Toward Inclusive Learning Analytics: A Multi-Profile Approach

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Abstract

The application of game learning analytics in the field of serious games can yield significant benefits throughout the entire game lifecycle. The effective utilization of game learning analytics information derived from serious games hinges on two critical factors: understandability and user acceptance. While serious games offer a valuable opportunity to systematically capture educational process and outcome data, collecting and transforming this complex data into clear, actionable insights for key stakeholders—including game designers, researchers, and educators—remains a significant issue. This challenge is particularly acute for teachers, who require transparent, usable information to effectively integrate serious games into the classroom and support improvements in learning processes. Another challenge in learning analytics systems for validating serious games is their learnability and interpretability, especially for researchers not involved in their design. When these systems combine in-game data (e.g., via xAPI) with pre- and post-questionnaires, their complexity increases, requiring understanding of experimental design, data analysis, and the integration of multiple data sources. Additionally, embedded aspects such as data privacy, anonymization, and ethical compliance are not always transparent. This can make it difficult for third-party researchers to fully grasp how data is structured and interpreted, limiting trust and reuse, and highlighting the need for more transparent and user-centered LA frameworks. This paper explores the obstacles to achieving both interpretable and usable learning analytics, emphasizing the necessity for methods that successfully translate complex data structures into practical educational decision-making tools.

Keywords

Serious Games, Learning Analytics, Stakeholders, Technology-Enhanced Learning

1. Introduction

One of the proven methods to enhance students' engagement in the classroom is Game-Based Learning (GBL), where students play a game to achieve a learning outcome [1] [2]. Studies have proven that this type of game provides better learning experience [3] motivating students [4] and optimising their results. Games designed for purposes beyond entertainment (learning, training, professional developments) are referred to as Serious Games (SG) [5]. SGs are highly effective in learning activities that aim for different learning competencies such as increasing knowledge, improving skills or raising awareness. SGs are not limited to providing information, their interactive nature has the potential to develop other competencies like problem-solving and decision making skills [6]. With the emerging development of digital games, there is an increased interest in using digital games as learning activities, especially digital serious games [7]. Digital serious games (SG) have been embedded into learning environments in several domains like medicine, military, schools, etc [8][5].

Despite their multiple advantages, leveraging SGs in real educational environments faces different challenges. Hosting institutions should be equipped with digital devices (computer, laptops or tablets) and teachers managing the play sessions should possess enough technical skills in order to help students if there are any issues and to be able to actually deploy and use the games in their classes.

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Another vital challenge is the need for evidence-based validation for the SG before deploying them in real educational environments. The most frequent method to validate SG in the literature is through external questionnaires (pre-post to gather knowledge before and after playing the game, post-game feedback evaluations). This data collection requires additional tools that automates the collection and analysis process. Validation using questionnaires can be combined with other sources, such videos, or interviews. After game validation, evidence is also needed to make data-driven decisions on their effectiveness and to appropriately assess students' progress with the game. Beyond these external measures, actual user interaction data within the game is also an essential source of insights, data captured from game-play logs such as time spent, scores, attempts, etc. This type of interaction provides a vast amount of raw data which [7], if properly labeled with learning objectives, can yield valuable insights.

Game Learning Analytics (GLA) is the collection and analysis of learning patterns and game interaction data in environments that use SG as learning activities. These interactions, probably combined together with external questionnaires, may yield relevant results towards the validation of serious games and the assessment of their actual impact on players. This evidence-based validation is essential for researchers trying to ensure serious games meet their intended educational goals, while the evidence provided by game interactions will also help game designers in the first place to iterate and improve their game and educational designs. GLA can be applied to data collected from various sources; in such cases, the data is often presented in different formats, which further complicates the process of recording and aggregating the data in order to draw meaningful conclusions.

Researchers have presented some mixed-methods and design-science frameworks to provide validated questionnaires and evaluation instruments to assess the educational impact and technology acceptance of SGs in real courses [9][10][11]. However, few commercial tools enable the collection of game-interaction logs, and the collected data usually targets the user experience with the game with the aim to improve the game for commercial use. For serious games, despite the rapid development of GLA, there are few free tools available to capture this data. Available GLA systems are game-dependent [12], and available tools are not developed to support scientific research. SG validation is usually conducted on controlled scientific experiments, where the experiments need to be prepared in a proper way and structured data should be collected and analyzed. In addition, the collection of this data should comply with data protection and privacy regulations, which is not guaranteed with commercial tools.

