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An Intelligent learning management platform for Data-Driven course improvement

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Title: **An Intelligent learning management platform for Data-Driven course improvement**

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Introduction

Digitalisation has expanded access to online learning, but most platforms replicate traditional instruction and offer limited feedback, leaving many cognitive difficulties hidden - especially in asynchronous environments where instructors cannot observe reasoning or adapt content in real time. Generative AI enables the analysis of learners' natural-language queries, revealing authentic misconceptions and instructional gaps, which can inform targeted improvements.

This article presents an educational platform as a self-improving ecosystem. By combining interactive H5P modules, formative assessments, and AI-driven analytics in a closed feedback loop, the system continuously detects and addresses learning obstacles while providing ongoing support. Implemented on WordPress with custom plugins, the platform demonstrates how AI analytics and micro-interactions can enhance evidence-based quality control in web-based education without relying on proprietary LMS solutions.

Anatomy of the learning module: a multilayered approach

The proposed platform is built around a learning module that addresses the limitations of static instructional content by combining explanation, practice, and checking within each lesson. Each lesson is designed as a multilayered system in which different types of materials complement each other and support both learning and diagnosis. This approach aligns with widely accepted principles of instructional design [1].

The module consists of three connected layers: the expository layer, the interactive layer, and the diagnostic layer.

Expository layer

The expository layer includes video lectures and presentation materials that introduce key concepts and terminology. The content is delivered in a concise, structured way and strictly follows the lesson objectives in order to avoid cognitive overload. Visual and textual

elements support each other, and this layer functions as preparation for further work rather than as a standalone learning stage.

Interactive layer

The interactive layer is embedded directly into the learning process through H5P activities such as in-video questions, practice tasks, and branching scenarios. Learners apply new knowledge immediately, make decisions, and observe their outcomes. This increases engagement and helps reveal difficulties in understanding before formal assessment. As a result, the interactive layer supports learning while also providing diagnostic information (figure 1).

