A bidirectional model for analytics-informed assessment and asynchronous learning design

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Abstract: *This paper presents a bidirectional model that connects asynchronous learning design and assessment using learning analytics and intelligent optimization. In the forward workflow, interaction data from a Moodle-based LMS are analyzed to identify usage patterns of asynchronous activities and to derive an assessment-oriented ATS (Achievement–Transfer–Stability) profile through fuzzy interpretation. In the backward workflow, a genetic algorithm is used to generate and optimize asynchronous learning paths aligned with a desired ATS target. The results show how learning analytics can support both the analysis of existing course designs and the generation of assessment-driven learning activity sequences, contributing to more coherent and stable online learning experiences.*

Keywords: Asynchronous learning, Assessment design, Instructional design, Learning analytics.

1. Introduction

In online and asynchronous learning environments, assessment is increasingly supported by data generated by digital learning platforms, yet the relationship between learning activity design and assessment design often remains implicit. As a result, assessment design frequently remains a separate layer, configured independently from the activity structure that shapes learning behavior.

This separation creates a structural gap: the same instructional design may lead to different learning contexts depending on how learners interact with activities, while assessment instruments often assume stable learning conditions and comparable exposure to learning tasks. Consequently, designing evaluation in asynchronous contexts requires more than selecting tests or rubrics; it requires an explicit model that connects the learning design context (what learners actually do in the LMS) with the dimensions of learning performance that can be validly inferred. However, current LMS implementations rarely provide a conceptual framework capable of explaining this relationship in a bidirectional and adaptive way.

To address this gap, this paper proposes a bidirectional model linking Asynchronous Learning Design (ALD) with a multidimensional assessment

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framework, Achievement–Transfer–Stability (ATS). The model integrates a forward workflow, in which learning analytics indicators extracted from Moodle logs inform the configuration of assessment dimensions, and a backward workflow, in which a desired ATS profile drives the generation and optimization of asynchronous learning paths. In this way, assessment becomes a dynamic design component, informed by real interaction data and aligned with instructional structure.

This paper proposes a conceptual model for an intelligent and dynamic assessment system based on a bidirectional relationship between Asynchronous Learning Design (ALD) and a multidimensional assessment framework (Achievement–Transfer–Stability), integrating learning analytics and intelligent optimization. Structurally, the paper first introduces the ALD–ATS conceptual model, then presents the research methodology and workflows based on LMS log data, and finally illustrates the approach through an exploratory analysis of real asynchronous learning data.

2. Literature research

Educational assessment theory views evaluation as an inferential process about learning outcomes, emphasizing validity and the relationship between learning context, assessment tasks, and interpretation of results (Messick, 1995; Kane, 2013). From this perspective, separating instructional design from assessment design weakens evaluation claims, a concern addressed in instructional design research through constructive alignment and backward design, which stress the alignment of assessment with learning activities and intended outcomes (Biggs, 1996; Wiggins & McTighe, 2005), particularly in asynchronous online learning contexts with diverse learner behaviors. Beyond achievement, learning quality is also reflected in knowledge transfer and stability over time (Perkins, 1992; Bransford et al., 2000), motivating multidimensional assessment perspectives. In parallel, learning analytics and educational data mining demonstrate that LMS activity logs can inform assessment and instructional design by capturing learner engagement and self-regulation (Siemens & Baker, 2012; Viberg et al., 2018), while research on intelligent educational systems shows that machine learning, fuzzy logic, and evolutionary algorithms can support instructional decision-making when embedded in pedagogically grounded models (Dede, 2014; Holmes et al., 2019). Together, these perspectives support combining analytics-informed assessment with backward design of asynchronous learning paths to better synchronize instructional design and evaluation.

3. Model description

3.1 General description

The proposed model presents a dynamic assessment framework that aligns asynchronous learning design with evaluation through a bidirectional process. It integrates Asynchronous Learning Design (ALD) and a multidimensional assessment profile based on Achievement, Transfer, and Stability (ATS), mediated by an intelligence layer combining machine learning, fuzzy logic, and genetic algorithms. The model supports context-aware and goal-driven assessment design in online learning environments without relying on direct assessment data.