The lack of tools that capture and analyze GLA, complicates the adoption of SG in real world scenarios and makes it difficult to evaluate the learning process and make appropriate decisions. A recent literature review [13] highlighted the lack of integrated and accessible tools that support the design, implementation, and evaluation of SGs combined with Learning Analytics, as well as the gap between educational design, games, and analytics, which restricts their effective adoption in educational settings.

Similarly, serious games typically create their own ad-hoc analytics and reporting systems. Game-dependent analysis and visualizations are useful on a case by case basis, but add an additional layer of complexity. This complexity may be easily overcome by some stakeholders (e.g., researchers with advanced data analysis expertise) but it may make the tasks of other stakeholders (e.g., teachers) more difficult to obtain meaningful information from the collected data.

To the best of our knowledge, there is a lack of generic tools that simplify evaluation, classroom application, and generate reports on player behavior. In this paper, we propose a learning analytics system (SIMVA) that simplifies the use of serious games throughout their different possible scenarios (design, validation, application) for the three key stakeholders: game designers, researchers, and teachers. We focus on the needs and requirements of each of these stakeholders, and describe how the tool has been designed and integrated to support the tasks needed for these three different users. The system combines the collection of data for experimental research on SG validation, simplifies the analysis of the multimodal data with its standardization system and provides meaningful insights. SIMVA is accessible and usable by all interested stakeholders with their different conceptual frameworks and backgrounds.

The rest of this paper is organized as follows: Section 2 describes Learning Analytics focusing on its potential support on three domains (SG design, research on SG, Application of SC in a class), Section 3 presents SIMVA, our proposed solution for multi-profile learning analytics system and how this system covers the different requirements different users have when using serious games; and Section 3 presents the conclusions of this work, as well as lines of future work.

2. Learning Analytics Needs for Different Profiles

SGs have the potential to generate massive data on players' interactions with the game. Game Learning Analytics captures players' interactions in educational environments on learner behaviour, progress, processes, and results. As such, the information that GLA can provide is of interest to different stakeholders, including (but not limited to): serious game designers, researchers, and teachers. Figure 1 illustrates how these different stakeholders aim to capture different insights from SG: game designers use GLA to identify bugs or issues in the learning design to improve the next version of the game, researchers validate the game effectiveness as a learning source and whether it achieves the goal it was designed for (e.g., to increase knowledge). Both game designers and researchers should access this data with anonymous identifiers for data privacy regulations (e.g., GDPR). Teachers use GLA to monitor student's progress in the class, they need reports about the students' performance while playing the game (e.g., student X is struggling with topic A).

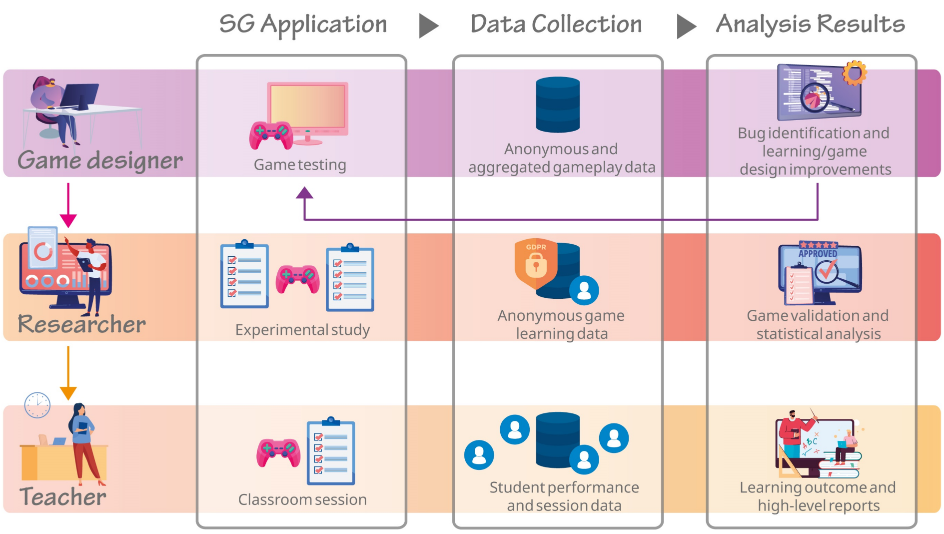

Figure 1: GLA for different profiles needs and insights

In the following subsections, we analyze which particular requirements each of these stakeholders has, from the specific GLA data that is of their interest, to the higher-level information that they need to make evidence-based decisions towards their goals.

