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Editors

**Dr. Divya Sharma, Prof.(Dr.) Gurpreet Kaur, Dr. Geeta
Rawat, Dr Dhanashri Rajashri Ravindra Jadhav**

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List of Contributors

Chapter	Contributor	Designation	Institution	Location
1	Dr. Kavita Silwal	Assistant Professor	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
2	Dr. Simrann Rajesh Vermaa	Assistant Professor, Department of English	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
3	Dr. Soju Samuel	Counsellor	Delhi Public School	Bhilai, Chhattisgarh
4	Dr. Ratri Lahri	Assistant Professor	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
5	Dr. Usha Lahare	Guest Lecturer	Government Minimata Girls' College	Korba, Chhattisgarh
6	Dr. Sumita Singh	Assistant Professor, Department of Education	St. Thomas College	Bhilai, Chhattisgarh
7	Mamta Rani Yadu	Research Scholar	Anjaneya University	Raipur, Chhattisgarh
8	Suravi Bhattacharya	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
9	Dr. Pushpa Sharma	Associate Professor	Mansa College of Education	Kohka, Kurud, Chhattisgarh
10	Dr. Sangeeta Shrivastav	Assistant Professor	Mansa College of Education	Bhilai, Chhattisgarh
11	Prof. (Dr.) Gurpreet Kaur	Principal	Sanskar City College of Education	Thakurtola, Rajnandgaon, Chhattisgarh
12	Dular Das	Research Scholar	Hemchand Yadav University	Durg, Chhattisgarh
13	Namita Roy	Research Scholar, Department of Education	Anjaneya University	Raipur, Chhattisgarh
14	Madhubala Shrivastava	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
15	Dr. Ruchi Sachan	Head, Department of Education	Maharaja Agrasen International College	Raipur, Chhattisgarh
16	Dr. Juhi Peter	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
17	Mrs. Preeti Mishra	Assistant Professor, Department of Education	Mansa College of Education	Bhilai, Chhattisgarh

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Chapter	Contributor	Designation	Institution	Location
18	Renuka Sahu	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
19	Dr. Surekha Vinod Patil	Principal	Bhilai Maitri College	Durg, Chhattisgarh
20	Dr. Shweta Bhatia	Professor & Head, Department of Education; IQAC Coordinator	M.J. College, Kohka	Bhilai, Chhattisgarh
21	Dr. Archana Pandey	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
22	Dr. Rita Gupta	Head, Department of Education	GDR CST, Rungta International Skill University	Bhilai, Chhattisgarh
23	Dr. Anjana Sharad	Principal	Prism School of Education, Mahkakurd, Utai	Bhilai, Chhattisgarh
24	Dr. Divya Sharma	Head & Assistant Professor, Department of Education	<i>[Institution missing — see note]</i>	—
25	Dr. Shalini Verma	Assistant Professor	Bhilai Maitri College	Bhilai, Chhattisgarh
26	Tulsi Sahu	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
27	Mona Gupta	Guest Lecturer, Department of Commerce	Government Shaheed Kaushal Yadav College	Gunderdehi, Balod, Chhattisgarh
28	Kiran Sonatiya	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
29	Ranjana Solanki	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
30	Dr. Gopa Sharma	Headmistress	Government Primary School, Hatband	Raipur, Chhattisgarh
31	Dr. Manju Sahu	Associate Professor	M.J. College, Kohka	Bhilai, Chhattisgarh
32	Dr. Nirmala Parganiha	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
33	Dr. Sandhya Pujari	Head (ITEP)	Sandipani Academy, Achhoti	Durg, Chhattisgarh
34	Dr. Atul Kumar Soni	Assistant Professor	Pt. Kishori Lal Shukla Vidhi Mahavidyalaya	Rajnandgaon, Chhattisgarh

International Conference On Multidisciplinary Research

Chapter	Contributor	Designation	Institution	Location
35	Smt. Anupama Ambast	Assistant Professor	College of Teacher Education (CTE)	Raipur, Chhattisgarh
36	Dr. Shraddha Bhardwaj	Assistant Professor	Jagadguru Shankaracharya College of Education	Bhilai, Durg, Chhattisgarh
37	Smt. Anupama Ambast	Assistant Professor	College of Teacher Education (CTE)	Raipur, Chhattisgarh
38	Dr. Sandhya Pujari	Head (ITEP)	Sandipani Academy, Achhoti	Durg, Chhattisgarh
39	Meenakshi Yadav	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
40	Smt. Pramila Patel	Assistant Professor	Bhilai College of Information Technology, Jamul	Durg, Chhattisgarh

Chapter 14: Interactive Multimedia Learning and Conceptual Understanding among Secondary Students

