https://doi.org/10.23095/ETI.2023.24.2.295

Educational Technology International
2023, Vol. 24, No 2, 295-329

Learning Analytics Framework on Metaverse

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The recent development of metaverse-related technology has led to efforts to overcome the limitations of time and space in education by creating a virtual educational environment. To make use of this platform efficiently, applying learning analytics has been proposed as an optimal instructional and learning decision support approach to address these issues by identifying specific rules and patterns generated from learning data, and providing a systematic framework as a guideline to instructors. To achieve this, we employed an inductive, bottom-up approach for framework modeling. During the modeling process, based on the activity system model, we specifically derived the fundamental components of the learning analytics framework centered on learning activities and their contexts. We developed a prototype of the framework through deduplication, categorization, and proceduralization from the components, and refined the learning analytics framework into a 7-stage framework suitable for application in the metaverse through 3 steps of Delphi surveys. Lastly, through a framework model evaluation consisting of seven items, we validated the metaverse learning analytics framework, ensuring its validity.

Keywords : Metaverse, Virtual world, Learning analytics, Learning analytics framework

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Introduction

With the advent of the Fourth Industrial Revolution, the rapid advancement of ICT technologies, which are at the core of the metaverse, is merging physical and virtual spaces, thereby expanding the concept of space. Specifically, the evolution of technologies such as Augmented Reality (AR), Virtual Reality (VR), and Mixed Reality (MR) is transforming the methods of interaction between the real and virtual worlds, offering users an enhanced immersive experience(Suh & Ahn, 2022). Key application areas of the metaverse include education, healthcare, culture, and military sectors. Currently, VR/AR learning is attracting attention as a new educational platform in the field of education, and the New Media Consortium (NMC), a global educational research institute, highlights the metaverse as a promising educational innovation technology that is expected to be introduced in the educational field in conjunction with various ICT technologies within the next 2 to 3 years (Han et al., 2022; NMC, 2019).

In the field of education, the utilization of the metaverse has been sporadic and fragmentary. However, in the wake of COVID-19, there has been an explosive surge in interest towards the metaverse as an expanded and novel medium for educational communication (KERIS, 2021). In this context, there are suggestions that the metaverse can be closely linked with the Learning Management System (LMS), a system that supports and manages learners' education, serving as an enhanced online educational platform (Jeong et al., 2022; Yoon, 2021). To leverage the metaverse beyond mere entertainment or interest generation and as a comprehensive online educational platform, it is imperative to address various associated learning-related challenges. These challenges encompass issues such as management of learning activities, tracking interactions among learners, detecting signs of fatigue related to learners' doubts, frustrations, and stress, standardization of learning-related data and the lack of relevant indicators, and the workload required for successful operation of the learning process (Oliveira et al., 2016; Sukon et al., 2012; Wojciechowski & Cellary, 2013). To address these raised concerns, the application of learning analytics is proposed as an optimal pedagogical decision-making support mechanism. Learning analytics, grounded in data, offers a systematic and scientific approach to minimize learning-related issues from an objective perspective (Kim, 2019).

For the appropriate application of learning analytics in teaching and learning activities, it is essential to understand the specific rules and patterns inherent to learning analytics and to structure it within a systematic framework that can be provided to educators as a guideline. In the metaverse, the concept of learning activities expands based on avatars, 3D content objects, and virtual space-based interactions. The variables derived from this are intertwined more intricately than those discussed in traditional learning analytics research, emphasizing the need for a systematic and explicit learning analytics framework that can track related data (Reis et al., 2020). To trace data related to metaverse variables, it is worth considering the recommended standards of Instructional Management Systems Learning Design (IMS LD) that reflect the characteristics of the learning environment (Fernández-Gallego et al., 2013). The framework should include content, standards, and scenarios of teaching and learning activities, written as scripts and organized as modular units. In the metaverse, there is a demand to structure the learning analytics framework from a multidisciplinary perspective, incorporating fields such as computer science, education, data engineering, and psychology (Christopoulos et al., 2020).

Despite the emphasized importance of a learning analytics framework applicable in the metaverse learning environment, previous studies (Christopoulos et al., 2020; Fernández-Gallego et al., 2013; Reis et al., 2020) have not adequately defined and classified teaching and learning content, learning activities, and learning activity data based on the technical characteristics of the metaverse. This limits the detailed explanation of data flow in the learning analytics process. Existing frameworks either superficially describe the hardware system structure of computer science or merely present an overarching concept of learning analytics, lacking specific procedures or application methods. This makes it challenging to use them as step-by-step guidelines for actual learning analytics applications or pedagogical interventions.

In response, this study aims to develop a framework for the tangible application of learning analytics by educators in the metaverse learning environment. Focusing on virtual worlds, which are among the most actively used types of metaverse in the field of education (ASF, 2007), this research utilizes the Activity System model of Activity Theory as a framework for literature analysis. It derives the fundamental components of the metaverse learning analytics framework centered on learning activities and their context, forming a conceptual framework. Additionally, based on the Delphi study, expert validation was conducted to ultimately develop a metaverse learning analytics framework for application in the metaverse learning environment.

Related Work

Due to the spread of remote education amidst the COVID-19 pandemic, various studies are being conducted on advanced technologies such as artificial intelligence (AI), metaverse, and other futuristic tools for education. Recently, virtual experiential learning activities have increased significantly, and interest in metaverse has exploded (Suh & Ahn, 2022). It does not merely combine the physical and virtual worlds, but it allows for interactive combinations, enabling social, economic, educational, and cultural activities, extending the possibilities of the physical world (Dincelli & Yayla, 2022; Han et al., 2022). Metaverse provides opportunities for identity exploration, situational learning, experience expansion, increased immersion, problem-solving, and systematic thinking, accompanied by innovative environmental changes. This is because virtual worlds contain key components such as 3D space, avatars representing users, communication channels where users can interact in real-time, and a sense of reality.

Especially in the metaverse, the pedagogical characteristics of various educational programs differ from traditional Learning Management Systems (LMS). Considering these unique characteristics, it's essential to establish a learning analytics framework that can analyze the flow of learning activities and track related data, serving as a comprehensive guideline (Fernández-Gallego et al., 2013). Moreover, in the open learning environment of the metaverse where learners are granted autonomy, there's a tendency for learners to design and develop content that actively promotes learning, as opposed to the traditional instructor-centric passive approach. Given the vast amount of data sporadically generated based on learning activities, it's crucial to provide a consistent framework and criteria for efficiently collecting and analyzing this data (Christopoulos et al., 2020). In the virtual world of the metaverse, the concept of learning activities expands based on avatars, 3D content objects, environments, and virtual space-based interactions. The variables derived from these activities are intricately intertwined with the variables addressed in traditional learning analytics research. This complexity underscores the need for a systematic and explicit learning analytics framework capable of tracking related data (Reis et al., 2020).

Fernández-Gallego et al. (2013) developed a learning analytics framework in the relatively early stages of the metaverse. Specifically, they proposed a flow for learning analytics applicable in 3D virtual reality, one of the subfields of the metaverse, based on the technical aspects of data mining. Central to their framework, they highlighted the IMS LD engine and the mining system. The IMS LD serves a role to a guidebook associated with learning analytics, facilitating the flow of learning activities and monitoring and registering events generated by avatars based on a set of scripts. In the mining system, the process of automatically discovering information through a predefined algorithm is carried out using data collected from event logs. Figure 1 presents the learning analytics framework developed in this study.

