

# Formulating an Innovative Gamified Personalized Learning Ecosystem Integrating 3D/VR Environments, Machine Learning, and Business Intelligence

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Latest digital advancements have intensified the necessity for adaptive, data-driven and socially-centered learning ecosystems. This paper presents the formulation of a cross-platform, innovative, gamified and personalized Learning Ecosystem, which integrates 3D/VR environments, as well as machine learning algorithms, and business intelligence frameworks to enhance learner-centered education and inferred decision-making. This Learning System makes use of immersive, analytically assessed virtual learning spaces, therefore facilitating real-time monitoring of not just learning performance, but also overall engagement and behavioral patterns, via a comprehensive set of sustainability-oriented ESG-aligned Key Performance Indicators (KPIs). Machine learning models support predictive analysis, personalized feedback, and hybrid recommendation mechanisms, whilst dedicated dashboards translate complex educational data into actionable insights for all Use Cases of the System (Educational Institutions, Educators and Learners). Additionally, the presented Learning System introduces a structured Mentoring and Consulting Subsystem, thence reinforcing human-centered guidance alongside automated intelligence. The Platform's modular architecture and simulation-centered evaluation approach actively support personalized, and continuously optimized learning pathways. Thence, it exemplifies a mature, adaptive Learning Ecosystem, supporting immersive technologies, analytics, and pedagogical support, hence, contributing to contemporary digital learning innovation and sociotechnical transformation in education.

*Keywords:* gamified learning ecosystems, learning analytics business intelligence, personalized education, virtual reality, machine learning

## Introduction

The technological, social, pedagogical, and organizational logics which formulate contemporary educational systems have been massively redefined by education's latest digital transformation. Learning environments have turned into complex sociotechnical ecosystems, where learners, educators, platforms, data flows, and institutional practices are dynamically (hence, non-linearly) interconnected (Dede, 2010; Siemens, 2013).

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Within this framework, the urge for adaptive, immersive, analytically transparent, and socially responsive learning systems has become non-negotiable, in both research and practice.

Digitized education started off from early e-learning platforms, only to evolve towards integrated learning ecosystems, which combine interactive content, analytics, and personalization (Garrison, Anderson, & Archer, 2000; Long & Siemens, 2011). Nevertheless, there still are limitations, such as the fact that immersive technologies are often isolated, analytics are largely descriptive, and personalization remains limited in scope (Ferguson, 2012; Avella, Kebritchi, Nunn, & Kanai, 2016). Concurrently, the growth of educational data has recently raised challenges related to data governance issues, as well as to the proper interpretation of educational analytics (Greller & Drachsler, 2012; Pardo & Siemens, 2014).

From a sociotechnical perspective, learning platforms should be perceived as systems where social practices, institutional norms, and power relations, co-exist with technology and its advancements (Wenger, 1998; Hevner, March, Park, & Ram, 2004). Within this context, learning analytics, machine learning, and business intelligence may actively shape how learning is interpreted and governed; certainly, as long as transparency, inclusion, and sustainability issues are explicitly addressed as critical design concerns (Buckingham Shum & Ferguson, 2012; Dawson, Gašević, Siemens, & Joksimovic, 2014).

This paper presents an innovative, cross-platform, gamified (in 3D and VR Environments), and personalized (via Machine Learning Algorithms) learning ecosystem, which addresses the aforementioned challenges, via an integrated sociotechnical approach. The proposed Learning Ecosystem combines immersive 3D/VR environments, machine learning-driven personalization, and a business intelligence, KPIs-oriented framework, including ESG-aligned dimensions. Emphasizing simulation-centered evaluation, system re-parameterization, and a structured Mentoring Subsystem, the System aims to position human judgment as the backbone of data-driven educational decision-making. Built upon a coherent sociotechnical framework, it, hence, aims to support personalized, accessible, and socially responsible digital education (Clow, 2012; Gašević, Dawson, & Siemens, 2015).

## **Related Work**

### **Digital Learning Ecosystems and Sociotechnical Perspectives**

Modern research conceives digital learning environments as sociotechnical systems. Within them, technologies, pedagogical practices, institutional structures, and learner behaviors co-exist (Dede, 2009; Siemens, 2013). Learning platforms, thus, function as ecosystems, aiming to mediate social interaction and decision-making via data-driven processes (Garrison et al., 2000; Wenger, 1998). Within this paradigm, learning analytics and business intelligence frameworks actively formulate the interpretation and governance of learning, whilst embedding assumptions, regarding engagement, success, and risk (Buckingham Shum & Ferguson, 2012; Greller & Drachsler, 2012). The presented System is explicitly positioned within this integrated sociotechnical perspective.

### **Gamification and Personalized Learning**

Gamified learning environments are capable of enhancing motivation and engagement when designed beyond ostensible reward structures (Hamari, Koivisto, & Sarsa, 2014; Boyle et al., 2016). For this to occur, effective gamification must support feedback, progress visualization, and adaptive challenges, so that clearly stated pedagogical objectives and personalized learning pathways are met and achieved (Deterding, Dixon, Khaled, & Nacke, 2011; Kapp, 2012). In other words, personalized learning has, now, shifted towards data-driven adaptivity, via which, analytics manage to inform instructional sequencing and feedback

(Zimmerman, 2002; Sun & Rueda, 2012; Ifenthaler & Yau, 2020; Joksimović, Gašević, Kovanović, Riecke, & Hatala, 2015). The presented System operationalizes this convergence through real-time, KPI-driven personalization.

### **Virtual Reality and Immersive Learning Spaces**

Virtual Reality (VR) has become a medium for experimental, embodied learning. This is achieved, by active enhancement of engagement and conceptual understanding (Dede, 2009; Fowler, 2015; Radianti, Majchrzak, Fromm, & Wohlgenannt, 2020). However, for pedagogical effectiveness to be met, apart from immersion, analytical instructional monitoring alignment is also necessary. Otherwise, VR risks to remain nothing but a rather isolated experiential layer (Slater & Sanchez-Vives, 2016; Cromley, Chen, & Lawrence, 2023). Recent research has, therefore, put a strong emphasis on the integration of learning analytics and consequent assessment frameworks within immersive environments (Li & Tsai, 2013). The proposed System responds to this very necessity, by embedding VR/3D spaces directly into its BI infrastructure, enabling systematic and evidence-based evaluation of its immersive learning.