2.1. GLA to support SG design

SG designers usually perform different evaluations or tests with users to verify the game and educational design. A common example is A/B testing to evaluate the different versions of the games before deploying them in real life environments. With that information, they perform iterative game testing and redesign until a refined version of the game is released. Game testing is vital to detect any problems in game design. For instance, time spent in different parts of the game may provide insight into the design: if players spent too much time in a specific part of the game, it may mean that there are missing instructions or a poor design of that game part. Another example is that of areas or levels reached: a low number of players reaching a specific game path (or needing too many attempts to reach it) may point out a harder-than-expected behaviour and may require a game redesign.

GLA has the potential to capture detailed information about players behaviours and learning patterns. SGs include intensive interactions and several alternatives which result in lots of possible game paths a player may go through which are hard to be captured in traditional ways. Effective SG testing should consider all the possible paths, tracking all the movements and decisions the player makes. Manual testing does not support testing on a large number of players, usually not more than 100 players. The issue is with small numbers of players, it is not guaranteed to detect rare issues that have low probability of occurrence (e.g., 0.001%). Moreover, some games are impossible to be completed in a one day play session and need to be played in many days. The challenge with manual testing is the complexity to detect what actions taken in one day affected the decision made in another.

2.2. GLA to support research on SG

Before they may be applied in real scenarios, SGs need to be validated as effective educational tools, which is a complex and time consuming process. Researchers conduct experimental research sessions across several participants samples in order to get meaningful insights. This process usually includes executing multiple research sessions to collect game-play logs along with participants' reflections (e.g., post-game feedback questionnaires). This process requires adequate preparation about which game-data to be collected, how to carry out the actual data collection, and the storage and later analysis of the collected data. Effective management of the sessions is challengeable and needs to be performed in a controlled environment where appropriate data are collected and analysed. The issue is that aggregating GLA with user reflections which are usually presented in natural language is a complicated process and needs to be structured under well-defined systems.

Moreover, as the most common way to validate SGs is through pre-post questionnaires, researchers would also conduct these and integrate them with the gameplay. If they also want to combine the information from the questionnaires with the actual interaction data, some link between these different data sources need to be established. This link, however, in most contexts could not be performed by means of any personal data, to be able to comply with privacy regulations such as the EU GDPR. Particularly risky would be the case of collecting data from minors, which have specific restrictions under these privacy regulations. This would be a common case as one of the applications of SGs is for learning purposes.

Besides pre-post questionnaires, researchers may also want to conduct different types of experimental designs: experiments with a control group for comparison purposes, only post-game questionnaires, follow-up questionnaires some time after the intervention, etc. These experimental setups have their own issues including the management of participants across different activities, or the performance of sessions on different dates.

2.3. GLA to support application of SG in class

SGs have the potential to act as powerful tools for teachers in the classroom. GLA can provide teachers with real-time insights on the students progress while learning with a SG. For example, GLA can inform teachers in real-time about students who are struggling on learning, providing opportunities for teacher intervention while the activity is still in place. Additionally, the information collected from GLA (and, possibly, evaluation questionnaires) would also allow teachers to conduct a more precise assessment of students' learning with the game.

While the benefits are substantial, successful implementation of serious games in classes can face several hurdles. First of all, teachers may require support to be able to deploy and use the games in their classes, as they may lack specific technological knowledge required. They may also lack the time or training to interpret the collected data or follow the activity. Technology issues and the risk of technostress are also factors to take into account. Additionally, research shows that without proper support, dashboards can sometimes be misused (for example, as a simple summative grading tool rather than for formative insights). Being aware of these challenges is the first step to overcoming them.