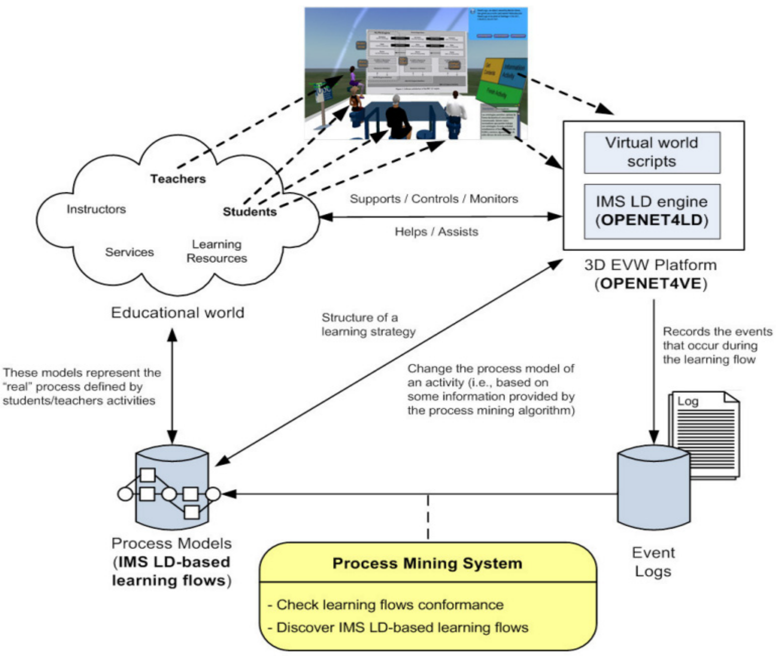

Figure 1. Framework for learning analytics in 3D educational virtual worlds (Fernández-Gallego et al., 2013)

This framework presents a learning analytics framework for 3D virtual reality and structures the overall process of learning analytics according to the flow of data mining. It also suggests that there is a need to be wary of the large amount of noise data that can arise in relation to learning activities in a virtual reality environment and proposes controlling this through IMS LD. However, despite emphasizing the importance of learning analytics due to the need to track learning activities, the framework primarily addresses the hardware from a computer science perspective, leaving a gap in content related to learning activities that educators would need for the actual design or application of learning analytics. In particular, details on the learning activity content, standards, and scenarios presented by the IMS LD in the framework need to be more specifically described and included.

Christopoulos et al. (2020) proposed a four-dimensional framework for VR-based learning analytics, categorizing the major components into Technology, Pedagogy, Psychology, and Learning Analytics. They presented this as a four-dimensional theoretical framework, as illustrated in Figure 2, explaining the information that can be collected to support VR and suggesting a set of components that can be utilized in the development of a learning analytics prototype system.

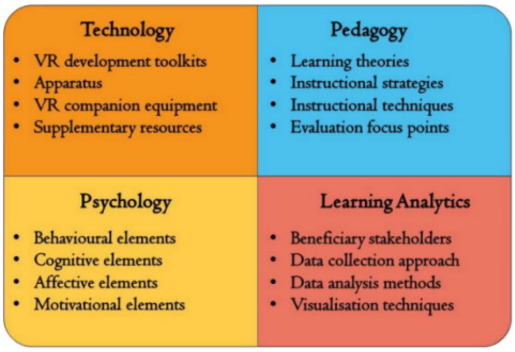

Figure 2. The four-dimensional framework for VR-based learning analytics (Christopoulos et al., 2020)

This framework presents a four-dimensional conceptual model for the application of learning analytics in virtual reality, integrating elements from education, psychology, learning analytics, and computer science. The significance of this research lies in its presentation of specific details within each dimension. It underscores the multidisciplinary nature of learning analytics, illustrating how elements from various fields converge simultaneously within the framework and visualizing the considerations for each domain. However, the framework describes the components of each domain in a broad sense, capturing only their general meanings. This leaves gaps in the content of the components, the interrelationships between them, and strategies for utilizing learning analytics. Therefore, there is a need for further discussion on the detailed elements and explanations for the practical application of learning analytics.

Reis et al. (2020) proposed a learning analytics framework aimed at enhancing the outcomes of the teaching and learning process by analyzing learners' activities in a new learning environment, 3D virtual reality, through avatars. Central to this framework are the elements of learners, data, metrics, and interventions. The study emphasizes that for the application of this framework, considerations such as object modeling based on the 3D virtual reality environment, communication between avatars, and navigation should be taken into account. Figure 3 illustrates the learning analytics framework presented in this study.

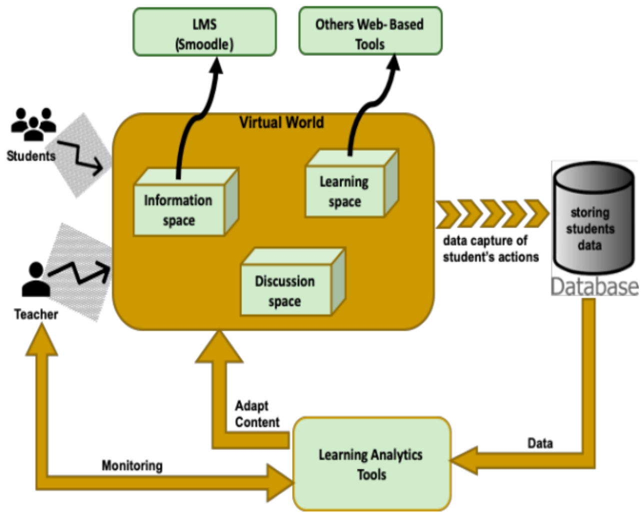

Figure 3. Learning analytics framework for educational virtual worlds (Reis et al., 2020)

In this study, a framework is presented with a significant emphasis on the design of virtual reality and an integrated learning analytics tool. In the design of virtual reality, while it is premised that the design varies depending on the system environment, it is suggested that spaces be fundamentally structured into Information Space, Learning Space, and Discussion Space. Additionally, in the integrated learning analytics tool, processes such as data collection, analysis, and monitoring occur in a consolidated manner. Initially, in data collection, elements like data schema and sensors detecting avatar behaviors are highlighted. However, the study's description of how to populate the mentioned data schema seems somewhat abstract, necessitating specific considerations for the utilization of the metaverse space. To address this, empirical learning analytics research is required to meticulously analyze related variables and structure a data schema that can form a storyline of learning analytics, which should then be reflected in the framework.

Research Methodology

Procedure and Overview

This study began by literature review related to empirical learning analytics research and expanded the idea to characterize it for application in the metaverse learning environment. Furthermore, to objectify the process, the Delphi survey and framework model evaluation method were employed, systematically consolidating expert opinions to ensure validity. The specific research methods and procedures for this study are shown in Table 1.

Table 1
Research procedure

Phase	Procedure	Contents
1	Data collection	- Data collecting & selection based on PRISMA - Identification > Screening > Eligibility > Included
2	Literature review	- Literature review based on Activity Theory - Extraction of the core elements of the framework
3	Framework model development	- Deduplication, categorization, and proceduralization - A prototype development of framework model
4	Delphi survey	- Delphi surveys conducted in 3 steps - Consolidation of expert opinions - Framework model revisions and expansion of the ideas
5	Framework model evaluation	- Validation of framework model - The evaluation tool of seven section

The specific content of the research performed at each major stage is as follows: In the first phase ‘Data collection’, the PRISMA method, a systematic literature review approach, was employed to ensure the validity of literature selection. PRISMA provides a practical guideline for systematic literature collection and selection. In the second phase ‘Literature review:’, the collected literature was analyzed using an activity system model based on activity theory, which was restructured to fit the research purpose. In the third phase 'Framework model development', a prototype of the learning analytics framework model was developed based on a literature review. the elements analyzed through the activity system model were integrated into a framework. In the fourth phase 'Delphi survey', the prototype was characterized and revised to align with the metaverse based on expert opinions, leading to an expansion of the ideas. Lastly, for experts validation, the framework model was evaluated based on seven criteria: validity, explanation, usability, applicability, comprehension, acceptability, and testability.

Data Collection and Literature review

In this study, to conduct the data collection step of framework modeling, we utilized PRISMA, a systematic literature review method. PRISMA serves as a method for systematic literature reviews, offering a structured process to evaluate the reliability and applicability of review results based on extensive research overviews (Moher et al., 2009). This study was conducted following the guidelines of PRISMA as outlined by Page et al. (2021). Through this, literature was searched using the specified method, and selections were made objectively based on predefined questions. PRISMA consists of four stages: Identification, Screening, Eligibility, and Inclusion.