### **Learning Analytics, Business Intelligence, and Predictive Modeling**

Learning analytics and Business Intelligence support the systematic measurement and interpretation of educational data for all key educational stakeholders (Educational Institutions, Educators and Learners—Long & Siemens, 2011; Picciano, 2012; Holsapple, Lee-Post, & Pakath, 2014). Integrated KPI frameworks, on the other hand, treat and analyze performance, engagement, and behavioral indicators as interdependent signals (Avella et al., 2016). Parallely, predictive analytics and machine learning models are able to identify early disengagement and dropout risks (Kizilcec, Piech, & Schneider, 2013; Ahmed & Ali, 2023). The latter, is an approach operationalized in the proposed Learning Ecosystem, via its Business Intelligence-Oriented Dashboards.

### **Mentoring, Human-Centered Design, and Ethics**

In a world of automation, research underscores the importance of human-centered mentoring in digital learning environments, so that learners are properly instructed and further motivated (Hattie & Timperley, 2007; Tinto, 1993; Kuh, 2009). Moreover, ethical concerns related to data privacy, transparency, and learner autonomy further reinforce the need for human mediation in analytics-driven systems (Drachler & Greller, 2016). The implemented educational Platform addresses this by embedding a structured Mentoring Subsystem, ensuring interpretive human accountability and oversight.

### **Physical Infrastructure and Deployment Architecture of the Proposed Learning System**

The implementation of the proposed System follows a three-tier (N-tier) physical architecture. This architecture ensures System stability, scalability, availability, as well as secures data access. This deployment model, also supports modular expansion, and high availability, while safeguarding data integrity and controlled application access (refer to Figure 1 below, for a graphical overview of the System's physical architecture).

The Platform adopts an N-tier architecture. This architecture enables parallel scaling, through multiple virtual Application Servers, Web Servers, and Database Servers. In addition, System capacity can be increased both vertically (through server upgrades) and horizontally via load-balanced clusters. As a result, the proposed Learning System is able to adapt, dynamically, to increased usage and computational demand.

At the data tier, MySQL Database Servers handle all persistent storage and respond exclusively to requests issued by the Application Servers. The database layer supports both vertical scaling and horizontal clustering.

More particularly, it uses failover mechanisms, which ensure service continuity, preventing data loss in the event of server failure. This failover cluster architecture operates transparently to the System’s end users.

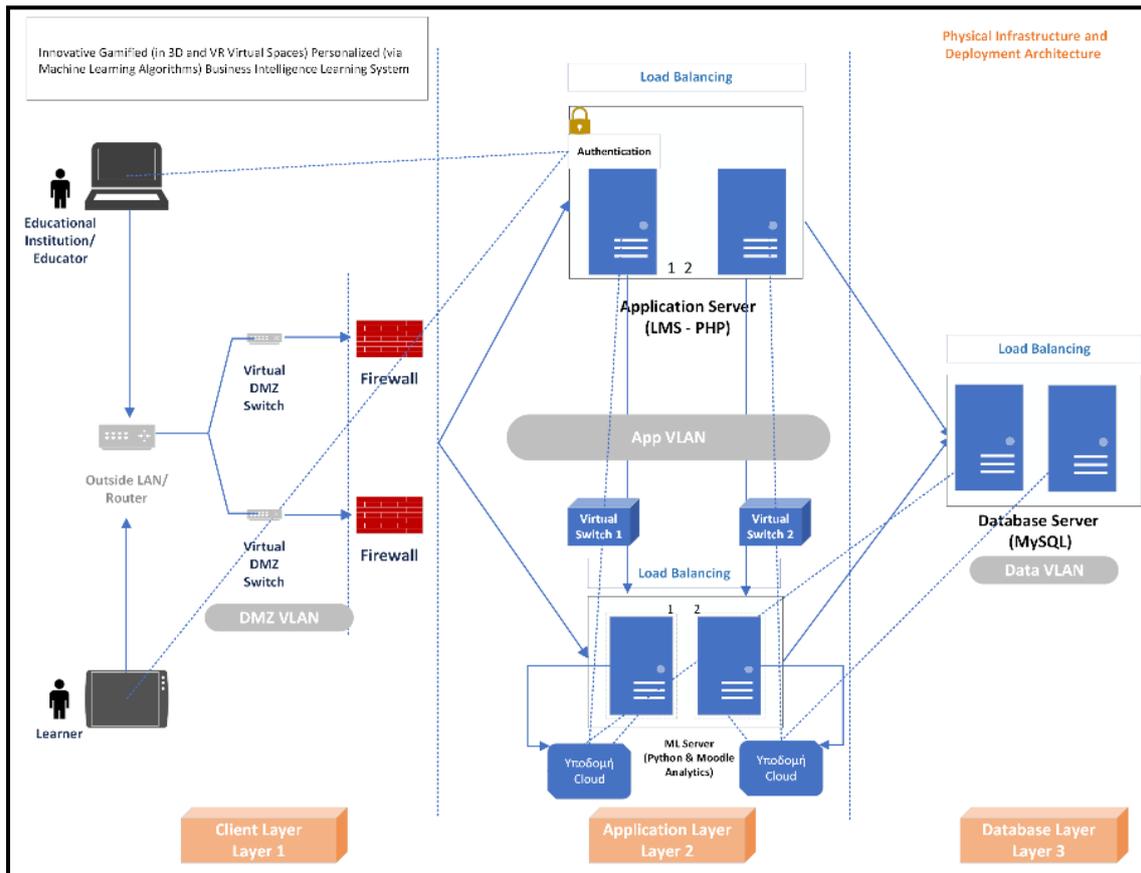


Figure 1. Physical infrastructure and deployment architecture of the system.

The application tier consists of Application Servers and Machine Learning Servers, which operate in a Network Load Balancing environment. They manage incoming requests from the Web Server. Additionally, they execute business logic, also orchestrating all of the System’s analytics and machine learning workflows. This results in ensured uninterrupted service delivery, as well as, efficient workload distribution.

User access is provided via standard web browsers and platform-specific applications (Windows, Android) using HTTP/HTTPS and RESTful APIs. Internet Information Services (IIS) is employed as the Web Application Server.

The Machine Learning Subsystem is implemented using PHP and Python and communicates with the application layer through REST APIs. PHP supports dynamic backend operations, Moodle integration, and database interaction. Python, on the other hand, handles computationally intensive analytics and predictive machine learning models. Thence, this API-based design enables future extensibility without the necessity for structural redesign.

All of the System’s Subsystems are hosted on dedicated cloud infrastructures, including the Moodle-based learning environment and the Unity-based immersive authoring and execution Subsystem (“Educational Content Development Subsystem”—please refer to the “System’s Architecture and Subsystems” section, below), ensuring scalable delivery of 3D and VR learning experiences.