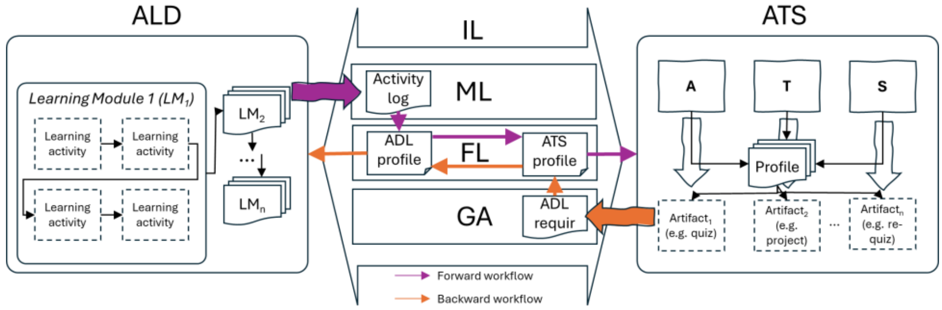

Figure 1. The conceptual representation of the model

In simple terms, the model uses data about how learners interact with online activities to determine what kind of assessment makes sense in a given context, and then uses the desired assessment goals to guide the design of asynchronous learning activities.

3.2 Model structure

3.2.1 General structure

The model consists of three main components: Asynchronous Learning Design (ALD) includes the activity set, Achievement–Transfer–Stability (ATS) profile, and an intelligence layer.

3.2.2 Asynchronous Learning Design Component (ALD)

Asynchronous Learning Design (ALD) represents the instructional scheme of an online learning environment and defines how learning activities are selected, structured, and sequenced over time. It captures the intended learning path independently of learner behavior or assessment outcomes, focusing exclusively on the pedagogical organization of asynchronous activities and the cognitive processes they are designed to support. The elements of the ALD component are:

- the activity set, which comprises the complete set of asynchronous learning activities available in a course;

- the individual learning activity, which is the basic design unit of ALD and has the next characteristics: (1) type: (e.g., resources, quizzes, assignments, forums, reflections), (2) cognitive role (consolidation, application, reflection), (3) temporal position within the course, (4) mode of participation (individual or collaborative), (5) degree of openness (closed, semi-open, open), (6) estimated workload.

The organisational structures of the ALD component are: (1) the hierarchical organisation (micro – individual activity, meso – module, and macro – learning path levels); (2) the sequential learning path, which is the explicit ordering and flow of activities, usually in a linear sequencing.

The main proprieties of this component are: the balance between consolidation, application, and reflection, the supported cognitive depth, the temporal distribution of learning activities, the overall workload structure.

Within the proposed framework, ALD defines the pedagogical space in which learning occurs and constrains the types of learning outcomes that can be evaluated validly. By explicitly modeling the structure and flow of asynchronous activities, ALD provides a stable foundation for analytics-informed assessment design and for the backward generation of learning paths driven by assessment objectives.

3.2.3 Assessment Design (ATS)

Assessment Design based on Achievement–Transfer–Stability (ATS) represents the evaluative intent of a learning environment by modeling learning performance along three core dimensions. ATS does not describe assessment instruments or scores but defines which dimensions of learning are targeted for evaluation and to what extent, in a form that can be operationalized and aligned with asynchronous learning design. The elements of the ATS component are:

- the assessment dimensions: (1) Achievement (A) – evaluation of immediate knowledge acquisition and understanding; (2) Transfer (T) – evaluation of the ability to apply knowledge in new or different contexts; (3) Stability (S) – evaluation of the persistence of learning outcomes over time.
- the profile (assessment configuration), which specifies how the assessment dimensions are combined and prioritized: (1) active assessment dimensions (A, T, S); (2) relative weights or emphasis assigned to each dimension; (3) overall assessment orientation (e.g., achievement-focused, transfer-oriented, balanced).
- the assessment artifacts, which are concrete realizations of the ATS profile within a learning environment, described by: (1) artifact types (e.g., quiz, project, case study, reflection task); (2) targeted ATS dimension(s).