The core concepts of learning analytics to be included in this study’s metaverse learning analytics framework can be described as the learning activities of the learners, which are the objectives of learning analytics, and their surrounding context. The necessity of activity theory-based analysis is emphasized for this purpose (Sun et al., 2021). The activity system model, grounded in activity theory, is evaluated as a valuable analytical framework for understanding the context of learning activities by distinguishing between learners and the system as a tool (Park & Jo, 2014). In this study, Engeström (1987)'s second-generation activity system was adapted for research purposes, and the components were divided into behavioral and contextual areas (Florian et al., 2011). Subjects, objects, and tools were analyzed as behavioral area which is the center of the research. Community, rules, and role were analyzed as the context area which is peripheral of the study. The activity system used in this study is shown in Table 2.

Table 2
Activity system reconfigured (Engeström, 1987)

Activity System		Contents	Description
Contents	Activity Area	Subject	Learning activity subjects, Learners' characteristics
		Object	Domains of learning, Learning activity, Learning activity data
		Tools	Systems, Interaction tools, Analysis tools/methods
	Context Area	Community	Stakeholders related to learning analytics
		Rules	Learning conditions/limitation, Assessment criteria, Teaching methods
		Roles	The roles of stakeholders
Results		Outcome	Purpose and type of learning analytics

* *Refer to Appendix A: Details of Literature review tool based on the Activity System*

Delphi survey and framework model evaluation

To gather expert opinions for the development of the metaverse learning analytics framework in this study, a Delphi survey was conducted. Delphi surveys can be used as a mediator for collecting multiple opinions and are a type of panel survey research method that can prevent negative effects that may arise during the discussion process (Green, 2014). The criteria for panel selection to conduct a professional Delphi survey in this study were based on experts in fields related to educational technology, learning analytics, computer engineering, metaverse, and data engineering who hold a Ph.D degree and have more than 10 years of experience in the field. A total of 10 experts participated. The Delphi survey proceeded in three rounds, and based on the data from the previous survey, the panelists had the opportunity to modify or supplement their judgments. To eliminate negative effects such as ignoring minority opinions, influence of one authoritative figure's statement, and the weakness of group dynamics due to prior coordination among members, the anonymity of respondents was secured, and the survey was conducted without in-person contact. The overview of the Delphi survey conducted in this study, following the structured communication method of the Delphi survey, is presented in Table 3, and the results of the Delphi survey were analyzed and presented in terms of descriptive statistics such as mean, standard deviation, median, minimum, maximum, and quartiles, as well as content validity, degree of convergence and consensus.

In this study, the convergence value of 0.5 or lower and the agreement value of 0.75 were set as criteria for meeting the expert consensus standards (You et al., 2021). And the result of CVR is 0.62 or higher for a panel of 10 experts, the developed content is considered valid (Lawshe, 1975).

As the final step in the research procedure, the evaluation of the framework model requires an assessment of the appropriateness of the metaverse learning analytics framework. In this study, the evaluation tool for the framework model was reconstructed based on the evaluation tool presented by Birken et al. (2018). The evaluation tool used in this study consists of seven categories: validity, explanatory power, usefulness, universality, comprehensibility, acceptability, and testability. Each category is composed of optional questions using a Likert 4-point scale and open-ended questions for expert review. The evaluation items for the evaluation sheet for validating the framework model are presented in Table 4.

Table 3
Delphi survey overview

Step	Contents	Result values
1	- Initial opinion gathering for framework development - Semi-structured open-ended questions · Descriptive questions: Composed of 'Procedures', 'Categories', 'Elements', and 'Features'	Content analysis: categorization, sequencing, & proceduralization
2	- Modification based on 1st Delphi survey responses - Semi-structured closed-ended and open-ended Questions · Multiple-choice questions: Surveying the validity of each item in the initial model on a Likert 5-point scale · Descriptive questions: surveying the opinion of each question	Mean, Standard deviation, Convergence, Agreement, Content validity ratio (CVR)
3	- Final opinion agreement based on 2nd Delphi survey responses - Semi-structured closed-ended and open-ended questions · Multiple-choice questions: Surveying the validity of each item in the modified model on a Likert 5-point scale · Descriptive questions: Surveying the opinion of each question	Mean, Standard deviation, Convergence, Agreement, Content validity ratio (CVR)

Table 4
Framework model evaluation questions

Items	Description
Validity	This framework is valid for use in learning analytics on metaverse
Explanation	This framework explains the elements and their relationships step by step
Usability	Elements, relationships, and structures of this framework are useful
Applicability	This framework can be universally applied to learning analytics
Comprehension	This framework is understandable for language and visual representations
Acceptability	This framework is familiar and acceptable to the person concerned
Testability	This framework presents an empirical and reproducible hypothesis

Results and Discussion

Data Collection and Literature review

The step of analyzing the basic components of the learning analytics framework is a process of exploring the essential elements for developing a learning analytics framework on metaverse. In this phase, the foundational components of the learning analytics framework were derived based on prior research on learning analytics. The data collection phase was conducted using the PRISMA method, a systematic literature review approach, which explicitly delineated an objective and structured process for data collection. The PRISMA process, which consists of four stages: Identification, Screening, Eligibility, and Inclusion, is illustrated in Figure 4. Ultimately, 32 pieces of literature were selected. These selected articles served as foundational materials for theoretical exploration to analyze the basic components of the learning analytics framework.

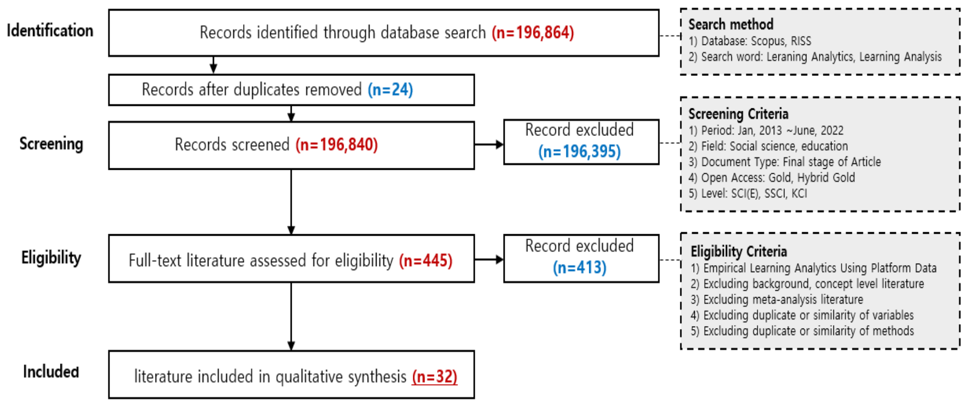

Figure 4. Data collection results
(* Appendix B: Reference Lists for Literature Review)

During the literature analysis process, the 32 articles selected in the data collection phase were analyzed based on the Activity System model tailored to the research objectives. Specifically, the literature was examined according to the categories defined in the literature review tool(*Appendix A) of Activity System: Subject, Object, Tools, Community, Rules, Roles, and Outcomes. A portion of the conducted literature review is presented in Table 5.

Table 5
An example of the conducted literature review through activity system (1 of 32)

1. Literature review 1: Kim (2021)
- Subject: Undergraduate students (1st to 3rd year) from J University
- Object: · All lectures from 2020-1, 2,204,058 content pieces · Studying lecture videos, materials · Learner Information: department, grade level, credits, Course Information: course name, lecture type, department, lecture evaluation, Learning Activities: Learner login, Studying lecture videos(date/week/time/ duration of attendance, device used)
- Tools · J university LMS, log extractor, SAS 9.4 · Lecture video, material menu, Assignment/quiz/exam menu · Descriptive statistical analysis, Correlation analysis, t-test, Multiple regression analysis, Structural equation modeling (SEM)
- Community: Instructors and administrators
- Rules: Analysis centered on data; no specific norms
- Division of Labor: Professors, Administrator · Providing lecture videos, materials · formative, summative assessment
- Outcome: · Analysis of academic achievement through student information · Significant predictive factors: Course information, Learning activities, Student information (year level), Viewing lecture videos (duration/week) · Academic achievement · Prescription, Diagnosis

The basic components of the learning analytics framework derived based on the activity system model are integrated as a framework for learning analytics through the results of the literature review phase. The literature review results of 32 documents were collated according to the elements of the activity system model, and the tasks were performed in the order of deduplication, categorization, and proceduralization.