### **Proposed Learning System's Architecture & Subsystems**

As mentioned above, the proposed System is a modular, cross-platform learning ecosystem. It integrates immersive technologies, analytics, and human-centered pedagogical support, all within a unified sociotechnical architecture. Its layered design ensures interoperability between learning content, user interaction, data processing, and decision-support mechanisms. Therefore, scalability, adaptability, and continuous system optimization are being supported.

At its foundation, the System operates on a Learning Management System (LMS) responsible for authentication, course orchestration, activity sequencing, and learning object management. The LMS supports SCORM-compliant content, as well as synchronous and asynchronous activities. It also continuously logs user interactions (i.e., content access, assessments, and session duration), into a persistent analytics layer.

An immersive learning layer extends the LMS through integrated 3D and Virtual Reality (VR) environments. These environments function as analytically traceable learning spaces, generating fine-grained data on exploration time, task completion, navigation, and engagement, all of which are evaluated alongside conventional learning activities.

An analytics intelligence layer aggregates data across subsystems. Furthermore, it applies a comprehensive KPI framework, covering learning performance, engagement, content usage, temporal behavior, system efficiency, and ESG-aligned indicators. Machine learning models operate on this very KPIs-supported feature space, aiming to support predictive risk detection, personalization, and informed pedagogical intervention. Personalized Dashboards complement the image of the System, with an embedded Mentoring Subsystem finalizing the intercommunication of all of the System's Subsystems.

To achieve the aforementioned interoperability across all System components, the System is structured into five (5) primary Subsystems, as outlined at a high level in earlier design phases, and further decomposed into nine (9) fully interconnected Subsystems that collectively constitute the Platform's functional architecture. These Subsystems, as shown in Figure 2 below, are:

1. User Management Subsystem (authentication, authorization, and role-based access control).
2. Educational Content Development Subsystem (delivery of gamified 3D and VR learning modules, all as part of a centralized educational content library).
3. Machine Learning Subsystem for the Analysis of the Educational/Learning Experience (analysis of learner behavior, performance patterns, and engagement dynamics).
4. Personalized Learning Analytics Reporting Subsystem (individualized assessment reports and a Personalized Feedback Reporting Dashboard for learners).
5. Key Performance Indicators (KPIs) and Business Intelligence Subsystem (aggregation, visualization, and interpretation of learning, engagement, system, and sustainability, ESG-oriented, metrics).
6. Mentoring/Consulting Support Subsystem (human-centered guidance and intervention).
7. General Reporting Subsystem (generation of aggregated analytical and strategic reports for Educational Institutions, Educators and Learners).
8. Machine Learning Services Subsystem (REST API) (scalable and interoperable access to predictive and analytical models).
9. MySQL Database Layer (central data repository for all operational, analytical, and System data).

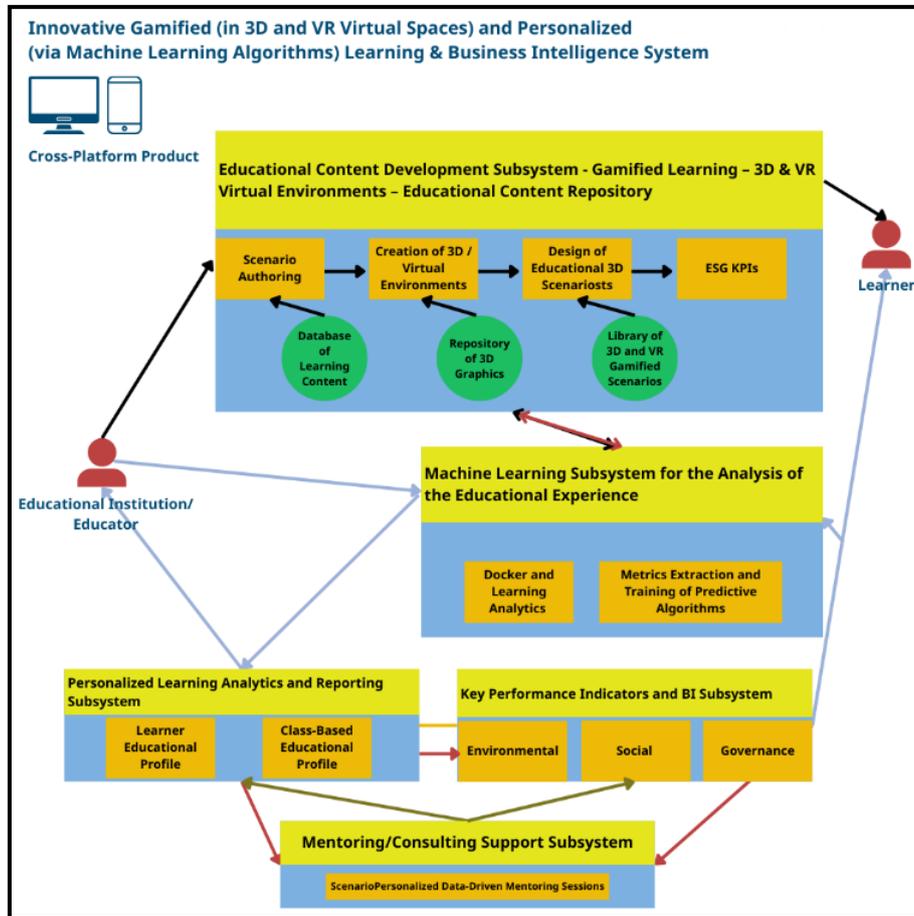


Figure 2. Proposed educational ecosystem's subsystems.

### Educational Content Development Subsystem—Gamified 3D & VR Learning Environments of the Proposed Learning Ecosystem

All immersive learning activities in the proposed System are developed using cross-platform 3D gamification engines and Virtual Reality frameworks, so as to ensure device compatibility and scalable deployment. We mention that, three-dimensional interactive content is implemented in “Unity”, while immersive VR experiences are delivered through “Reach”, supporting desktop, mobile, and dedicated VR environments. Immersive content is therefore treated not as a visual add-on, but as an analytically traceable learning component embedded in the Platform’s intelligence architecture. Central to this approach is the System’s Repository of 3D Objects: a modular asset library including all 3D objects, which are being used in the proposed Learning System’s 3D and VR STEAM-oriented Experiments (Gamified Educational Activities in 3D and Virtual Spaces). Each asset generates structured interaction data that feed directly into the Platform’s Business Intelligence and Machine Learning pipelines, enabling systematic evaluation, optimization, and personalization of immersive learning experiences. More particularly, within the proposed Ecosystem, the following are being developed:

1. 10 Virtual Thematic Experimental Laboratory Simulations in the fields of Physics, Chemistry, and Biology.
2. 5 Virtual Laboratories in Engineering and Information and Communication Technologies (ICT).
3. 10 Interactive Storytelling (Narration) Scenarios in English Language and Mathematics.