Teachers may use the information provided by GLA both at student- and class-level. Individual data would be required for interventions during the activity as well as for assessment or feedback after the activity. Meanwhile, class-level aggregated data would also be relevant for teachers to have an overview of the difficulty of topics, areas that may require additional explanation in class, etc. While these data is essential for teachers, students would in many cases be minors. Therefore, it is particularly crucial to consider high data privacy protection and considerations to ensure that only teachers are allowed to access the students' information within the context of the educational activity.

3. Multi-Profile Approach

Deployment of SG in classes requires intensive data collection, analysis and visualization for different profiles including game designers, teachers and researchers to help them make evidence-based decisions. Designers evaluate the game before releasing it, researchers validate the game effectiveness as educational tools and that it achieves its intended purpose before integrating it into the real environments and teachers monitor student progress when playing the validated SG in their class. These different profiles need different analysis and information from the collected data, from simple insights presented in natural language like who are the students getting struggled (e.g., for teachers) to advanced insights and visualisation on the learning patterns (e.g., for researchers).

We propose our tool (SIMVA) that is useful and accessible by all interested stakeholders, it allows them to work with an abstracted framework that does not require advanced skills on research or programming. This tool aggregates the collected data from game-play user interactions along with the external data on participants' reflections while complying with data privacy regulations. Also, SIMVA automates and simplifies all the required steps to integrate game learning analytics across all phases of a serious game life cycle, design, development, validation and deployment.

In the following, we describe in more detail the characteristics of the system emphasising the data aggregation carried out from the different sources, to be able to collect the required data for all stakeholders' needs; and the tool's interface that aims to meet the identified needs of the three stakeholders (researchers, game designers, and teachers) describing the functionality that was added for each specific profile.

3.1. Heterogeneous Data Aggregation

To obtain the insights that the different stakeholders require, the first step is to collect relevant data from participants. SIMVA provides telemetry libraries to capture game-play data regardless of the game proprietary technology. These game data are sent and stored in standardized statements, in particular, Experience API (xAPI) supported format statements. Experience API is a standard developed to describe learning interactions in a structured and descriptive way as JSON statements. This standard was extended for SGs in a profile (xAPI-SG) that identifies the main actions in SGs which are referred to as game-independent interactions. These actions could be extended to include game-dependent interactions which are constructed from each game separately [14].

In many scenarios, stakeholders would need to use questionnaires besides interaction data. For instance, researchers for SG validation (e.g., pre-post experiments), designers to evaluate acceptance, or teachers for additional assessment after the gameplay. Since survey responses would be represented in vendor-specific format, the combination of them with interaction data may add another layer of complexity in the analysis. To solve this, we integrate an external platform to manage and create questionnaires (LimeSurvey) and a custom telemetry module to transform questionnaires survey data into an xAPI-compliant format, the same format of game traces. For that, we used the xAPI SCORM (Sharable Content Object Reference Model) profile to transform the received responses from surveys (using the survey manager tool LimeSurvey) into structured statements. SCORM is a proven profile for managing assessments and is well-known for its verb identifiers that could be used to represent the different states of a survey. Using this approach, the system can collect game-logs from any SG and any survey which enhance its scalability.

The challenge is in aggregating the data from these different resources (game traces and survey responses) while considering data protection and privacy regulations (e.g., GDPR). Game designers and researchers should not know which data belongs to which participant, they just need to collect the anonymized data to get their required insights. Thus, our system generates random tokens to be used as participants' identifiers. These identifiers can be exported as a pdf file to be printed and provide an identifier for each participant (in person), in case teachers are using the game in their classes, they write the real name or the ID of the student beside each token in the printed pdf file. By doing so, teachers may monitor students progress in real-time during a class session, being able to perform interventions to the students as needed.

SIMVA generates credentials using these identifiers, which games can use via an API to anonymously register each participant and send their interaction data. Additionally, these anonymous identifiers allow to map participants' responses to surveys with play interaction data without using any personal information identification. Using this approach, the multimodal data (GLA and survey responses) are unified, aggregated and stored in our system and linked to the corresponding participant providing semantic insights and reports without violating data privacy regulations (e.g., GDPR).

3.2. User-Friendly Platform

SIMVA aggregates the functionalities required for the three main stakeholders (game designers, researchers, and teachers), combining the collected data from different sources, managing participants and sessions, and including additional requirements for specific profiles (e.g., experimental designs for researchers).