In the deduplication, repeated words were removed, words with redundant meanings were consolidated, and words without distinguishing significance in the research context were eliminated. In the process of removing repeated words, words with the same expression or slight character differences in theoretical exploration were eliminated. The integration of words with redundant meanings involved refining words that, although expressed differently, had the same meaning or partially overlapping semantic ranges. Also, words without distinguishing significance in the research context were identified and removed.

Next, in the categorization, the analytical content from the theoretical exploration in the de-duplication process was objectively classified and assigned to specific domains. This step involved finding shared attributes among words and clustering them. The categorization process was conducted without compromising the domains of the activity system model.

Lastly, in the procedural process, work was based on the 6-step learning analytics workflow of international standards on learning analytics interactivity (ISO/IEC TR 20748-1, 2016). Excluding the visualization phase, which was not analyzed in the theoretical exploration process, the overall structure was built based on the five steps of learning activity, data collection, data storage, data analysis, and feedback and intervention. The results from de-duplication and categorization were then arranged, and the flow was connected.

The prototype of the framework developed through such a process is as shown in Figure 5.

This process is further refined in the subsequent phase, the 1st Delphi survey, along with open-ended questions, and is further detailed by incorporating the characteristics of the metaverse.

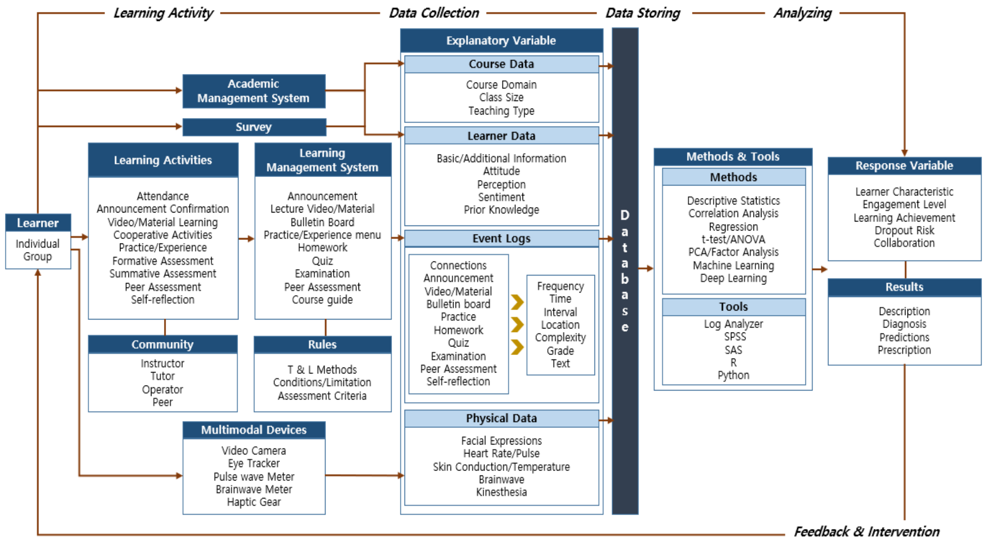

Figure 5. Prototype of learning analytics model

Delphi Survey

The 1st Delphi survey for the development of the 1st revision framework model can be summarized as follows. First, the procedures of the framework should be designed comprehensively to enable educational prescription based on the recognition of problems according to educational purposes. Based on expert opinions related to this, a comprehensive procedure for the framework can be presented with (a) Goals Setting: Problem awareness, (b) Planning, (c) Collecting data, (d) Storing data, I Analyzing/Visualizing data, and (f) Utilizing results. Second, in terms of the categories of frameworks and the characteristics of metaverse, it should further explained how the interconnectivity between the framework categories of metaverse, including the space of metaverse, learning activities that take place in that space, and the data associated with those activities. In particular, as the content of learning activities and related data varies greatly depending on the classification and role of metaverse space, it is necessary to prioritize considerations on conceptualizing and classifying metaverse space. Additionally, following the classification of IMS

Global data, activity data linked to metaverse space needs to be reorganized to suit the learning environment of metaverse. It is necessary to give priority to considering how to conceptualize and classify the space of the metaverse, as the content of the learning activities and related data can vary greatly depending on the distinction and role of the metaverse space. Furthermore, depending on the space of the metaverse, the learning activity data linked to it needs to be restructured to fit the learning environment of the metaverse. The data can be categorized into learner profile data, learning activity data, operational data, and biometric data, etc. Third, the framework's elements and characteristics were presented as specific ideas for extending the framework to the metaverse, involving both systemic and learner elements. Systematic elements include designing a metaverse-based learning environment, such as space, time, and affordance. In addition, learner elements can be organized into avatar-related contents such as appearance, behavior, identity, representation, verbal/non-verbal interaction, and cognitive and emotional characteristics of learners.

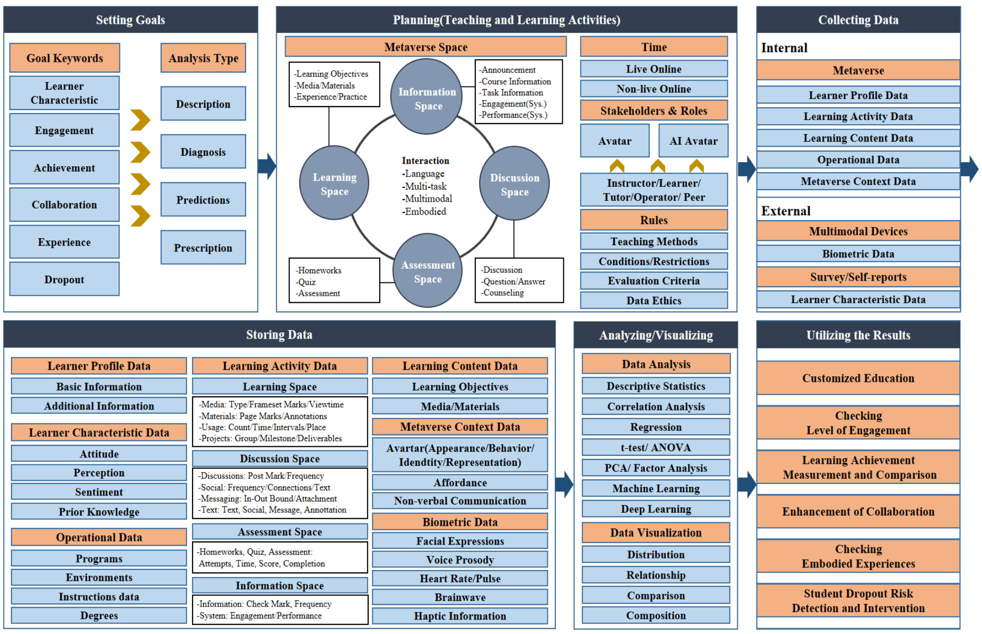

Figure 6. The 1st revision learning analytics framework model on metaverse

The key findings from the 1st Delphi survey were used to establish the development direction for the 1st revision framework model. A model is presented in Figure 6.