4. 5 Simulations and Case Studies in Literature and Arts.

5. 2 Educational Interactive Storytelling and Decision-Making Scenarios, implemented through virtual worlds, for the familiarization of learners with the concepts of entrepreneurship and innovation.

6. 20 Virtual Reality (VR) Exploration Scenes across STEAM sectors, including: Information Technology–Telecommunications–Digital Skills; Agriculture–Food Safety and Hygiene–Environment; Tourism–Recreation–Leisure Activities; Pedagogy–Educational Sciences; Blue (Maritime) Economy.

7. 1 Articulate eGame (Blue Economy).

8. 1 Interactive eVideo (Information Technology–Telecommunications–Digital Skills).

9. 3 Interactive eGames (Information Technology–Telecommunications–Digital Skills).

10. 4 Interactive 3D–VR–Text-to-Speech EBooks (Pedagogy–Educational Sciences; Information Technology–Telecommunications–Digital Skills).

11. 2 Simulation-Based Practical Theory Training Activities (Information Technology–Telecommunications–Digital Skills).

12. 12 Moodle Quizzes across the domains of Information Technology–Telecommunications–Digital Skills; Agriculture–Food Safety and Hygiene–Environment; Tourism–Recreation–Leisure Activities; Pedagogy–Educational Sciences; and the Blue Economy.

13. 12 Repositories of 3D Objects covering the aforementioned thematic domains.

14. 10 Synchronous Mentoring and Consulting Activities delivered via “BigBlueButton”, spanning the above-mentioned STEAM and vocational domains.

### **Machine Learning Subsystem for the Analysis of the Educational Experience in the Proposed Learning Ecosystem**

The System’s Machine Learning (ML) Subsystem models learner behavior, assesses educational risk, and supports data-driven personalization. More precisely, it analyzes learning activity data generated across the platform, including, among others, course participation, assessment performance, interaction frequency, and engagement with the immersive content of the System.

Using supervised and unsupervised machine learning techniques [including dimensionality reduction techniques such as Principal Component Analysis (PCA) and Singular Value Decomposition (SVD); clustering algorithms such as K-Means and DBSCAN; classification methods including Support Vector Machines (SVM), Naïve Bayes, k-Nearest Neighbors (k-NN), Decision Trees, and Random Forests; regression models including Linear, Logistic, and Ordinal Logistic Regression; recommender system approaches such as collaborative, content-based, and hybrid filtering; artificial neural networks; ensemble learning techniques; and outlier detection methods], the Subsystem enables predictive modeling of learners’ academic trajectories, identification of behavioral patterns associated with successful progression or disengagement, and early detection of risks related to dropout, inactivity, or failure to meet course requirements. These insights, thence, not only support proactive pedagogical intervention, but also, adaptive System behavior.

The Machine Learning Subsystem of the proposed Learning Ecosystem operates across two complementary layers. The first layer supports educators and instructional designers: it aggregates and analyzes learner data at predefined checkpoints (e.g., completion of learning units, weekly cycles), enabling class-level and individual-level monitoring. The second layer is embedded directly within the System’s gamified and immersive

learning activities. This way, it manages to continuously log user action (attempts, time-on-task, navigation behavior, and interaction sequences), via background instrumentation.

Collected data are processed automatically and presented through Business Intelligence Dashboards and Personalized Feedback Reports, including visual analytics, progress indicators, and actionable recommendations. Educators receive decision-support insights (e.g., identification of learners at risk of dropout), while learners receive individualized feedback supporting self-regulation and learning continuity.

From a methodological perspective, the Subsystem supports a broad spectrum of educational data mining and ML techniques (as mentioned above). Subsequently, containerized execution (e.g., Docker-based workflows) enables scalable processing and dynamic storage of model outputs, supporting continuous system adaptation.

Overall, the Ecosystem's Machine Learning Subsystem allows it to function as an adaptive learning ecosystem, where learner models are continuously refined and educational pathways dynamically adjusted, delivering genuinely personalized and evidence-driven learning experiences.

### **Key Performance Indicators and Business Intelligence Subsystem of the Proposed Learning Ecosystem**

The proposed System's analytical core is built around an integrated Business Intelligence (BI) and Machine Learning (ML) framework, which transforms learning interaction data into actionable pedagogical, organizational, and institutional insight. The Platform follows a simulation-centered, data-driven methodology, within which, learner behavior is perpetually measured, interpreted, and reintegrated into adaptive system processes and personalized learning pathways.

At the core, lies a unified KPI ecosystem structured across seven analytical dimensions (based, exactly on all of the metrics that are being measured within the proposed System): Learning Performance, Engagement and Collaboration, Learner Assessment Analytics, Content and Learning Experience, Temporal and Behavioral Analytics, System Efficiency, and ESG-aligned Sustainability and Governance. Rather than functioning as isolated metrics, KPIs are, therefore, operationalized as interdependent signals that jointly inform predictive modeling, recommendation mechanisms, and mentoring interventions.

All KPIs implemented within the System are systematically organized into these seven core categories. Each one of them, comprises both primary indicators and analytically derived or predictive metrics. As a result, methodological coherence, exhaustiveness, and non-redundancy is being ensured across analytics, machine learning feature spaces, and pedagogical decision-making processes. Analytical outputs are, then, presented through the Ecosystem's Personalized Learning Analytics and Reporting Subsystem and are accessible to learners, educators, and institutional stakeholders.

By maintaining semantic consistency across BI reporting, ML modeling, and instructional intervention, the System, consequently enables transparent, interpretable, and actionable educational intelligence that supports continuous system optimization and informed human decision-making.

#### **Core KPI Framework and Quantification Logic**

Learning performance indicators function as primary outcome measures and early-warning signals. The Course Completion Rate ("CCR") of the System is one of its primary, core KPIs, which captures the proportion of learners completing all required activities (in comparison to the total learners involved/enrolled—Gašević, Dawson, Rogers, & Gasevic, 2016):

$$CCR = \frac{N_{completed}}{N_{enrolled}}$$

To accommodate immersive learning flows, the System also introduces additional rates: an important one is the VR Completion Rate (“VRC”); an extension of CCR, enabling detection of immersive drop-off phenomena within VR-based instructional units:

$$VRC = \frac{N_{VR\_completed}}{N_{VR\_started}} \times 100,$$

where  $N_{VR\_completed}$  denotes the number of learners who successfully complete a VR activity and  $N_{VR\_started}$  those who initiate it.