In this work, ATS is intentionally limited to a compact, operational profile describing the relative emphasis on Achievement, Transfer, and Stability, which is used directly for reasoning and optimization.

3.2.4 Intelligence Layer (IL)

The Intelligence Layer provides the computational mechanisms that connect Asynchronous Learning Design (ALD) and the Assessment profile (ATS). It does not introduce new pedagogical constructs but operationalizes the bidirectional relationship between learning design and assessment through data interpretation, pedagogical reasoning, and optimization. The IL elements are:

- Context Extraction (usage of Machine Learning): its role is to interpret LMS activity data and derive a contextual description of how the asynchronous learning design is used in practice. It has the next structure: (I) Input: (1) LMS activity logs and (2) derived indicators, described in Variables section. (II) Process: includes: (1) pattern detection and clustering and (2) context classification. (III) Output: ALD context profile.
- Pedagogical Reasoning (usage of Fuzzy Logic): its role is to generate and optimize asynchronous learning paths that align with a desired ATS profile under given constraints. It has the next structure: (I) Input: (1) ALD context profile and (2) ATS target profile (forward) / ATS current profile (backward). (II) Process: includes: (1) linguistic variables, (2) membership functions and (3) fuzzy rules. (III) Output: ATS profile (forward) / ALD requirements (backward).
- Design Optimisation (usage of Genetic Algorithms): its role is to generate and optimize asynchronous learning paths that align with a desired ATS profile under given constraints. It has the next structure: (I) Input: (1) ATS target profile, (2) ALD activity set and (3) design constraints. (II) Process: includes: (1) population of candidate ALD paths, (2) fitness evaluation based on ALD–ATS alignment and (3) selection, crossover, mutation. (III) Output: optimized ALD paths.

Within the ALD–ATS framework, the Intelligence Layer acts as a mediator that translates data into context, context into pedagogical decisions, and assessment goals into instructional structures.

3.3 Variables

The proposed model operates on a compact set of pedagogical, contextual, and optimization variables that enable the alignment between asynchronous learning design and assessment. Variables are defined at three levels—ALD, ATS, and the Intelligence Layer—and are intentionally limited to those used directly for context interpretation, pedagogical reasoning, and design optimization.

Table 1. The variables used within the model

Component	Variable	Description
ALD	a_type	Type of asynchronous activity
	a_role	Cognitive role of the activity (consolidation, application, reflection)

	a_time	Temporal position of the activity
	a_mode	Participation mode (individual / collaborative)
	N_app	Number of application-oriented activities
	N_revisit	Number of planned revisits
	TD	Temporal distribution of activities
ATS	A	Achievement dimension
	T	Transfer dimension
	S	Stability dimension
	A_w, T_w, S_w	Relative weights of ATS dimensions
ML	freq	Activity frequency
	regularity	Regularity of activity over time
	revisit_rate	Rate of repeated access
	temporal_spread	Distribution of activity in time
Fuzzy	ALD_applicative	Applicative level of ALD (low–high)
	ALD_temporal	Temporal quality of ALD
	A_support, T_support, S_support	Degree of support for ATS dimensions
GA	K	Fixed number of activities in a learning path
	fitness	Alignment between ALD and ATS
	constraints	Design constraints (time, workload)

These variables provide a minimal but sufficient representation of instructional structure, assessment intent, and intelligent mediation.

3.4 Methods and tools

The proposed methodology combines learning analytics, fuzzy reasoning, and evolutionary optimization to support a bidirectional alignment between asynchronous learning design (ALD) and assessment intent (ATS).