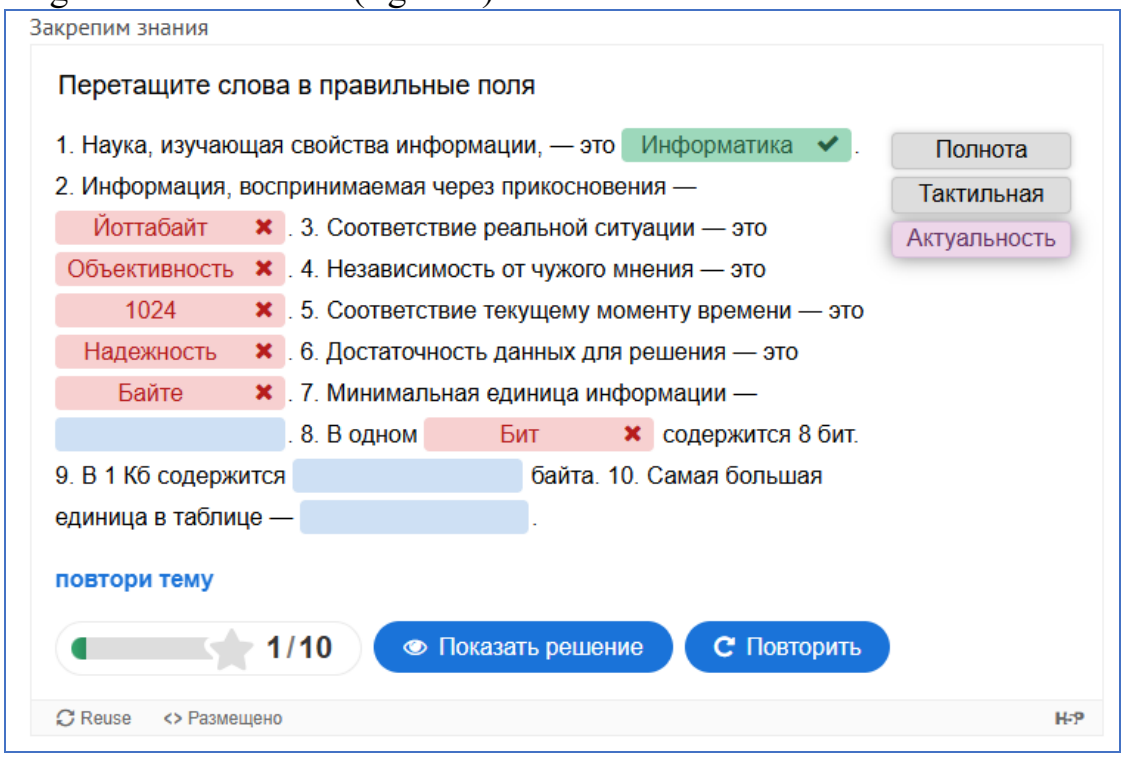

Figure 1. *H5P drag-and-drop activity used to reinforce key concepts and identify misconceptions at the consolidation stage of the lesson.*

Diagnostic layer

Each lesson ends with a short diagnostic quiz consisting of ten tasks. Its purpose is to check how clearly the material was presented, not to evaluate or rank learners. The results highlight problematic topics and can be compared with data from interactive activities(figure 2). Repeated errors are treated as signals for improving explanations and lesson structure.

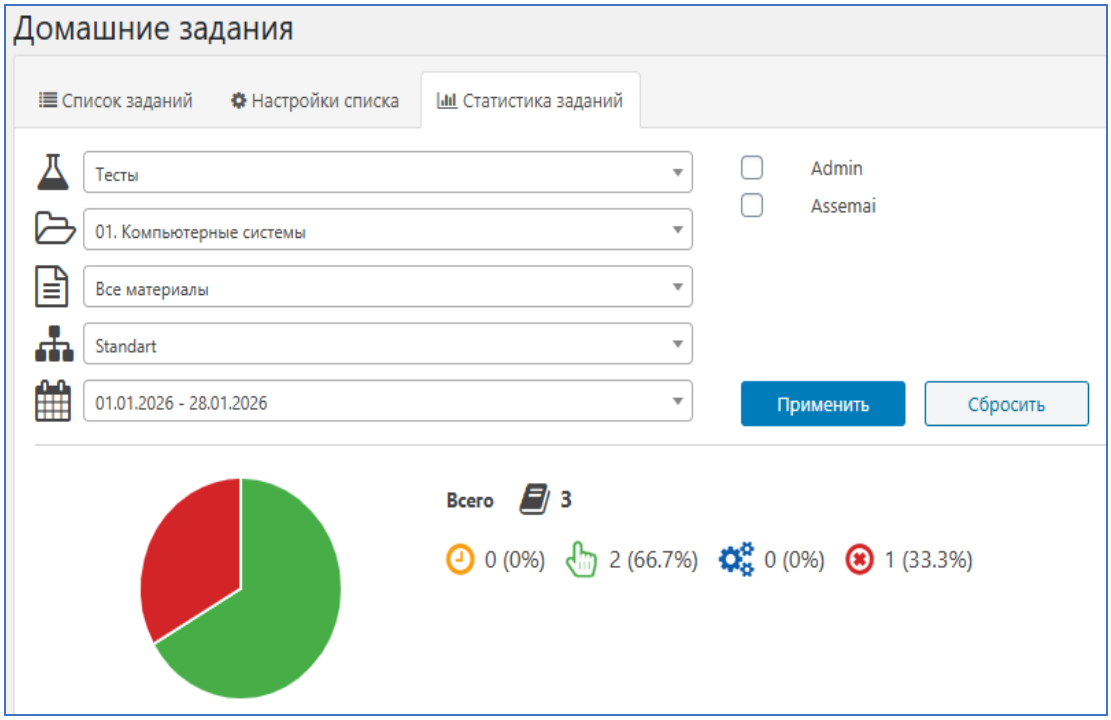

Figure 2. *Aggregated results of diagnostic tasks used to evaluate instructional clarity and identify recurring misconceptions.*

Integration of Layers

The effectiveness of the module comes from the combined function of all three layers. The expository layer explains, the interactive layer reinforces, and the diagnostic layer shows what needs improvement. Together, they form a closed cycle within each lesson and make it possible to continuously refine course content based on learning data.