Moreover, learner progression and cognitive load are monitored through the Learner Progress Rate (“LPR”):

$$LPR = \frac{A_{completed}}{T},$$

where  $A_{completed}$  represents the number of completed learning activities (e.g., lessons, assessments, or immersive tasks), and  $T$  denotes the total number of required activities within the instructional unit (Kizilcec et al., 2013), as well as through the Average Completion Time (“ACT”):

$$ACT = \frac{1}{N} \sum_{i=1}^N t_i,$$

where  $t_i$  denotes the time required by learner  $i$  to complete a given activity and  $N$  the total number of learners considered (Bosch et al., 2016).

Additionally, the Average Course Grade (“ACG”) is the mean grade a learner receives:

$$ACG = \frac{1}{N} \sum_{i=1}^N G_i,$$

where  $G_i$  denotes the grade obtained in the  $i$ -th graded activity (e.g., quiz, assignment, assessment, or evaluated immersive task), and  $N$  is the total number of graded activities considered.

Moreover, longitudinal consistency is captured through the Learning Growth Index (“LG”):

$$LG_i = G_{i,t} - G_{i,t-1},$$

where  $G_{i,t}$  represents the learner’s performance (e.g., grade or achievement score) at the current instructional unit  $t$  and  $G_{i,t-1}$  corresponds to performance at the immediately preceding unit (Tempelaar, Rienties, & Giesbers, 2015).

The Learning Growth Index therefore captures performance change across successive learning units, allowing the System to assess not only absolute achievement (“what grade learners received”), but also learning progression over time (“whether learners are improving”).

Additionally, Engagement Dynamics are quantified using composite indicators. These include, among others, the core Learning Engagement Index (“LEI”). This is a core pedagogical indicator that captures the level of learner involvement and commitment to the instructional process. It integrates multiple behavioral dimensions of engagement, including:

- Access frequency to learning materials;
- Study session duration;
- Participation in interactive learning activities, such as forums, assignments, and immersive VR exercises.

The index is computed as:

$$LEI = \frac{Accesses+Duration+Activities}{3 \times Max_{observed}},$$

where *Accesses*, *Duration*, and *Activities* represent normalized measures of the respective engagement components, and *Max<sub>observed</sub>* denotes the maximum observed value across the learner population.

The resulting LEI produces a weighted engagement score normalized between 0 and 1. Higher LEI values indicate active participation and sustained engagement, whereas declining LEI values function as an early warning signal of potential learning disengagement (Fredricks, Blumenfeld, & Paris, 2004).

The Forum Engagement Index (“FEI”) captures the degree and quality of a learner’s participation in asynchronous discussion activities. It is computed as a weighted sum of distinct interaction types, reflecting varying levels of cognitive and pedagogical contribution:

$$FEI_i = w_1P_i + w_2R_i + w_3K_i,$$

where:

- $P_i$  denotes the number of original posts created by learner  $i$ ;
- $R_i$  denotes the number of replies or explanatory responses contributed by learner  $i$ ;
- $K_i$  denotes low-effort interactions (e.g., reactions, acknowledgments);
- $w_1, w_2, w_3$  are weighting coefficients.

The weighting scheme may be re-parameterized as an amelioration, provided that the conceptual intent of the indicator remains unchanged. Specifically, higher weights are assigned to cognitively productive interactions (e.g., replies and explanations), while lower weights are applied to surface-level actions (e.g., reactions).

An increase in FEI reflects meaningful, learning-oriented social interaction, whereas low or declining FEI values may signal limited peer engagement or superficial participation (Wise, Zhao, & Hausknecht, 2014).

The BigBlueButton Participation Rate (“BPR”) provides a direct indicator of learner involvement in synchronous learning activities. It is calculated as:

$$BPR = \frac{N_{participants}}{N_{invited}} \times 100.$$

BPR captures attendance behavior in live mentoring, tutoring, or collaborative sessions. Persistently low BPR values in courses that otherwise exhibit high individual engagement (e.g., high LEI or login frequency) reveal an “asynchronous dominance” pattern, indicating learner preference for self-paced, individual learning over synchronous interaction (Martin & Parker, 2014).

By combining BPR with engagement and performance indicators, the System distinguishes between episodic participation and sustained, socially embedded learning behavior.

### **Predictive Analytics—Machine Learning Subsystem and KPIs and BI Subsystem Interoperability in the Proposed Learning Ecosystem**

Building on the previously mentioned KPIs, the presented System implements supervised machine learning models, which are designed to identify learners at risk. These Models are, namely, the following (Kizilcec et al., 2013; Gašević et al., 2015; Romero & Ventura, 2020):

- Courses at risk of not starting;
- Learners at risk of dropping out;
- Learners with recent or prolonged inactivity;

- Learners at risk of not achieving the minimum passing grade;
- Learners at risk of not meeting course completion conditions.

They operate within defined analytical windows and rely on standardized instructional settings (enabled completion tracking, activity completion rules, and gradebook configuration—Long & Siemens, 2011; Pardo & Siemens, 2014). Consequently, by aligning ML model requirements with LMS instructional design parameters, the Ecosystem ensures methodological consistency and reliable risk detection (Greller & Drachsler, 2012).

Central to this predictive layer are probabilistic estimators of the System such as the Predictive Success Index (“PSI-ML”) and Risk Prediction (“RP”):

$$PSI_{ML}(i) = P(success_i | X_i)$$

$$RP(i) = P(dropout_i | X_i),$$

where  $X_i$  represents a feature vector composed exclusively of normalized KPI inputs (e.g., LPR, LEI, ACT, FEI). Restricting the feature space to KPI-derived variables ensures transparency, explainability, and semantic alignment between analytics, prediction, and pedagogical interpretation, consistent with principles of explainable and responsible learning analytics (Drachsler & Greller, 2016; Khosravi, Gašević, Mirriahi, & Dawson, 2022).

Temporal disengagement is captured through the Inactivity Risk Index (“IRI”):

$$IRI(i) = P(inactive \text{ within } \Delta_t | X_i),$$

which estimates the probability that a learner will exhibit inactivity within a predefined temporal window  $\Delta_t | X_i$  (Kizilcec et al., 2013; Clow, 2012). Threshold-based activation transforms these probabilistic outputs into actionable system signals. In consequence, triggering personalized feedback, content resequencing and mentoring escalation are being accounted for (Gašević et al., 2015).

In terms of model reliability and operational responsiveness, these are monitored using indicators such as the Inactivity Detection Accuracy (“IDA”):

$$IDA = \frac{TP+TN}{TP+TN+FP+FN},$$

where TP (True Positives) denotes correctly identified inactive learners, TN (True Negatives) correctly identified active learners, FP (False Positives) active learners incorrectly flagged as inactive, and FN (False Negatives) inactive learners not detected by the model (Romero & Ventura, 2020).