Table 6
Results of the 2nd Delphi Survey Multiple Choice Questionnaire survey

Item	*M*	*SD*	*Conv.*	*Agrmt.*	*CVR*
a1	4.2	0.9	0.9	0.6	0.4
a2	3.7	0.8	0.4	0.8	0.4
a3	4.3	0.8	0.5	0.8	0.6
b1	4.2	0.6	0.1	1	0.8
b2	3.8	0.6	0.4	0.8	0.4
b3	4.3	0.9	0.9	0.7	0.4
b4	3.7	0.8	0.4	0.8	0.4
b5	4	0.6	0.0	1	0.6
c1	4.1	0.5	0.0	1	0.8
c2	4.2	0.6	0.1	1	0.8
c3	4.4	0.7	0.5	0.8	0.8
c4	4	0.4	0	1	0.8
d1	4.4	0.7	0.5	0.8	0.8
d2	3.5	1.1	0.9	0.6	0.2
d3	4.2	0.7	0.4	0.8	0.6
d4	4.4	0.9	0.5	0.8	0.8
d5	4.2	0.6	0.1	1	0.8
d6	3.8	0.7	0.5	0.8	0.2
d7	4.3	0.6	0.4	0.8	0.8
d8	4.2	0.7	0.4	0.8	0.6
e1	4.3	0.5	0.1	0.9	1
e2	4.4	0.8	0.5	0.8	0.6
e3	4.3	0.6	0.4	0.8	0.8
f1	3.9	0.7	0.4	0.8	0.4

**** Refer to the question items in Figure 6.***
A1: stage1-setting goals(overall), a2: stage1(goal keywords), a3: stage1(analysis type), b1: stage2-planning(overall), b2: stage2(metaverse space), b3: stage2(time), b4: stage2(stakeholders & roles), b5: stage2(rules), c1: stage3-collecting data(overall), c2: stage3(metaverse), c3: stage3(multimodal devices), c4: stage3(survey/self-reports), d1: stage4-storing data(overall), d2: stage4(learner profile data), d3: stage4(learner characteristic data), d4: stage4(operational data), d5: stage4(learning activity data), d6: stage4(learning content data), d7: stage4(learning context data), d8: stage4(biometric data), e1: stage5-analyzing/visualization(overall), e2: stage5-data analysis, e3: stage5-data visualization, f1: stage6- utilizing the results(overall)

The 2nd Delphi survey employed a mixed-method questionnaire to evaluate the validity of the initial learning analytics framework and gather input for refinement. The descriptive questions solicited input to confirm the validity of items and components of the 1st revision framework model. The findings are presented in Table 6.

Analysis of the 2nd Delphi survey found that 13 items (a1, a2, a3, b2, b3, b4, b5, d2, d3, d6, d8, e2, f1) out of 24 in the metaverse learning analytics framework failed to meet the validity threshold of 0.62. These items showed high convergence and low consensus, with disagreement among experts. In particular, the overall direction for modification was set based on the opinions of experts with relatively low response scores on specific items. The 2nd Delphi survey for the development of the framework modification model can be summarized as follows. First, in the 6th stage of the initial model of the framework, the planning stage is the contents of course operation, and it is unreasonable to view it as a plan for learning analytics. Secondly, spatial analysis is crucial for metaverse learning analytics since the unique characteristic of metaverse space distinguishes it from traditional LMS. The context of learning activities and related data in these spaces is a significant aspect of learning analytics. Therefore, the metaverse space classification should reflect its characteristics, such as collaboration-related spaces, and experience-related spaces for the activities of interaction, cooperation, and projects. Thirdly, since the learning activity data and metaverse context data at the storing data stage include the characteristics that distinguish between existing learning analytics and metaverse learning analytics, it needs to be upgraded to suit the environment of metaverse. Therefore, learning activity data should be linked to the space of the metaverse and the systematic elements of the metaverse context data to derive more specific elements and include them in the framework. Fourthly, it suggests a need for a more refined and comprehensive approach to classifying data analysis methods, to ensure that they are accurately differentiated and presented to users effectively. Currently, the contents of general statistical analysis, machine learning, and deep learning are listed in the data analysis method item, but the distinction is not clear due to overlapping contents in the analysis method. This could involve revising the current list of methods, presenting them according to clear criteria, and potentially expanding the range of options to include additional data analysis methods that are relevant to specific contexts or applications. Finally, the contents constructed in the utilizing results stage of the initial model of the framework are in the same context as the setting goals stage of the model, so it has no meaning other than the role of reaffirming the goals setting. Therefore, presenting a step-by-step procedure for results utilization is effective in utilizing the framework's analytics results. The modified framework model was developed by reflecting the results of the 2nd Delphi survey organized as above, and in particular, the work was conducted by focusing on items that did not meet the validity in multiple-choice questions. The 2nd revision framework model developed through this is shown in Figure 7 below.

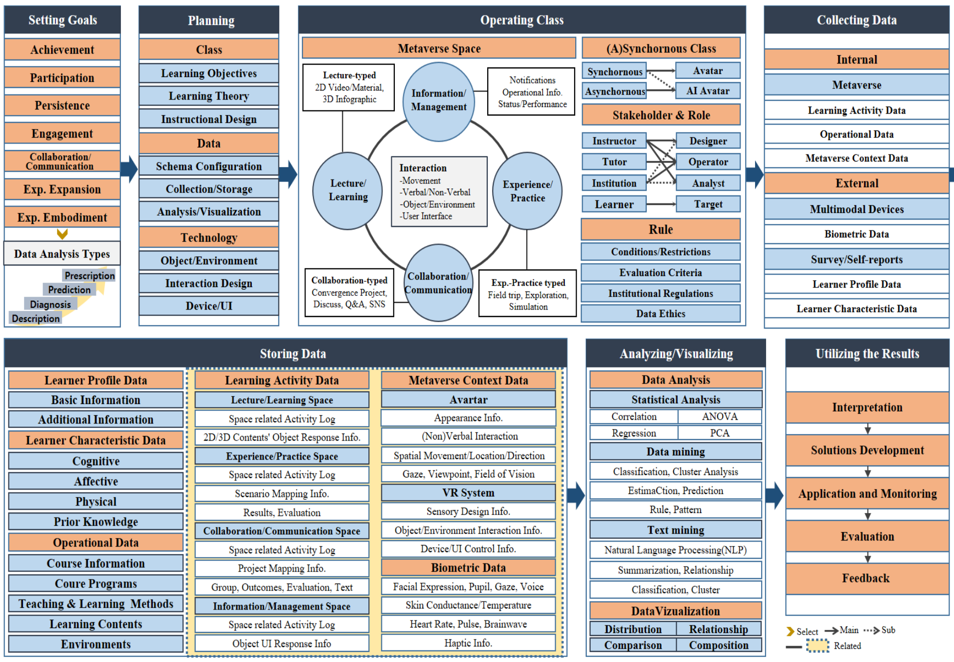

Figure 7. The 2nd revision learning analytics framework model on metaverse

Table 7
Results of the 3rd Delphi survey multiple choice question

Item	*M*	*SD*	*Conv.*	*Agrmt.*	*CVR*
a1	4.6	0.49	0.5	0.8	1
a2	4.5	0.5	0.5	0.78	1
a3	4.6	0.49	0.5	0.8	1
b1	3.8	0.40	0	1	0.6
b2	3.9	0.54	0	1	0.6
b3	4.4	0.49	0.43	0.79	1
b4	4.2	0.40	0	1	1
c1	4.6	0.49	0.5	0.8	1
c2	4.4	0.49	0.43	0.79	1
c3	4.5	0.5	0.5	0.78	1
c4	4.6	0.49	0.5	0.8	1
c5	4.6	0.49	0.5	0.8	1
d1	4.6	0.49	0.5	0.8	1
d2	4.4	0.66	0.5	0.78	0.8
d3	4.6	0.49	0.5	0.8	1
d4	4.4	0.49	0.43	0.79	1
e1	4.6	0.49	0.5	0.8	1
e2	4.6	0.49	0.5	0.8	1
e3	4.6	0.49	0.5	0.8	1
e4	4.3	0.64	0.5	0.75	0.8
e5	4.7	0.46	0.38	0.85	1
e6	4.6	0.49	0.5	0.8	1
e7	4.6	0.49	0.5	0.8	1
f1	4.6	0.49	0.5	0.8	1
f2	4.5	0.5	0.5	0.78	1
f3	4.5	0.5	0.5	0.78	1
g1	4.8	0.4	0	1	1

**** Refer to the question items in Figure 7.***

A1: stage1-setting goals(overall), a2: stage1(goal keywords), a3: stage1(data analysis type), b1: stage-planning(overall), b2: stage2(class), b3: stage2(data), b4: stage2(technology), c1: stage3-operation class(overall), c2: stage3(metaverse space), c3: stage3((A)316synchronous class), c4: stage3(stakeholders & roles),c5: stage3(rules), d1: stage4-collecting data(overall), d2: stage4(metaverse), d3: stage4(multimodal devices), d4: stage4(survey/self-reports), e1: stage5-storing data(overall), e2: stage5(learner profile data), e3: stage5(learner characteristic data), e4: stage5(operational data), e5: stage5(learning activity data), e6: stage5(metaverse context data), e7: stage5(biometric data), f1: stage6-analyzing/visualization(overall), f2: stage6-data analysis, f3: stage6-data visualization, g1: stage7- utilizing the results(overall)

The 3rd Delphi survey conducted to verify and consolidate expert opinions based on the modified framework model. This survey included a combination of multiple-choice questions (Likert 5-point scale) to validate the component items and descriptive questions regarding the development direction of the modified framework model. The results of the closed-ended multiple-choice questions for the 3rd Delphi survey are presented in Table 7.