Implementation platform: WordPress-based intelligent learning environment

The intelligent learning management system described in this research is an online learning platform that has been built using WordPress. Traditionally, WordPress has been used only for publishing content; however, its extendable architecture enables it to also be used as a lightweight learning management system when paired with specific educational plugins and other custom integration options. The central feature of this platform's architecture is its modular structure, which separates the mechanisms used for delivering content from those used for tracking and analytics. Instructional content is delivered through traditional WordPress page structures, whereas interactivity is provided via H5P, an interactive component of the platform. H5P allows all types of interactive videos, quizzes, branching scenarios, and micro-activities to be embedded directly into the course lesson pages creating engaging experiences for learners seamlessly throughout the instructional flow.

User interaction data generated by H5P activities are stored and aggregated through WordPress-compatible analytics mechanisms. These data streams provide fine-grained behavioral indicators, such as task completion rates, error frequencies, and interaction sequences, which are later correlated with diagnostic assessment results.

AI-supported learner interaction is implemented via an integrated conversational assistant connected to external large language model services. Learner queries submitted through the platform interface are logged and anonymized before being processed for analytical purposes. Rather than treating the AI assistant solely as a support tool, the platform captures these natural-language interactions as diagnostic signals reflecting learner cognitive states (figure 3, figure 4) [2].

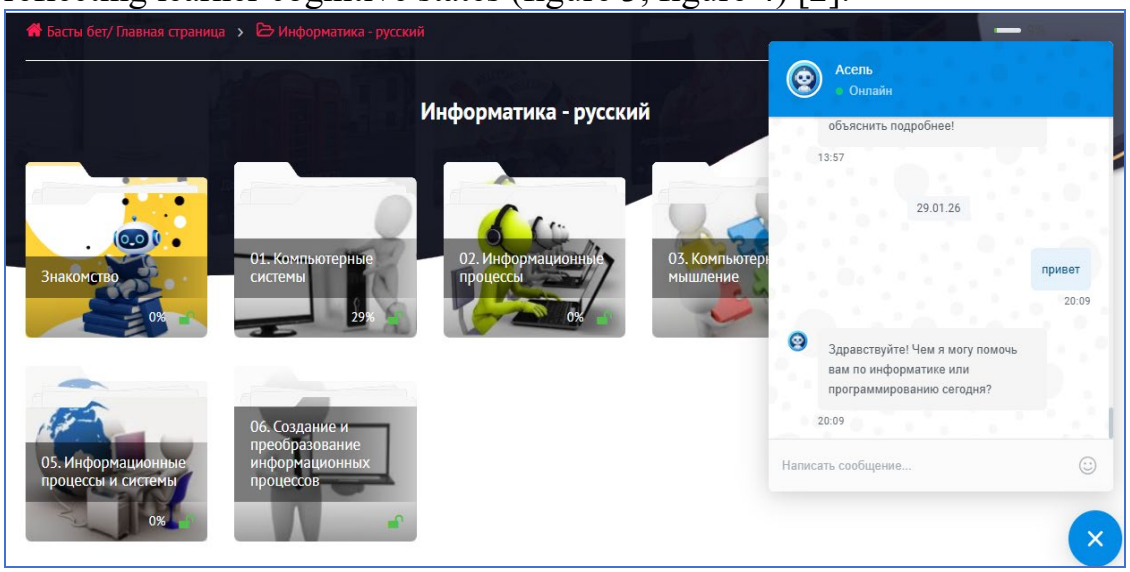

Figure 3. *Course interface with integrated AI assistant and modular lesson structure*