Crucially, acceptable performance ranges for IDA and related metrics are not derived from abstract benchmarks, but from pilot-based empirical baselines. As a result, model performance is evaluated against real usage behavior observed during the System’s pilot phase. This recalibration is operationally critical: a machine learning model may perform well under generic evaluation criteria while failing to capture the specific behavioral dynamics of immersive learning and mentoring-driven engagement (Gašević et al., 2016; Buckingham Shum & Ferguson, 2012).

By anchoring predictive intelligence to empirically observed system behavior, the System ensures that its machine learning models are product-specific, context-aware, and aligned with the sociotechnical realities that constitute its core innovation (Selwyn, 2016; Williamson, 2017).

Time-to-Intervention (“TTI”) is a responsiveness indicator measuring the elapsed time between the detection of learner inactivity and the activation of the first pedagogical or mentoring intervention:

$$TTI = \text{Timestamp of Intervention} - \text{Timestamp of Inactivity Detection}.$$

TTI is typically expressed in hours or days and reflects a combination of technical system responsiveness and pedagogical readiness (Hattie & Timperley, 2007; Gašević et al., 2015).

The indicator is critical for:

- the effectiveness of preventive interventions, as shorter response times increase the likelihood of successful re-engagement;
- evaluating the efficiency of automated alerts and recommendation mechanisms;
- aligning technical response times with pedagogical mentoring protocols.

From an ESG perspective, TTI falls within the Governance dimension, as it captures the institution’s capacity to respond promptly and responsibly to early signs of disengagement (Prinsloo & Slade, 2018; Williamson, 2017). At the Business Intelligence level, TTI enables correlations between response time and successful re-engagement rates (“RSR”), providing actionable evidence for improving mentoring workflows and automation strategies.

Together, these indicators form a closed analytical system in which performance, engagement, immersion, and intervention are continuously observed, interpreted, and re-parameterized.

### Immersive and Content-Specific Analytics

Moving on to the assessment of the pedagogical value of immersive environments, the proposed Learning Ecosystem operationalizes Digital Resource Utilization (“DRU”) as a composite indicator capturing the extent, intensity, and temporal distribution of learner interaction with digital instructional resources, including conventional learning objects as well as immersive 3D and VR activities:

$$DRU_i = \sum_{m=1}^M w_m \cdot U_{i,m},$$

where:

- $DRU_i$ : Digital Resource Utilization for learner  $i$ ;
- $U_{i,m}$ : normalized utilization of resource modality  $m$  (e.g., LMS content, 3D environments, VR simulations);
- $w_m$ : modality-specific weighting factor;
- $M$ : number of content modalities.

DRU does not reflect merely access frequency, but meaningful engagement with learning resources across modalities, and functions as a bridge between content design and observed learning behavior (Avella et al., 2016; Ferguson, 2012).

In practice, the proposed System decomposes DRU into modality-specific sub-indicators to preserve interpretability and avoid masking heterogeneous engagement patterns.

Accordingly, these include the 3D Exploration Time Index (“3DET”) and the VR Simulation Time Index (“VRST”), enabling fine-grained analysis of learner interaction within immersive learning environments (Radianti et al., 2020; Makransky, Andreasen, Baceviciute, & Mayer, 2021).

The core 3D Exploration Time Index of the System is being provided by the following formula:

$$3DET = \frac{1}{N} \sum_{i=1}^N t_{3D,i},$$

where  $t_{3D,i}$  denotes the total time learner  $i$  spends interacting with 3D objects or scenes, and  $N$  is the number of learners or interaction sessions considered. This indicator captures exploratory depth, spatial engagement, and interaction persistence within non-immersive 3D learning activities.

The VR Simulation Time Index (“VRST”) is provided by:

$$VRST = \frac{1}{N} \sum_{i=1}^N t_{VR,i},$$

where:

- $t_{VR,i}$  represents the total active time learner  $i$  spends within VR simulations (excluding idle or background time);
- $N$  denotes the number of learners participating in the VR activity.

It enables the Platform to distinguish superficial exposure from sustained immersive engagement and is analytically examined in relation to learning outcomes (e.g., ACG, LG) and engagement indicators (e.g., LEI).

Together, 3DET and VRST allow immersive learning activity to be evaluated alongside traditional instructional components, supporting analytical correlations with learning outcomes (e.g., ACG), engagement stability, and completion rates. This decomposition ensures that immersion is not treated as a visual enhancement, but as a measurable, analyzable, and pedagogically accountable dimension of the learning process.

The Learning Experience Quality Index (“LEQ”) is a composite indicator designed to capture the perceived and behavioral quality of learners’ interaction with immersive 3D and VR learning environments within the proposed Learning Ecosystem.

LEQ integrates objective interaction metrics and subjective learner feedback, reflecting both experiential engagement and usability. Specifically, it is derived from a weighted aggregation of:

- Immersive engagement indicators, such as 3D Exploration Time (3DET) and VR Simulation Time (VRST);
- Engagement stability and continuity metrics, including User Engagement Stability [“UES”—it captures the temporal consistency of a learner’s engagement behavior across instructional units, reflecting the degree to which engagement indicators (e.g., LEI, activity participation, session frequency—Joksimović et al., 2015; Gašević et al., 2015) remain stable rather than episodic or volatile over time] and Learning Engagement Index [“LEI”];
- Usability and accessibility signals, inferred from interaction patterns (e.g., task completion consistency, navigation smoothness, repetition frequency);
- Learner-reported experience measures, collected through standardized post-activity questionnaires evaluating perceived clarity, immersion, and instructional alignment (Khosravi et al., 2022; Ifenthaler & Yau, 2020).

Formally, LEQ can be expressed as a normalized composite score:

$$LEQ_i = f(3DET_i, VRST_i, LEI_i, UES_i, UX_i),$$

where  $UX_i$  represents aggregated learner-reported experience measures related to usability, clarity, accessibility, and perceived instructional alignment of immersive activities, collected through standardized post-activity questionnaires, and  $f(\cdot)$  denotes a weighted aggregation function calibrated during pilot evaluation.

We stress that, these metrics, are, all, analytically correlated with learning outcomes, through derived insights (Makransky et al., 2021; Radianti et al., 2020) such as the LEQ–ACG correlation ( $\rho_{LEQ,ACG}$ ). More particularly, the LEQ–ACG correlation denotes the core statistical correlation coefficient of the System, between:

- LEQ (Learning Experience Quality): the composite indicator capturing learners’ perceived quality of immersive 3D/VR experiences, derived from interaction metrics (e.g., immersion time, engagement stability, usability signals) and learner feedback;

- ACG (Average Course Grade): the mean academic performance score achieved by learners within a course or instructional units.