Table 2. Methods and tools used within the model

Layer	Method	Key elements (what is used)	Input/Output	Tools
Data	Log analysis	Activity access events, course structure	Input: Moodle logs Output: aggregated indicators	Moodle DB, SQL
ML	Unsupervised learning	Variables: frequency, regularity, revisit rate, temporal	Input: normalized indicators	Orange Data Mining, Python

		spread, activity focus	Output: ALD context variables	(scikit-learn)
Fuzzy Logic	Rule-based inference	Linguistic variables (low/medium/high), membership functions, IF-THEN rules (ALD ⇄ ATS)	Input: ALD variables or ATS targets Output: ATS profile or ALD requirements	Python fuzzy libraries
GA	Evolutionary optimization	Gene: (activity type, cognitive role, participation mode) Chromosome: ordered fixed-length sequence of genes (learning path) Operators: selection, crossover, mutation Fitness		
Integration	Bidirectional workflow	Forward: ML → Fuzzy → ATS	Backward: ATS → Fuzzy → GA → ALD	Synchronized design-assessment

These methods are integrated into a coherent framework where learning analytics inform assessment configuration, and assessment objectives drive the generation of asynchronous learning designs.

3.5 Model workflow

3.5.1 Forward workflow (FW)

The forward workflow (FW) describes the process through which information derived from the use of asynchronous learning activities is employed to configure a context-aware assessment profile. This workflow operates from learning design usage (ALD) toward assessment intent (ATS) and is driven by LMS activity data rather than assessment results. The steps of the FW are:

1. ALD usage data collection. Interaction data are extracted from LMS activity logs, capturing how learners' access and revisit asynchronous learning activities over time;
2. Feature extraction and aggregation. Raw log data are transformed into aggregated indicators describing activity frequency, regularity, temporal distribution, revisits, and activity focus at the course level;
3. Context identification (Machine Learning). Machine learning techniques are applied to the derived indicators to identify patterns of ALD usage and to generate an ALD context profile (a pattern combination of ML variables);
4. Pedagogical interpretation (Fuzzy Logic). The ALD context profile is

mapped to linguistic variables and processed through fuzzy rules that model expert pedagogical judgment. This step determines the degree to which the instructional design supports each assessment dimension;

5. ATS configuration. The output of the fuzzy inference process is a contextualized ATS profile, specifying the active dimensions (Achievement, Transfer, Stability) and their relative emphasis, consistent with the observed learning context.

The forward workflow results in an assessment configuration that is grounded in the actual use of asynchronous learning activities, ensuring that evaluation focuses only on learning dimensions that are pedagogically supported by the instructional design.

3.5.2 Backward workflow (BW)

The backward workflow describes the process through which desired assessment objectives are used to generate and optimize an asynchronous learning design. This workflow operates from assessment intent (ATS) toward learning design (ALD). The BW steps are:

1. Definition of target ATS. Specify the desired emphasis on Achievement, Transfer, and Stability.
2. Infer of the design requirements (fuzzy logic). Translate ATS goals into qualitative ALD requirements (e.g., applicative level, temporal distribution, revisits).
3. Set design constraints. Define limits on number of activities, duration, and workload.
4. Generate and optimize ALD (GA). Produce and optimize candidate learning paths under the given constraints.
5. Select optimized ALD. Output one or more asynchronous learning paths aligned with the target ATS.

The backward workflow enables assessment-driven instructional design by ensuring that learning activities are intentionally structured to support the targeted dimensions of learning performance.

3.6 Mathematical formalisation

Let $A=\{a_1,a_2,\ldots,a_n\}$ denote the set of asynchronous learning activities, and let an asynchronous learning design be defined as an ordered sequence $ALD=(a_{i1},\ldots,a_{ik})$ of fixed length k, while LMS logs are mapped to normalized variables $x\in[0,1]m$ and transformed via a fuzzy inference function $f:x\rightarrow p=(A,T,S)$ that captures Achievement, Transfer, and Stability. The backward process is formulated as a genetic optimization problem in which candidate learning designs encoded as chromosomes are evolved under pedagogical constraints toward a target profile $p*=(A*,T*,S*)$, using a fitness function that estimates ATS alignment solely from the structural composition and ordering of activities.