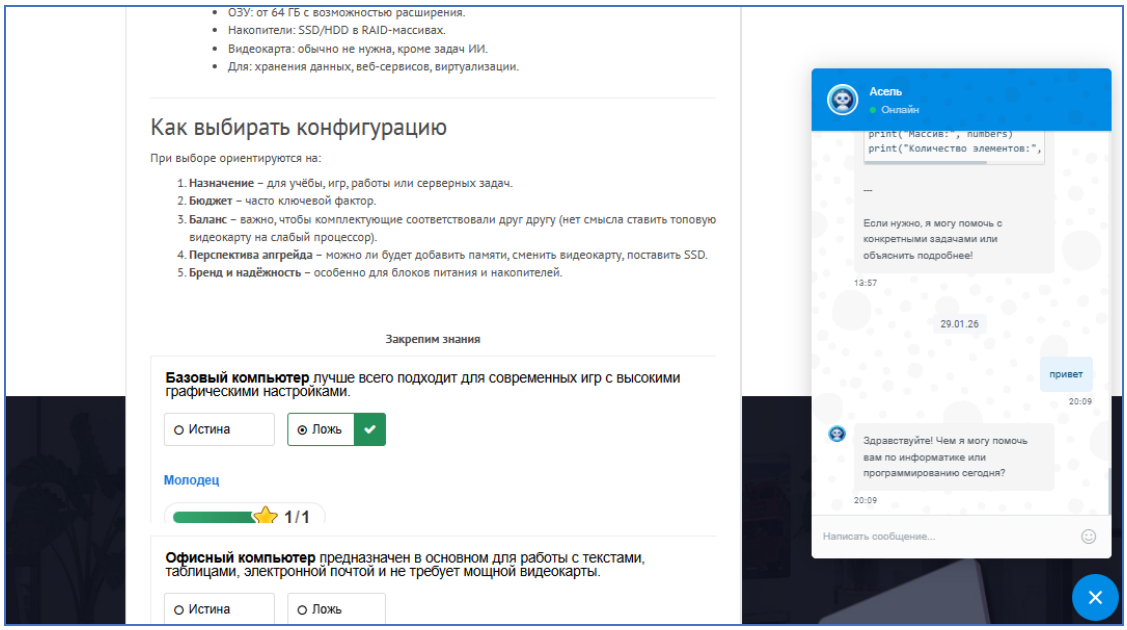

Figure 4. *Course interface with integrated AI assistant and modular lesson structure*

From a management perspective, WordPress functions as the orchestration layer that connects instructional content, interaction data, and AI analytics into a unified system. This approach demonstrates that intelligent learning management principles can be realized within widely available open-source technologies, lowering barriers to adoption and enabling iterative, data-driven improvement of educational content without reliance on monolithic or closed LMS solutions.

Three-level course management model

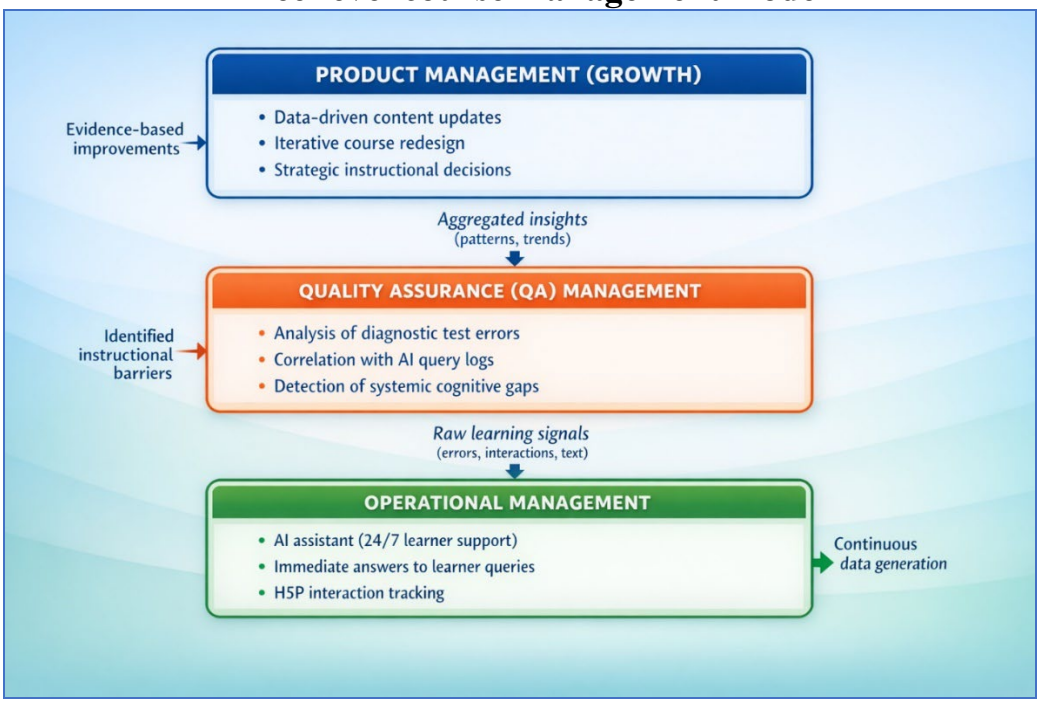

Figure 5*. Three-level data-driven course management model*

To enable continuous quality improvement, the platform uses a three-level course management model (Figure 5) that separates automation, quality diagnostics, and strategic development. This structure aligns with evidence-based educational management principles, treating operational efficiency, pedagogical validity, and product evolution as interconnected but analytically distinct processes [3].