The system is designed to be accessible to all potential stakeholders and does not require prior conceptual or technical expertise. There are three main elements in the proposed platform: a SIMLET, a session and an activity. The main element is the SIMLET (white box in Figure 2) which is a container of collected data for a specific purpose. SIMLET is an abbreviation for SIMVA Applet, we selected this term to adapt the different cognitive backgrounds of the potential users.

Let's consider this scenario: in Figure 2 researchers want to validate the effectiveness of a SG called "SG1" in learning computational thinking among several groups of students. They decide to use pre-post surveys to collect students' reflections and knowledge before and after playing the SG1 game in order to compare the responses to these surveys. In SIMVA, the researchers create an element (SIMLET1, the white box in Figure 2) that hosts all the received data for that particular objective. Then, inside this SIMLET they create sub elements called "sessions" to assign each group of students with whom the game will be tested. In Figure 2, SIMLET1 has two sessions: in session1 the game will be tested with 10 participants, while it will be tested with 5 participants in session2. Each session may include from one to several activities as required; an activity is a container for collected data from a particular action to be performed by participants (e.g., game-play, pre-survey). In Figure 2, session2 has three activities, a pre-survey to collect data before playing the game, only those who complete the pre-survey are redirected to game-play activity where game interactions are also collected. When participants complete playing the game, they will be redirected to the post-survey activity to collect the reflections after playing the game.

In addition, SIMVA displays a detailed dashboard for each activity, where the users can check the overall completion status at the activity level as well as the progress of each participant in the activity in a detailed table. In Figure 2, the dashboard shows the progress of the game-play activity (the grey box), and for the survey activities (the orange boxes) where participants are identified with the anonymous tokens.

Moreover, users can create customized colored tags to help them navigate among their different SIMLETs. In Figure 2, SIMLET1 has two tags: SG1 and test. Moreover, as some experiments are conducted in several days, we need to ensure that our system collects the data only during controlled sessions. For that, users can select from three possible states for a session: open, paused and terminated. Open state is used when participants are undertaking the activities, a paused state is needed when the experiment has not finished yet but we need to collect more data later, setting the session into pause state ensures irrelevant data are not collected. When the experiment is finished and there is no need to collect more data, a session is set to terminated state.

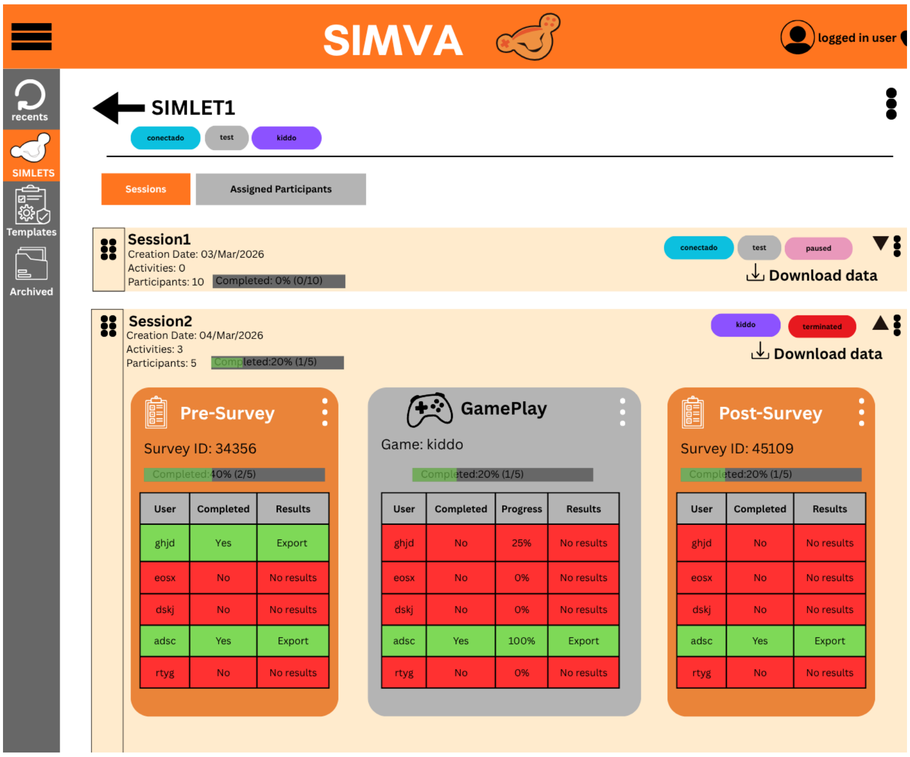

Figure 2: A SIMLET with two sessions: Session4 is terminated, and Session5 still open showing the progress of the students on a visual dashboard