As a result, it expresses the strength and direction of the relationship between immersive learning experience, quality and measurable academic performance. It, hence, enables empirical evaluation of whether immersive engagement translates into measurable learning outcomes.

### **Recommendation and Personalized Intervention Mechanisms within the Proposed Learning Ecosystem**

Beyond analytics and prediction, the proposed System incorporates a recommendation layer. This layer translates Business Intelligence indicators and machine learning outputs into pedagogical actions. As a result, data-driven intelligence is operationalized into personalized recommendations for learners, educators, and mentors. This way, direct alignment between analytics and instructional decision-making is ensured.

The System's recommendations are derived from a unified KPI-based feature space, which allows for the maintenance of semantic consistency between observation, prediction, and intervention. At the learner level, the System supports adaptive content resequencing. This occurs by pacing adjustments, and immersive activity selection, including targeted repetition or modulation of VR experiences. Furthermore, predictive risk signals trigger proportional interventions, which range, from automated re-engagement prompts, to escalation towards human mentoring. In addition, educator- and mentor-facing recommendations focus on cohort patterns and intervention prioritization, while recommendation outcomes are continuously reintegrated into the analytics pipeline to refine system responsiveness. Overall, this layer enables the System to move from descriptive analytics towards adaptive, explainable, and human-centered educational intelligence.

Subsequently, beyond technical measurement, the Key Performance Indicators and Business Intelligence Subsystem of the proposed Learning Ecosystem function as a decision-support and reflexive governance layer. By rendering learning processes, risks, and outcomes visible in real time, the Platform enables educators and institutions to observe the consequences of pedagogical and organizational decisions as they unfold. This continuous feedback loop, thereby supports evidence-informed adaptation rather than retrospective evaluation, reinforcing the System's transparency, accountability, and institutional learning within its broader sociotechnical ecosystem.

### **Personalized Learning Analytics Reporting Subsystem of the Proposed Learning Ecosystem**

All of the outputs of the Machine Learning Subsystem for the Analysis of the Educational Experience are integrated into the System's Business Intelligence layer and, then, delivered through role-specific Dashboards. These Dashboards emphasize progress, engagement, and actionable guidance for learners. They also support monitoring, and evidence-based suggestions related to content sequencing, intervention prioritization, and instructional adjustment, when targeted to Educational Institutions and Educators.

Importantly, Machine Learning-driven insights also feed the System's recommendation and mentoring mechanisms, enabling a closed feedback loop in which predictions inform interventions, and intervention outcomes are reintroduced into the analytics pipeline for continuous model refinement.

The Personalized Learning Analytics Reporting Subsystem synthesizes outputs from the proposed System's Analytics and Machine Learning components, together with learner demographic and interaction data, so as to construct comprehensive, individualized learning profiles. In parallel, the Subsystem generates

aggregated class- and cohort-level profiles, enabling multi-level insight into learning dynamics and performance trends. This way, by making use of advanced statistical analysis and data-driven modeling techniques (including data mining, deep learning analytics, clustering, decision trees, and neural networks, as mentioned above), the Subsystem translates analytical results into actionable feedback for all of its users (Educational Institutions, Educators and Learners).

Therewith, beyond evaluation, the Subsystem functions as a recommendation-oriented feedback mechanism (“Recommendation System”). It proposes targeted pedagogical adjustments, enrichment activities, or follow-up immersive experiments aligned with learners’ interests, proficiency levels, and identified learning challenges. To this extent, feedback is not limited to retrospective reporting. Instead, it actively supports forward-looking instructional planning and personalized learning pathways.

Overall, the proposed Learning Ecosystem’s Personalized Learning Analytics Reporting Subsystem operationalizes the System’s analytics into interpretable, role-specific insights. On that wise, unceasing educational improvement, learner self-regulation, and data-informed pedagogical decision-making, are all being, optimally, reinforced.

It should, also, be noted that, at the macro level, the Personalized Learning Analytics Reporting Subsystem extends way beyond learner- and class-level feedback to support institution-wide evaluation and strategic decision-making. More concretely, by aggregating analytics outputs across courses, thematic domains, and deployment phases, the System enables comparative analysis of learning effectiveness, immersive content utilization, and system performance.

Ultimately, the whole of these aggregated insights is being presented through the System’s organizational Dashboards and exportable Reports. Consequently, evidence-based planning, quality assurance, and continuous improvement of the proposed Learning Ecosystem is being sustained and reinforced, holistically.

### **Mentoring/Consulting Support Subsystem & Human-Centered Design of the Proposed Learning Ecosystem**

Research in sociology of education consistently shows how human interaction remains critical for learner motivation, persistence, sense-making, and social integration, particularly in complex or immersive learning environments (Vygotsky, 1978; Wenger, 1998; Selwyn, 2016).

Effective learning ecosystems, therefore, massively depend on the interplay between technological mediation and human guidance. For this reason, it was decided that the presented Ecosystem would also integrate a human-centered Mentoring/Consulting Support Subsystem, beyond automated personalization.

This very Subsystem is implemented as an integrated Subsystem rather than an auxiliary feature. More particularly, synchronous mentoring is supported through the “BigBlueButton” framework, which enables structured one-to-one and small-group interactions. Mentoring activity is analytically embedded within the Business Intelligence layer using indicators such as Mentoring Sessions Count (“MSC”), BigBlueButton Participation Rate (“BPR”), Learning Engagement Index (“LEI”), and User Engagement Stability (“UES”).

It becomes elucidated that, methodologically, the System’s Mentoring/Consulting Support Subsystem functions as a human-in-the-loop extension of the System’s predictive analytics, translating machine learning signals into context-sensitive interventions. This way, ethical, interpretable, and pedagogically accountable decision-making is being reinforced (Ifenthaler & Yau, 2020; Holmes et al., 2022; Williamson, 2017; Prinsloo & Slade, 2018).

Last, but not least, it should be noted that, all mentoring interventions, within the proposed Learning Ecosystem, are dynamically activated, based on analytically identified needs rather than applied uniformly. Proportional support is, hereby, ensured, while preserving learner autonomy, whilst avoiding over-intervention.

### **Evaluation/Simulation-Centered Analysis of the Proposed Learning Ecosystem**

The evaluation of the proposed Learning Ecosystem follows a simulation-centered analytical approach: it examines system behavior and learning dynamics under realistic conditions of use, rather than isolated feature testing. This methodology comes in complete accordance with learning analytics research emphasizing iterative feedback loops and data-driven system reconfiguration based on authentic usage data (Clow, 2012; Gašević et al., 2015).