Operational level: automated learning support

At this level, an AI assistant based on large language models provides 24/7 learner support, answering about 80% of queries without human intervention. It clarifies concepts, explains examples, and guides task completion, reducing cognitive friction without replacing the instructor. Research shows such systems effectively prevent uncertainty and

disengagement in asynchronous learning [4]. Automation also ensures scalability and generates data for higher-level quality analysis.

Quality assurance level: identifying cognitive gaps
This level shifts focus from outcomes to the causes of learning difficulties. The platform triangulates incorrect responses in diagnostic quizzes, interactions in H5P activities, and text queries to the AI assistant. This approach reveals mismatches between course design and learner cognition, showing not only where learners struggle but why. Analysis of natural-language queries is particularly valuable, as they reflect authentic student misconceptions [5].

Product development level: data-driven iterative improvement
At the strategic level, QA analytics guide iterative course updates. Changes are data-driven rather than intuition-based: persistent misunderstandings lead to revised explanations, added interactive elements, or adjusted assessments. This aligns with continuous improvement models in learning analytics [5], turning the course into a self-improving system where each cohort contributes to enhanced instructional quality for the next.

AI analytics as a tool for decoding learning barriers

The defining innovation of the platform lies in its ability to access the learner's implicit cognitive processes through the analysis of AI-mediated dialogue. Unlike traditional analytics that focus on clicks and scores, AI query logs capture learners' reasoning attempts, confusion points, and unmet expectations in natural language.

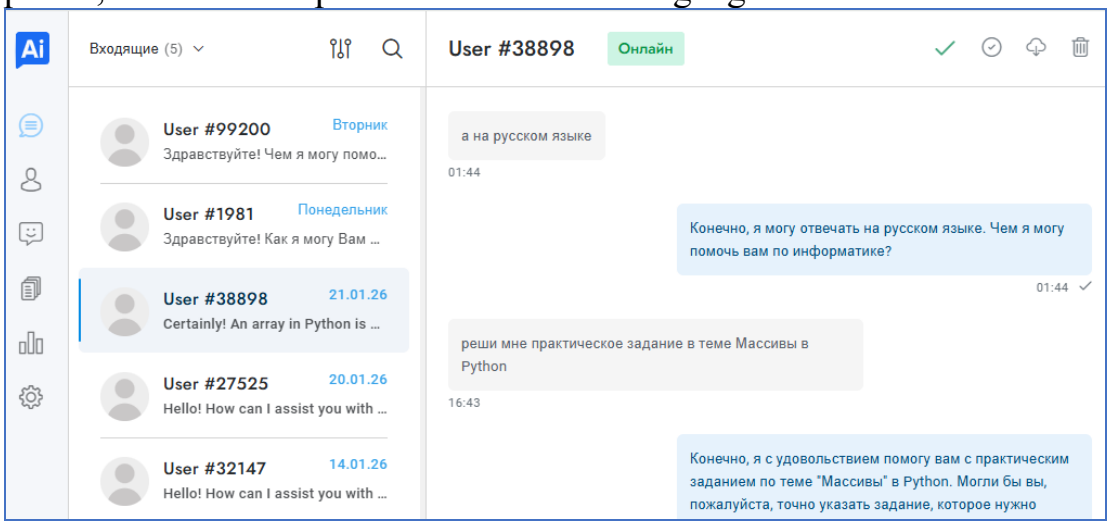

Figure 6. *Example of learner–AI dialogue used as a source of diagnostic data for identifying cognitive barriers in an asynchronous learning environment.*

Learning analytics research emphasizes that such qualitative data are essential for understanding learning as a process rather than an outcome [6]. By systematically classifying and aggregating learner queries, the platform constructs a diagnostic symptom map that links observable linguistic patterns to underlying instructional design flaws.

Diagnostic symptoms table as a management instrument

The diagnostic symptoms table operationalizes AI analytics into actionable management decisions. Each recurring query pattern is interpreted as a signal of a specific cognitive barrier and mapped to a corresponding instructional intervention.