Upon analyzing the results of the multiple-choice questions in the 3rd Delphi survey, it was found that out of the 27 items, 25 framework items satisfied the validity threshold of 0.62 for CVR. However, two framework items, b1 and b2, pertaining to the planning process in the modified framework model did not meet the validity threshold of 0.6 for CVR. The supplementation of the framework modification model reflected the specific opinions of experts on questions that did not meet the validity of CVR below 0.62, and other questions also reflected revised opinions such as terminology modification and location change.

The multiple-choice and descriptive responses of the 3rd Delphi survey for the development of the final model of the framework can be summarized as follows. First, it was found that the items of the framework corresponding to 25 out of a total of 27 items met the validity. First, in the 3rd Delphi survey, it was found that the items of the framework corresponding to 25 out of a total of 27 items met the validity. Specifically, CVR is 1 in 23 items in 25 items, and 2 items also responded with CVR 0.8, and It can be concluded that expert opinions were relatively consistent, as the convergence was less than 0.5 and agreement was above 0.75. Of the 25 items in the survey, 19 items were not separately presented with extra expert opinions. The framework items corresponding to these were included in the final framework model with a change status of maintenance. Second, in the modified framework model, some items related to the newly established the planning stage did not meet the validity criteria, resulting in the need for revisions to the planning stage. Specifically, it was necessary to reorganize the sub-elements and modify the names of the categories for 'Teaching-Learning', 'Data', and 'Support Technology' in the planning stage items. Third, even in framework items that meet the validity criteria, some items require re-evaluation, such as repositioning and rewording to improve their clarity. In this regard, it is necessary to reorder the goal keywords to match the flow of learning, such as participation, persistence, engagement, collaboration and communication, achievement, experience expansion, and experience embodiment. In addition, in the operating class stage, the name of the stage is changed to a term for 'Teaching & Learning Activities' that encompasses a wider meaning, and synchronous and asynchronous class are also required to be revised to 'Synchronous/ Asynchronous Activities'. Lastly, it is necessary to place the information and management space, which plays an auxiliary role in metaverse space, at the bottom according to its importance, and in the interaction, the user interface needs to change the term to device and UI by adding devices. The 3rd Delphi survey results were used to develop the final framework model, with a focus on improving the overall completeness of the framework rather than extensive revisions. The 3rd revision framework model developed through this is shown in Figure 8 below.

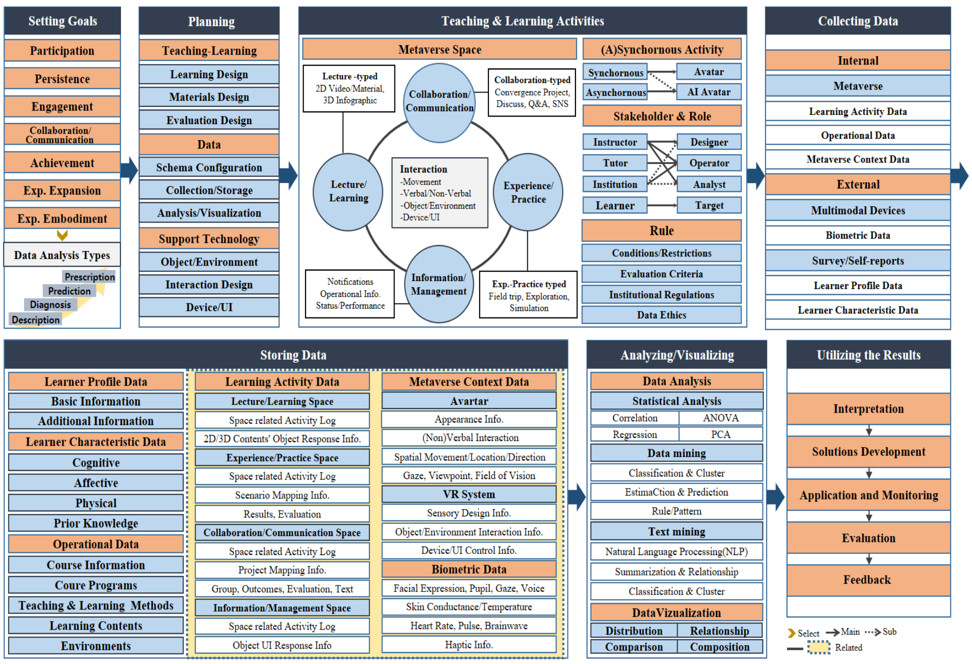

Figure 8. The 3rd revision learning analytics model on metaverse
(*Web link: Guideline for final learning analytics model on metaverse)

Framework Model Evaluation

In the evaluation of the learning analytics framework model on metaverse, the final framework model was evaluated based on seven items: Validity, explanation, usability, applicability, comprehension, acceptability, and testability. The evaluation of the framework model consisted of multiple-choice questions and descriptive questions on the Likert 4-point scale. The results of the framework model evaluation are shown in Table 8 as follows.

Table 8
Results of the framework model evaluation

Items	*M*	*SD*	*Conv.*	*Agrmt.*	*CVR*
Validity	4	0	0	1	1
Explanation	4	0	0	1	1
Usability	3.9	0.3	0	1	1
Applicability	3.6	0.49	0.5	0.75	1
Comprehension	3.8	0.4	0	1	1
Acceptability	3.7	0.46	0.39	0.81	1
Testability	3.9	0.3	0	1	1

As a result of the framework model evaluation targeting the final framework model, all items achieved CVR 1, confirming validity. In addition, the level of convergence was below 0.5 and the degree of agreement was above 0.75, indicating no difference in expert opinions. Therefore, the final framework model derived from the 3rd Delphi survey was confirmed as the learning analytics framework on metaverse.

Overall, the experts mentioned that the developed metaverse learning analytics framework systematically explains the components of each stage, and that the framework was refined in terms of coherence and logic through the Delphi survey during the development process. In this framework, the procedural scope of learning analytics involves not only measuring and analyzing data but also develops widely, focusing on learning activities from goal setting to result utilization. Moreover, It incorporates various fields of specialized knowledge, requiring detailed explanations on the usage of the elements and procedures. Lastly, there is a need to confirm the practical usability of the framework. Although the framework was systematically developed based on expert validation in this study, usability evaluation targeting actual users could not be conducted yet due to technical or resource limitations.

Conclusions

In this study, we focused on the potential of the metaverse as an integrated online education platform and developed a learning analytics framework for the effective application of learning analytics by instructors in the metaverse educational environment. The aim was to enhance the efficiency of instructors' application of learning analytics, improve the pedagogical decision-making process, and provide insights for subsequent research based on the metaverse. The significance and implications of this study are as follows: (a) Expansion to the Metaverse This study proposes learning analytics as an appropriate response to learning-related challenges in the virtual world metaverse, which is gaining attention as an online integrated education platform with the advancement of ICT. The framework extends the concept of learning analytics based on traditional LMS and provides guidelines that cater to the unique characteristics of teaching and learning activities in the virtual world metaverse. (b) Activity System Model: The framework, designed based on the activity system model, focuses on teaching and learning activities and their context. This practical guideline for the application of learning analytics is linked to teaching and learning activities, differentiating it from previous frameworks that primarily presented system structures or abstract concepts. (c) Practical Guidelines: The framework presents a total of seven actionable steps and strategies linked to teaching and learning activities. This allows for educational prescriptions and interventions at precise points, influencing the improvement of framework utilization through feedback from a learning analytics perspective. (d) Interdisciplinary Integration: This study presents core elements and features that can be applied not only in the field of education but also in other disciplines. Specifically, the framework incorporates expertise from computer science and data engineering in addition to pedagogy, considering the characteristics linked to advanced ICT convergence technologies. This provides instructors with comprehensive insights and allows for a multifaceted design of the learning analytics process.

