identify the most effective data types for predicting and enhancing insights into student learning behaviour. Building on these findings, the second study will develop an MMLA approach designed to support CPS and metacognitive strategies within VLEs. This framework will undergo validation through intervention studies to assess its impact on student learning outcomes. The final study will focus on improving the interpretability of MMLA results by developing an intuitive visualisation dashboard. A user-centred design approach will guide the creation of this dashboard, which will be evaluated for usability and effectiveness through user testing and feedback, ensuring its relevance in educational settings.

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