Symptom (AI Query)	Identified Cognitive Barrier	Management Decision
"Explain this simpler, with an example..."	Excessive theoretical complexity	Redesign presentation, simplify visuals
"How do I apply this in practice?"	Lack of practical orientation	Implement H5P Branching Scenarios
"Video says A, but the test asks B"	Content/Validation desynchronization	Correct the 10-question diagnostic test
"I'm confused by the terminology"	Cognitive overload	Add an H5P Interactive Glossary

Table 1. Mapping AI Query Patterns to Cognitive Barriers and Management Actions

This framework transforms unstructured conversational data into a formal quality management tool**,** enabling scalable pedagogical diagnosis without intrusive monitoring.

From individual confusion to systemic insight

While individual AI queries may reflect personal learning difficulties, aggregated patterns reveal systemic instructional weaknesses**.** For example, frequent requests for simplification indicate excessive intrinsic cognitive load [7], while repeated complaints about test inconsistency point to misalignment between instruction and assessment [8].

By focusing on frequency, semantic similarity, and temporal distribution of queries, managers can distinguish isolated learner issues from design-level problems requiring intervention.

Strategic value of AI-driven diagnostics

At scale, AI analytics enables a shift from reactive to proactive instructional design**.** Instead of waiting for poor outcomes to emerge, course teams can identify early warning signals of content failure during the learning process itself. This capability supports the broader goal of evidence-based education, where decisions are grounded in systematically collected data rather than anecdotal feedback.

Continuous Improvement Methodology

The intelligent learning platform implements continuous improvement through a data-driven feedback loop linking learner activity to instructional redesign. Unlike traditional revision cycles, this process operates continuously across cohorts, embedding improvement into daily course operations.

The cycle has four stages:

1. Signal collection: The platform continuously gathers learning signals - formative quiz results, H5P interaction logs, and AI-assistant queries - emerging naturally from learners' engagement. No additional surveys or reporting are needed, ensuring high ecological validity.

2. Anomaly and pattern analysis: Signals are analyzed at the cohort level to identify recurring misunderstandings, such as repeated quiz errors, high dropout in H5P activities, or clusters of semantically similar AI queries. Triangulation distinguishes individual difficulties from design-level issues.

3. Targeted instructional adjustment: Identified issues are addressed with focused interventions, including restructuring explanations, enhancing H5P interactions, aligning assessments with content, or adding auxiliary supports. This preserves instructional stability while resolving specific barriers.

4. *Verification and impact evaluation:* Effectiveness is assessed by comparing post-intervention signals with baseline data, tracking reductions in related AI queries, improved quiz performance, and higher completion rates. Persistent anomalies trigger iterative refinement.

Methodological significance: This iterative cycle transforms the course into a self-correcting system. Continuous improvement becomes an intrinsic feature, maintaining and enhancing instructional quality through systematic analysis of authentic learning data rather than intuition or periodic reviews.

Conclusion

Most online courses show what learners get wrong but rarely explain why, especially in asynchronous settings. This study demonstrates that treating learner interactions as data improves instructional quality. By combining H5P activities, diagnostic quizzes, and an AI assistant in a feedback loop, learning difficulties are revealed in real time, with AI queries highlighting confusion and knowledge gaps. Recurrent questions identify weaknesses in explanations, examples, or assessments, enabling targeted fixes instead of full redesigns. Implemented on WordPress, the platform exemplifies a self-improving system where each learner interaction contributes to ongoing course enhancement.

References

1. Clark, R. C., & Mayer, R. E. (2016). *E-learning and the science of instruction* (4th ed.). Wiley.
2. Educational platform. https://assel-academy.kz/wpm/start/
3. Slavin, R. E. (2002). Evidence-based education policies: Transforming educational practice and research. *Educational Researcher, 31*(7), 15–21.
4. Winkler, R., & Söllner, M. (2018). Unleashing the potential of chatbots in education: A state-of-the-art analysis. *Academy of Management Proceedings, 2018*(1), 15903. https://doi.org/10.5465/AMBPP.2018.15903abstract
5. Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 26*, 582–599. https://doi.org/10.1007/s40593-016-0110-3
6. Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x
7. Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory*. Springer. https://doi.org/10.1007/978-1-4419-8126-4
8. Black, P., & Wiliam, D. (1998). Assessment and classroom learning. *Assessment in Education: Principles, Policy & Practice, 5*(1), 7–74.

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