Through this, it was intended to increase the efficiency of instructors' application of learning analytics, improve the teaching and learning decision-making process, increase the effectiveness of prescriptions, and provide clues to follow-up studies based on metaverse. Based on the findings, this study proposes the following limitations and suggestions for future research. Firstly, it is necessary to supplement the framework by conducting empirical research on the relationships between new variables that arise in the teaching and learning activities within metaverse. As new variables are produced in the teaching and learning activities in metaverse, which are not covered in prior research on learning analytics, specific adjustments to the learning analytics framework should be made based on the measurement, collection and analysis of these new variables. Furthermore, these new variables may also affect the relationships between previous variables that were covered in prior research on learning analytics, which may result in different outcomes. Therefore, we suggest that subsequent research continually discovers the correlations between the variables arising in metaverse and modifies and improves the framework accordingly to increase its practical effectiveness. Secondly, it is essential to standardize strategies for learning analytics that correspond to individual situations by analyzing the diversification of teaching and learning activities resulting from the development of various educational contents and instructional designs within metaverse. The framework of this study has standardized the teaching and learning activities in metaverse at the present stage, but the possibility of expanding teaching and learning activities through ICT technologies in the future is still open. Since the teaching and learning activities directly affect the type, collection, and storage of relevant data in the process of learning analytics, it is necessary to pay attention to metaverse-related technologies and research and continuously update the framework.

References

ASF (2007). *Metaverse roadmap: Pathways to the 3D Web.* https://metaverseroadmap.accelerating.org/

Birken, S. A., Rohweder, C. L., Powell, B. J., Shea, C. M., Scott, J., Leeman, J., Grewe, M. E., Alexis Kirk, M., Damschroder, L., Aldridge, W. A., Haines, E. R., Straus, S., & Presseau, J. (2018). T-CaST: An implementation theory comparison and selection tool. *Implementation Science, 13*(1).

Christopoulos, A., Pellas, N., & Laakso, M. J. (2020). A learning analytics theoretical framework for STEM education virtual reality applications. *Education Sciences, 10*(11), 317.

Dincelli, E., & Yayla, A. (2022). Immersive virtual reality in the age of the Metaverse: A hybrid-narrative review based on the technology affordance perspective. *The Journal of Strategic Information Systems, 31*(2), 101717.

Engeström, Y. (1987). *Learning by expanding: An activity-theoretical approach to developmental research*. OrientaKosultit Oy.

Fernández-Gallego, B., Lama, M., Vidal, J. C., & Mucientes, M. (2013). Learning analytics framework for educational virtual worlds. *Procedia Computer Science, 25*, 443-447.

Florian, B., Glahn, C., Drachsler, H., Specht, M., & Fabregat Gesa, R. (2011). Activity-based learner-models for learner monitoring and recommendations in Moodle. *European Conference on Technology Enhanced Learning*, 111-124. Springer.

Green, R. A. (2014). The Delphi technique in educational research. *Sage Open, 4*(2), 2158244014529773.

Han, D. I. D., Bergs, Y., & Moorhouse, N. (2022). Virtual reality consumer experience escapes: Preparing for the metaverse. *Virtual Reality, 26*(4), 1443-1458.

ISO/IEC TR 20748-1 (2016). *Information technology for learning-education and training-learning analytics interoperability*-Part1: Reference model.

Jeong, Y., Choi, S., & Ryu, J. (2022). Work-in-progress-Design of LMS for the shared campus in metaverse learning environment. *2022 8th International Conference of the Immersive Learning Research Network (iLRN)*, 1-3.

Kim, T. G. (2019). Exploring learning data for the application of learning analytics to the regular teaching and learning setting. *Asian Journal of Education, 20*(4), 1181-1205.

Korean Educational Development Institute. (2021). *Educational use of the metaverse: Possibilities and limitations.* (RM 2021-6).

Lawshe, C. H. (1975). A quantitative approach to content validity. *Personnel Psychology, 28*(4), 563-575.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Annals of Internal Medicine, 151*(4), 264-269.

New Media Consortium (2019). The NMC horizon report. *EDUCAUSE.*

Oliveira, P. C. D., Cunha, C. J. C. D. A., & Nakayama, M. K. (2016). Learning management systems (LMS) and e-learning management: An integrative review and research agenda. *JISTEM-Journal of Information Systems and Technology Management, 13*, 157-180.

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *Bmj*, 372.

Park, Y. J., & Jo, I. H. (2014). Need analysis for learning analytics dashboard in LMS: Applying activity theory as an analytic and design tool. *Educational Technology Research, 30*(2), 221-258.

Reis, R., Marques, B. P., & Sampaio, I. (2020). Learning analytics framework for improving performance to students through educational virtual worlds.

International Journal of Education and Information Technologies, 14, 8-13.

Suh, W., & Ahn, S. (2022). Utilizing the metaverse for learner-centered constructivist education in the post-pandemic era: An analysis of elementary school students. *Journal of Intelligence, 10*(1), 17.

Sukon, K. S., Sharma, K., Boojihawon, D., Gatsha, G., & Panchoo, S. (2012). *Using ODL and ICT to develop the skills of the unreached: A contribution to the ADEA triennial of the working group on distance education and open learning.* ADEA.

Sun, W., Pinkwart, N., & Li, T. (2021). Current state of learning analytics: A synthesis review based on the combination of activity theory and pedagogy. *Advancing the Power of Learning Analytics and Big Data in Education*, 1-28.

Wojciechowski, R., & Cellary, W. (2013). Evaluation of learners' attitude toward learning in ARIES augmented reality environments. *Computers* & *Education, 68*, 570-585.

Yoon, J. H. (2021). *Metaverse, beyond the boundary of virtual and reality*. Science and Technology Policy Institute.

You, J., Kim, W., Lee, H. S., & Kwon, M. (2021). Best content standards in sports career education for adolescents: A Delphi survey of Korean professional views. *Sustainability, 13*(12), 6566.

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Received: September 11, 2023 / Peer review completed: October 14, 2023 / Accepted: October 19, 2023

Appendix A. Literature Review Tool Based on the Activity System

	Items
Subject	**Central subject of the Activity System model: Main actor and characteristics for learning analytics** - Who or what is the primary actor generating data for learning analytics, and what are its characteristics? (e.g., learner profile, learner characteristic data)
Object	**Object of the Activity System model: Curriculum, online learning activities, explanatory variables for learning analytics** - What is the curriculum information for the subject's learning activities? - What are the online learning behaviors (e.g., studying lecture materials, participating in discussions, note-taking, etc.) related to the event logs of the subject? - What are the explanatory variables (e.g., course operation data, learning activity data, biometric data, etc.) for learning analytics?
Tools	**Mediating learning environment, tools, and resources: System, interaction tools, analysis methods, and tools** - What online platform was used? - What are the features or menus of the platform used for data collection? (e.g., lecture materials, announcements, Q&A and community boards, quizzes, exams, etc.) - What methods and tools are used for data analysis? (e.g., analysis methods such as correlation analysis, multiple regression, machine learning, etc.; analysis tools such as log analyzers, statistical analysis tools, etc.)
Community	**Members of the Activity System model: Stakeholders related to learning analytics** - Who are the participants related to learning analytics? (e.g., instructors, teaching assistants, tutors, administrators, etc.)
Rules	**Regulations, norms, and conventions managing the activity: teaching methods, system usage rules, evaluation criteria** - What type of teaching method was applied? - What are the rules for using the system? - What are the methods and criteria for evaluating learning activities?
Division of Labor	**Role distribution in the activity community: Roles of stakeholders related to learning analytics** - What are the roles of the learning analytics community? (e.g., roles and activities of instructors, teaching assistants, tutors, administrators, etc.; strategies and implications)
Outcome	**Outcome of the Activity System model: Results of learning analytics, response variables for learning analytics, type of analysis** - What are the results of the learning analytics? - What are the response variables (dependent variables) for learning analytics? - What type of data analysis was conducted? (e.g., Descriptive, Diagnostic, Predictive, Prescriptive)