3.7 Example

Consider a Moodle-based asynchronous course for adult learners, from which activity logs are extracted and aggregated at course level. Log analysis yields the following normalized machine learning variables: activity frequency freq = 0.72, regularity = 0.65, revisit rate = 0.30, temporal spread = 0.75, and activity_focus = 0.60, indicating predominantly applicative and temporally distributed activity usage. These values are mapped to linguistic variables using fuzzy membership functions (e.g., applicative level = high, temporal distribution = high, revisit level = low–medium), resulting in an inferred assessment profile ATS = (A = 0.35, T = 0.65, S = 0.70), which reflects strong support for transfer, moderate learning stability, and lower emphasis on achievement through consolidation.

Given a target assessment profile ATS* = (A* = 0.30, T* = 0.60, S* = 0.70), the backward workflow generates aligned asynchronous learning designs using a genetic algorithm. Candidate learning paths are encoded as fixed-length chromosomes, where each gene represents an activity defined by type, cognitive role, duration, and participation mode. For example, ALD = [(assignment, application), (forum, reflection), (quiz, consolidation), (assignment, application)] yields estimated values $\hat{A} = 0.25$, $\hat{T} = 0.50$, $\hat{S} = 0.67$, and a fitness value $F(ALD) = |0.25 - 0.30| + |0.50 - 0.60| + |0.67 - 0.70| = 0.18$. Iterative selection, crossover, and mutation reduce this distance, producing learning paths structurally aligned with the intended assessment objectives.

4. Experimental results

4.1 Forward analysis

The analyzed course includes 27 asynchronous activities distributed across five sections (0–4). The learning design integrates activities targeting consolidation, application, and reflection, with a clear emphasis on application-oriented tasks complemented by reflective and consolidative components.

Table 3. Cognitive role distribution of asynchronous activities

Cognitive role	Modules	Count
Consolidation	lesson, url, data	9
Application	assign, hvp, h5pactivity	9
Reflection	forum, feedback, survey	9

Learner interaction logs were aggregated at user level to derive four behavioral indicators describing asynchronous engagement: interaction frequency, revisit behavior, temporal distribution, and pedagogical focus. These indicators capture complementary aspects of intensity, persistence, temporal spread, and orientation toward application-oriented activities.

Table 4. Descriptive statistics of interaction features

Feature	Mean	Median	Min	Max	Interpretation
freq	9.90	9.19	1.00	96.50	Moderate interaction intensity
revisit_rate	0.82	0.83	0.00	1.00	High recurrence of activity access
temporal_range	4,473,944	3,112,372	0	61,069,147	Variable temporal distribution
activity_focus	0.53	0.53	0.00	1.00	Balanced orientation toward application

The extracted interaction features indicate predominantly recurrent but moderate-intensity engagement with asynchronous activities, supported by a structurally balanced learning design. These usage patterns provide the contextual input for the subsequent assessment-oriented backward analysis.

The cluster-level statistics were interpreted using fuzzy reasoning to derive a course-level Achievement–Transfer–Stability (ATS) profile. Each interaction indicator was mapped to a linguistic scale (low–medium–high), allowing gradual transitions rather than crisp thresholds.

Table 5. Fuzzy interpretation of cluster profiles

Cluster	freq	revisit_rate	temporal_range	activity_focus	Fuzzy A	Fuzzy T	Fuzzy S
C1	0.065	0.71	0.05	0.53	Low	Medium	Low–Medium
C2	0.111	0.89	0.06	0.53	Low–Medium	Medium	Medium
C3	0.116	0.88	0.60	0.53	Medium	Medium	High
C4	0.738	0.98	0.52	0.96	High	High	High

Considering the dominance of clusters C1 and C2, complemented by a smaller but pedagogically significant C3 cluster, the fuzzy aggregation yields the following course-level ATS profile: (A: medium–low, T: medium, S: medium–high).

The course supports stable and recurrent engagement with asynchronous activities, while overall achievement readiness remains moderate due to low interaction intensity for most learners. Transfer potential is balanced, reflecting the consistent presence of application-oriented activities, whereas stability benefits from strong revisit behavior and a subset of temporally distributed learners.