On this spectrum, the System was deployed, during its simulation phase, as a fully integrated ecosystem. It incorporated LMS activities, 3D/VR environments, mentoring interactions, and personalized dashboards. On top of that, user interactions were continuously logged, enabling real-time monitoring of KPIs related to learning performance, engagement, immersive utilization, predictive risk, system efficiency, and ESG dimensions.

Machine learning models were evaluated not only for predictive accuracy but also for their integration into pedagogical and mentoring workflows, supporting evaluation based on actionable educational impact rather than statistical performance alone (Kizilcec et al., 2013; Romero & Ventura, 2020).

### **Empirical Foundations of the Proposed Learning Ecosystem for Socially Informed, Accessibility-Oriented Immersive Learning Design**

The design of the proposed Learning Ecosystem's immersive learning environment is informed by empirical evidence derived from advanced statistical modeling of learner perceptions regarding accessibility and the pedagogical integration of 3D and Virtual Reality technologies.

The Logistic Regression Model applied, estimates the probability that a learner perceives the need for improvement in the accessibility and pedagogical integration of VR and 3D technologies, as a function of age, learning domain, preferred interaction modality, and their interaction effects:

$$\begin{aligned} & \text{logit} \left( \hat{P}(\text{Accessibility and Improved Integration of VR/3D}) \right) \\ & \leq 1 | \text{"Improvement Required" or "Possibly Requires Improvement"} = \\ & \quad 22.2 + 5.0 \cdot \text{Age}_{21-23} - 6.4 \cdot \text{Gender}_{\text{PreferNotToSay}} \\ & \quad + 5.0 \cdot \text{MostBeneficialModule}_{\text{Engineering}} \\ & \quad - 9.8 \cdot (\text{Age}_{21-23} \times \text{MostBeneficialModule}_{\text{Engineering}}) \\ & \quad - 41.5 \cdot (\text{Age}_{21-23} \times \text{MostBeneficialModule}_{\text{Arts}}) \\ & \quad + 19.5 \cdot (\text{Age}_{18-20} \times \text{InteractiveContent}_{\text{EducationalGames}}) \\ & \quad + 3.4 \cdot (\text{Age}_{21-23} \times \text{InteractiveContent}_{\text{EducationalGames}}) \\ & \quad + 5.3 \cdot (\text{Age}_{21-23} \times \text{InteractiveContent}_{\text{VirtualTours}}) . \end{aligned}$$

The resulting model demonstrates that perceptions of accessibility and effective VR/3D integration vary across learners and are shaped by age group, disciplinary context, preferred interactive formats, and their interaction effects. In particular, learners aged 21-23 display differentiated perceptions depending on which Module the immersive content is about (in other words, whether the immersive content is associated with

Engineering, Arts, Educational Games, or Virtual Tours). This indicates that immersive experiences are mediated by both cognitive maturity and disciplinary epistemic culture.

The analysis further demonstrates that immersive formats (like educational games and virtual tours) are associated with a lower perceived need for improvement (especially among younger learners). This finding points to the fact that, familiarity, playfulness, and navigational clarity enhance perceived accessibility. Conversely, certain disciplinary contexts, especially when combined with specific age cohorts, exhibit greater sensitivity to usability, instructional alignment, and cognitive load, underscoring the limitations of uniform immersive design approaches.

The aforementioned findings informed the design of the proposed Learning System as a socially responsive and accessibility-oriented learning ecosystem. Therewith, rather than treating VR and 3D environments as static enhancements, the System conceptualizes accessibility as a dynamic, measurable construct that evolves through learner interaction. By translating all statistically significant variables identified in the model into measurable indicators that guide analytics, adaptive pathways, and recommendation logic, inclusivity, pedagogical alignment and empirically grounded immersive learning, are, thence, considerably ensured.

### **Discussion: Social, Pedagogical, Institutional, and Accessibility Implications of the Proposed Learning Ecosystem**

The proposed Learning Ecosystem, design-wise and evaluation-wise illustrates how contemporary learning platforms can operate as sociotechnical systems that actively shape participation, agency, and inclusion. Socially, the System exhibits that data-driven personalization, especially when combined with transparent analytics and structured mentoring, can mitigate disengagement, whilst also supporting diverse learner trajectories, rather than reinforcing uniform educational norms (Selwyn, 2016; Wenger, 1998). In this context, the integration of all of the System's ESG-aligned indicators comes to further enhance the Learning Ecosystem's learning outcomes, formulating broader frameworks of social responsibility and sustainability.

Pedagogically, the proposed Learning System advances adaptive and experiential learning. This occurs thanks to the embedment of 3D/VR activities, all within ceaseless cycles of measurement, feedback, and pedagogical re-parameterization. Therefore, immersion is aligned with evidence-based instructional practice (Hattie & Timperley, 2007; Zimmerman, 2002).

At the institutional level, the proposed Learning System's Business Intelligence framework supports strategic oversight. This happens without the urge to reduce pedagogy to managerial metrics. On the contrary, the Learning System's predictive indicators enable early, proportionate intervention (Gašević et al., 2015; Picciano, 2012).

Last, but not least, accessibility is a core design principle of the proposed Ecosystem's User Experience Interaction and User Experience Design framework, the whole of which, is implemented in complete accordance with the Web Content Accessibility Guidelines (WCAG 2.1), and operationalized analytically, via indicators such as the Digital Inclusion Index (W3C, 2018). As a result, inclusive design is clearly positioned as a measurable component of the presented Learning Ecosystem.

### **Conclusions**

This study presented the proposed Learning Ecosystem as an adaptive, sociotechnical learning ecosystem integrating gamification, immersive 3D/VR environments, machine learning, business intelligence, and

structured human mentoring. Thereupon, the System demonstrates how immersion, analytics, and personalization can be coherently combined to support learner-centered education, institutional decision-making, and socially responsible innovation.

Pedagogically, the System enables personalized learning pathways, continuous feedback, and experiential engagement. Additionally, analytically monitored VR environments and predictive models strengthen the System's capability to support early risk detection and targeted intervention. Crucially, these automated mechanisms are complemented by the System's human-centered Mentoring/Consulting Support Subsystem, which allows for fruitful dialogue, judgment, and pedagogical accountability.

Last, but not least, at the institutional level, the presented Learning Ecosystem's Key Performance Indicators (and ESG-driven) Business Intelligence Subsystem supports transparency, sustainability, and ethical data governance. Ultimately, by embedding accessibility and inclusive design as measurable system principles, the presented Learning Ecosystem manages to exemplify a mature shift towards ethical, adaptive, and socially grounded digital learning ecosystems.

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