Appendix B. Reference List for Literature Review

1. Kim, A. N. (2021). Analysis of Learner Behavior and Learning Performance using LMS Big Data in the COVID-19: Focused on J-University. *The Journal of Learner-Centered Curriculum and Instruction, 21*(6).
2. Lee, H. D. (2018). Clustering University e-Learning learners in the Perspective of Learning Analytics and Analyzing the Differences in Academic Achievement among Clusters: Focused on Spatio-Temporal Data Relate to e-Learning. *Journal of Lifelong Learning Society, 14*(3).
3. Jo, I. H., & Kim, J. H. (2013). Investigation of Statistically Significant Period for Achievement Prediction Model in e-Learning. *Journal of Educational Technology, 29*(2).
4. Jung, Y. R. (2020). A prediction analysis on the dropout of cyber university based on learning analytics. *The Korean Journal of Educational Methodology Studies, 32*(2).
5. You, J. W. (2014). Computer Education Curriculum and lnstruction: Dropout Prediction Modeling and Investigating the Feasibility of Early Detection in e-Learning Courses. *Journal of the Korean association of Computer Education, 17*(1).
6. Noh, I. K., & Lee, S. H. (2016). An Analysis of Employed Learners' Learning Behaviors and the Factors Affecting Learning Achievement: Using Learning Analytics. *Journal of Lifelong Learning Society, 12*(4).
7. Jeon, E. H., & Han, J. H. (2015). The Effect of Student Characteristics and Online Behaviors on Student Learning Achievement in Blended-learning Environments Using Learning Analytics Approaches. *Journal of Educational Technology, 31*(3), 431-457.
8. Han, J. H., Kwon, S. J., & Park, J. S. (2015). Binding the Factors Affecting Student Learning Outcomes in a Cyber University Using the 3P Model: Learning Analytics Approaches. *Journal of Korean Association for Educational Information and Media, 21*(2), 309-332.
9. Kim, S. Y. (2020). Exploring the Completion Determinants through the Analysis K-MOOC Learners' Learning Activities for Evaluation. *The Journal of Humanities and Social science, 11*(6).
10. Jo, I. H., Yoo, Y. S., Park, Y. J., & Kim, J. H. (2015). Mediation Effect of Online Student Activities between Network Centrality and Academic Achievement in Asynchronous Online Discussion. Journal of Educational Technology, 31(3).
11. Moon, K. B., Kim, J. W., & Lee, J. S. (2021). Early Prediction Model of Student Performance Based on Deep Neural Network Using Massive LMS Log Data. *Journal of the Korea Contents Association, 21*(10).

12. Oh, M. J. (2020). The Effect of Self-Regulation Learning, Teaching Presence, and Academic Achievement in the K-MOOC Setting. *Journal of Lifelong Learning Society, 16*(2).
13. Park, J. S. (2013). A Study on the Learning Effectiveness of Class Management Factors According to Characteristics of Subjects in Cyber University. *Journal of Educational Technology, 29*(3).
14. Lee, J. E., Kim, D. S., & Jo, I. H. (2020). Exploration of Predictive Model for Learning Achievement of Behavior Log Using Machine Learning in Video-based Learning Environment. *Journal of the Korean association of Computer, 23*(2).
15. Seong, H. O., & Jo, I. H. (2018). Utilizing Multimodal data to Predict Learning Achievement: Behavioral Log, Psychophysiological Response, and Test Anxiety. *Journal of Educational Technology, 34*(2).
16. Lee, H. W., Lee, J. M., & Cha, Y. M. (2021). Exploring a Model for Predicting Academic Achievement with Machine Learning for Off-line Courses in Higher Education. *The Korean Journal of Educational Methodology Studies, 33*(1).
17. Shin, J. H., & Choi, J. W. (2019). Developing the Prediction Model of At-risk Freshmen Students and Analyzing Characteristics of Cluster based on Learning Analytics. *Journal of Educational Technology, 35*(S).
18. Haya, P. A., Daems, O., Malzahn, N., Castellanos, J., & Hoppe, H. U. (2015). Analysing content and patterns of interaction for improving the learning design of networked learning environments. *British Journal of Educational Technology, 46*(2), 300-316.
19. Casey, K., & Azcona, D. (2017). Utilizing student activity patterns to predict performance. *International Journal of Educational Technology in Higher Education, 14*(1), 1-15.
20. Sun, J. C. Y., Lin, C. T., & Chou, C. (2018). Applying learning analytics to explore the effects of motivation on online students' reading behavioral patterns. *International Review of Research in Open and Distributed Learning, 19*(2).
21. Van den Beemt, A., Buijs, J., & Van der Aalst, W. (2018). Analysing structured learning behaviour in massive open online courses (MOOCs): an approach based on process mining and clustering. *International Review of Research in Open and Distributed Learning, 19*(5).
22. Sharma, K., Papamitsiou, Z., & Giannakos, M. (2019). Building pipelines for educational data using AI and multimodal analytics: A “grey-box” approach. British *Journal of Educational Technology, 50*(6), 3004-3031.
23. Rabin, E., Kalman, Y. M., & Kalz, M. (2019). An empirical investigation of the antecedents of learner-centered outcome measures in MOOCs. *International Journal of Educational Technology in Higher Education, 16*(1), 1-20.
24. Akçapınar, G., Altun, A., & Aşkar, P. (2019). Using learning analytics to develop early-

warning system for at-risk students. *International Journal of Educational Technology in Higher Education, 16*(1), 1-20.

25. Saqr, M., Nouri, J., Vartiainen, H., & Malmberg, J. (2020). What makes an online problem-based group successful? A learning analytics study using social network analysis. *BMC medical education, 20*(1), 1-11.
26. Huang, C., Han, Z., Li, M., Wang, X., & Zhao, W. (2021). Sentiment evolution with interaction levels in blended learning environments: Using learning analytics and epistemic network analysis. *Australasian Journal of Educational Technology, 37*(2), 81-95.
27. Massing, T., Reckmann, N., Blasberg, A., Otto, B., Hanck, C., & Goedicke, M. (2021). When is the Best Time to Learn?–Evidence from an Introductory Statistics Course. *Open Education Studies, 3*(1), 84-95.
28. Lu, C., & Cutumisu, M. (2022). Online engagement and performance on formative assessments mediate the relationship between attendance and course performance. *International journal of educational technology in higher education, 19*(1), 1-23.
29. Maldonado-Mahauad, J., Pérez-Sanagustín, M., Kizilcec, R. F., Morales, N., & Munoz-Gama, J. (2018). Mining theory-based patterns from Big data: Identifying self-regulated learning strategies in Massive Open Online Courses. *Computers in Human Behavior, 80*, 179-196.
30. Deeva, G., De Smedt, J., Saint-Pierre, C., Weber, R., & De Weerdt, J. (2022). Predicting student performance using sequence classification with time-based windows. *Expert Systems with Applications, 209*, 118182.
31. Tzeng, J. W., Lee, C. A., Huang, N. F., Huang, H. H., & Lai, C. F. (2022). MOOC Evaluation System Based on Deep Learning. *International Review of Research in Open and Distributed Learning, 23*(1), 21-40.
32. Davies, R., Allen, G., Albrecht, C., Bakir, N., & Ball, N. (2021). Using Educational Data Mining to Identify and Analyze Student Learning Strategies in an Online Flipped Classroom. *Education Sciences, 11*(11), 668.