4.2 Backward analysis

The backward analysis was conducted aiming to optimize the asynchronous learning design toward a desired ATS target profile defined as A = 0.30, T = 0.55, S = 0.75. The target ATS profile corresponds to low-to-medium achievement, medium-to-high transfer, and high stability, reflecting a formative, application-oriented, and engagement-sustaining assessment intent. The learning path length was fixed to K = 6 activities, reflecting a realistic instructional unit. The genetic algorithm operated on a synthetic activity pool of 48 candidate activities, under minimal pedagogical constraints requiring at least two application-oriented activities and one reflective activity per learning path.

Table 6. Backward optimization results (ATS profile)

Metric	Target	Initial (population mean)	Optimized
Achievement (A)	0.30	0.34	0.36
Transfer (T)	0.55	0.42	0.51
Stability (S)	0.75	0.29	0.58
Fitness	–	0.62	0.03

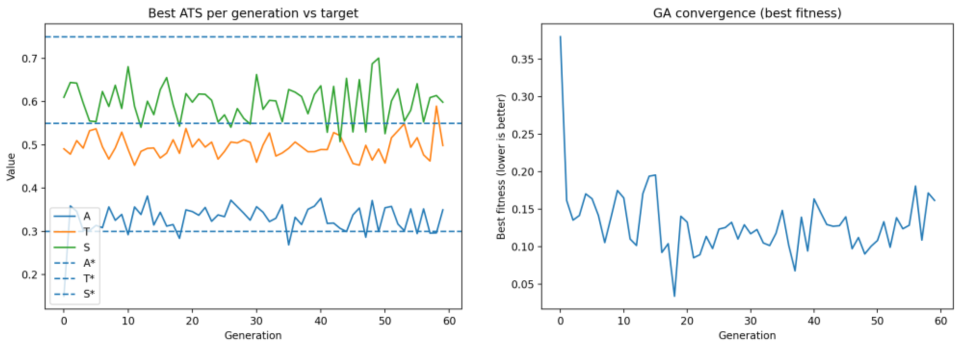

Figure 2. Evolution of best fitness values across generations (convergence) during backward optimization

The backward optimization significantly reduced the distance between the initial learning design population and the target ATS profile, as reflected by the decrease in fitness from 0.62 to 0.03. The most substantial improvement was observed in Stability (S), indicating that the optimized learning path promotes more sustained and distributed engagement over time. Transfer orientation also increased notably, while Achievement remained close to the target range. These results demonstrate that the proposed backward workflow can effectively generate asynchronous learning designs aligned with desired assessment outcomes.

Table 7. Optimized asynchronous learning path (chromosome)

Step	Activity type	Cognitive role	Duration	Mode
1	Assignment	Application	Medium	Individual
2	Assignment	Application	Low	Collaborative
3	Assignment	Application	Medium	Individual
4	Forum	Reflection	Medium	Collaborative
5	Resource	Consolidation	High	Individual
6	URL	Consolidation	Medium	Collaborative

The optimized learning path emphasizes application-oriented activities in the initial stages, supporting early transfer and task engagement. Reflective interaction is introduced mid-sequence through a collaborative forum, contributing to learner stability and cognitive integration. The sequence concludes with consolidation activities, allowing learners to stabilize acquired knowledge and reinforce learning outcomes. The alternation between individual and collaborative modes further supports sustained engagement.

For backward validation, the optimization target was defined using the structural assessment profile inferred from the instructor-designed baseline learning path of each Moodle course. Two courses were analyzed: Course 1 with K = 27 unique activities (the course presented at the Forward analysis section) and Course 2 with K = 38 unique activities. For each course, the inferred target profile was ATSforward=(A∗,T∗,S∗), computed from the baseline ALD using the same estimator employed in the fitness function. The genetic algorithm was executed with a population of 150 individuals, 200 generations, crossover probability pc=0.85, mutation probability pm=0.25, and minimal constraints ensuring a minimum number of application and reflection activities. Additionally, a randomized baseline set of N = 500 learning paths was generated under identical constraints, allowing comparison between the instructor baseline, GA-optimized output, and random designs.