The main functionalities provided in SIMVA are:

1. **Game's Integration**: Developers can integrate GLA using our telemetry modules or implementing a proprietary tracker that sends xAPI data. In this case, users can add the game's URL or upload the game's installation compressed file to the system. While participants play the game, their interaction data will be collected as xAPI-SG traces (statements). This functionality simplifies the tasks for all stakeholders, but particularly for those with less technological background (e.g., teachers).
2. **Surveys Creation**: From SIMVA, users can directly access an external survey management platform (LimeSurvey) using the same credentials. In LimeSurvey, users can create questionnaires for the experiments adding different types of questions (e.g., Likert scale, open-text, etc). With this functionality, researchers can customize validation experiments of SGs (e.g., pre-post experiments), game designers can obtain more information from the testing sessions (e.g., post-game feedback questionnaire) and even teachers could create assessment tests after the gameplay.
3. **Experimental Design**: Researchers can create controlled scientific experiments to validate SGs in our system, as they can set up different experimental designs (e.g., pre-post designs). SIMVA automates all required steps reducing manual intervention and cognitive complexity. Researchers create surveys and decide about the study setups such as the participants' groups and the experiment's flow, which surveys to use and when, before or after game play.
4. **Participants Management**: Users can assign a bunch of participants at a time to a SIMLET, organize them into defined groups, and assign them to different sessions or other SIMLETs with a reusability option. Once added to a session, participants can undertake the different activities which belong to this session. Participant's progress (solely identified by the anonymous token) in the activities is monitored in real-time with visual dashboards.
5. **Live Tracking**: While students are answering the surveys or playing the game, SIMVA provides information about each participant's progress in real-time on a visual dashboard. On this real-time dashboard, the teachers can identify students who are struggling in class since they can

know the names of these users (in the printed mapping table outside the system). Thus, they can help these students and make the appropriate intervention in the moment.

6. **Results Exportation**: SIMVA allows downloading the results of the experiments, both from interaction data and questionnaires responses, in xAPI format. This data can provide semantic insights and be analyzed with more complex data analysis techniques or visualizations. For that, we provide a tool, not-yet integrated in the system, that provides game-independent visualizations based on the xAPI format.

4. Conclusions and Future Work

The application of serious games and the collection of learning analytics data provides opportunities but also poses several challenges for the different stakeholders involved to meet their requirements and satisfy their needs. SIMVA is usable by different categories of stakeholders with their different background, technical experience in research and SG and provide them with field-specific insights. Teachers can apply games collecting relevant data to provide insight into their students' progress and learning results. Researchers can prepare for their validation experiments with pre-post surveys, manage participants and manage the sessions. Game designers can benefit from the data-driven insights to improve their game design and conduct tests. All the collected data is also aggregated in a unified manner to simplify later analysis. This is accomplished by standardised data format of the collected data from games and survey responses (xAPI format). Unifying data format simplified collecting and aggregating data from any survey and any game without having to make big changes in game code each time. Game-independent analytics and dashboards can also be included thanks to the xAPI profile, for different perspectives: game usability insights (for game designers), students progress (for teachers), SG impact (for researchers). Overall, our tool provides a GLA solution for a controlled experimental design accessible to different users regardless of their background.

Although the focus of this paper has been on serious game designers, researchers, and teachers, they are not the only stakeholders who can benefit from the multi-profile approach presented in this paper. Educational institutions and managers would also require evidence about SGs' effectiveness to allow and promote the application of SGs in their classes. More importantly, students are the indirect beneficiaries of these applications. We have not directly addressed them here, but the information gathered from their gameplays could also be used to provide high-level insights into their learning process and even recommendations of actions to take to improve with more advanced data analysis techniques.

As future work, we plan to fully integrate the visualization tool to provide further insight into the collected data, as well as using more advanced AI techniques for detecting students' patterns in their gameplay and provide higher-level information which would particularly be relevant for some stakeholders like teachers.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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