Table 8. Backward validation results (GA vs baseline and random designs)

Course	K	Design	Fitness	A	T	S
1	27	Human baseline	0.1001	0.2537	0.3653	0.4428
1	27	GA optimized	0.2354	0.2985	0.4660	0.6143
1	27	Random mean (N=500)	0.4856	0.4982	0.3268	0.3824
1	27	Random best (N=500)	0.1036	0.2937	0.4037	0.4409
2	38	Human baseline	0.0958	0.2884	0.5228	0.3211
2	38	GA optimized	0.0883	0.2475	0.5141	0.1894
2	38	Random mean (N=500)	0.5757	0.4985	0.3235	0.3842
2	38	Random best (N=500)	0.0810	0.2457	0.5021	0.2105

Across both courses, GA-generated learning paths strongly outperform randomized designs in average terms, confirming that the backward workflow produces non-arbitrary learning designs and effectively optimizes toward a target ATS profile. For Course 2, the GA solution achieves better alignment than the instructor baseline, indicating that evolutionary optimization can generate learning paths that are structurally more consistent with intended assessment characteristics. For Course 1, the instructor baseline remains the best aligned, suggesting that some course structures are already near-optimal with respect to their inferred ATS profile and that stochastic variability in ATS estimation may influence marginal optimization outcomes. Overall, these results support the feasibility of the backward workflow as a design-generation mechanism, while motivating further calibration and deterministic assessment validation in future work.

5. Conclusion

This paper introduced a bidirectional model that connects asynchronous learning design with assessment through learning analytics and intelligent optimization. The forward analysis showed how interaction data from an LMS can be used to derive meaningful assessment-related profiles, while the backward workflow demonstrated how desired assessment objectives can guide the generation of coherent asynchronous learning paths. Together, the results highlight the value of aligning learning activities and assessment intentions in a dynamic and data-informed manner, offering a practical framework for supporting more stable and application-oriented online learning.

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REFERENCES

Bransford, J. D., Brown, A. L. & Cocking, R. R. (2000) *How People Learn: Brain, Mind, Experience, and School*. Washington DC, National Academy Press.

Dede, C. (2014) The Role of Digital Technologies in Deeper Learning. Students at the Center: Deeper Learning Research Series. Boston, MA, *Jobs for the Future*.

Holmes, W., Bialik, M. & Fadel, C. (2019) *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Boston, Center for Curriculum Redesign.

Kane, M. T. (2013) Validating the interpretations and uses of test scores. *Journal of Educational Measurement*. 50(1), 1–73. doi: https://doi.org/10.1111/jedm.12000.

Messick, S. (1995) Validity of psychological assessment: Validation of inferences from persons’ responses and performances as scientific inquiry into score meaning. *American Psychologist*. 50(9), 741–749. doi: https://doi.org/10.1037/0003-066X.50.9.741.

Perkins, D. N. & Salomon, G. (1992) Transfer of learning. In: Husén, T. & Postlethwaite, T. N. (eds.) *The International Encyclopedia of Education*. 2nd ed. Oxford, Pergamon. pp. 425–441.

Siemens, G. & Baker, R. S. J. D. (2012) Learning analytics and educational data mining: Towards communication and collaboration. In: *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12), April 29–May 2, 2012, Vancouver, Canada*. New York, Association for Computing Machinery. pp. 252–254. doi: https://doi.org/10.1145/2330601.2330661.

Viberg, O., Hatakka, M., Balter, O. & Mavroudi, A. (2018) The current landscape of learning analytics in higher education. *Computers in Human Behavior*. 89, 98–110. doi: https://doi.org/10.1016/j.chb.2018.07.027.

Wiggins, G. & McTighe, J. (2005) *Understanding by Design*. 2nd ed. Alexandria, VA, Association for Supervision and Curriculum Development.

Zimmerman, B. J. (2002) Becoming a self-regulated learner: An overview. *Theory Into Practice*. 41(2), 64–70. doi: https://doi.org/10.1207/s15430421tip4102_2.