Madhubala Shrivastava

Assistant Professor

Sanskar City College of Education

Rajnandgaon, Chhattisgarh

Abstract— Interactive multimedia environments are increasingly embedded in secondary education, yet their contribution to deep conceptual understanding remains less certain than their effect on immediate engagement or factual recall. This study proposes an artificial-intelligence-supported framework for examining how adaptive multimedia interactions influence conceptual understanding among secondary students. The research addresses a gap in existing work by distinguishing productive multimedia interaction from passive digital exposure through learner-level behavioral indicators such as response latency, navigation patterns, replay behavior, hint utilization, and simulation manipulation. A multimodal learning dataset is conceptualized from curriculum-aligned science modules integrating animation, explanatory audio, interactive simulations, visual representations, formative questions, and adaptive feedback. Machine-learning analysis is proposed to model conceptual understanding using interaction sequences rather than relying exclusively on conventional post-test scores. The framework additionally investigates whether cognitive load and prior knowledge modify the relationship between multimedia engagement and conceptual development.

Keywords— Interactive multimedia learning, conceptual understanding, secondary education, adaptive learning, machine learning, multimodal learning analytics

Introduction

Digital technologies have shifted the secondary-school learning environment from predominantly static instructional materials toward combinations of animation, video, interactive diagrams, simulations, quizzes, audio explanation, virtual experimentation, and increasingly intelligent feedback. This transformation is pedagogically significant because many secondary-level concepts cannot be adequately understood through memorization alone. Scientific mechanisms, mathematical relationships, biological systems, environmental processes, and health-related phenomena frequently require students to construct relationships among multiple variables and translate between symbolic, verbal, spatial, and causal representations.

The educational importance of digital technology, however, should not be inferred simply from its availability. Contemporary international discussion increasingly distinguishes between technology access and pedagogically meaningful technology use. UNESCO's 2023 Global Education Monitoring Report cautions that educational technologies can produce different outcomes depending on context, implementation, learner characteristics, and pedagogical

purpose; technology itself should therefore not be treated as an automatic mechanism for educational improvement. Similarly, a recent systematic review of ICT integration in secondary education emphasizes that effective technology integration is conditioned by pedagogical, infrastructural, institutional, and teacher-related factors rather than mere deployment of digital devices.

Interactive multimedia learning represents a particularly relevant form of technology-supported instruction. Unlike conventional multimedia, where students may only watch a video or read digitally presented information, an interactive multimedia environment requires the learner to act upon instructional representations. Students may rotate a molecular structure, modify variables within a simulation, reveal explanatory layers, replay a difficult animation, select a representation, answer embedded questions, request hints, or receive immediate feedback. Consequently, the learner becomes an active participant in the instructional sequence.

The theoretical rationale for such environments is closely connected with multimedia learning principles. Human cognitive processing does not operate as unlimited information storage. Learning requires learners to select relevant information, organize it into meaningful representations, and establish relationships between new information and existing knowledge. Multimedia therefore becomes educationally valuable not because it increases the number of visual or auditory elements presented to students, but because appropriately coordinated representations may facilitate construction of a coherent mental model.

This distinction is especially important when conceptual understanding is considered as the principal outcome. A learner can reproduce a definition while remaining unable to apply the underlying concept to an unfamiliar problem. Conceptual understanding requires more than recognition or recall. It involves explaining relationships, interpreting mechanisms, predicting consequences, transferring knowledge across situations, identifying misconceptions, and integrating multiple representations of the same phenomenon.

For example, memorizing that increasing temperature affects particle motion demonstrates factual knowledge. Predicting how a temperature change modifies particle movement, interpreting that process from a molecular animation, and applying the same principle to an unfamiliar physical situation provide stronger evidence of conceptual understanding. Interactive multimedia potentially supports this transition because abstract processes can be represented dynamically while learners actively test relationships among variables.

Nevertheless, interactivity can also become counterproductive. Excessive animation, unnecessary sound, complex navigation,

decorative visual elements, simultaneous information streams, and frequent interface decisions may consume cognitive resources that should otherwise be allocated to learning. Students may consequently appear highly engaged with a platform while developing only superficial understanding. Behavioral activity and cognitive engagement therefore cannot be treated as synonymous.

This problem has become more consequential with the rapid expansion of AI-supported educational systems. UNESCO's guidance on generative AI emphasizes that AI applications in education should undergo both pedagogical and ethical validation and should preserve human agency, privacy, inclusion, and age-appropriate use. UNESCO has subsequently expanded its work toward AI competency frameworks for school students and teachers, reflecting a broader transition from simple digital access toward informed and responsible interaction with intelligent educational technologies.



Fig. 1: Interactivity in multimedia learning

Source:

<https://www.sciencedirect.com/science/article/pii/S0747563210000439>

These developments create an opportunity to reconceptualize multimedia learning through learning analytics. Conventional multimedia studies frequently compare an intervention group receiving multimedia instruction against a control group receiving traditional instruction and subsequently examine differences in mean achievement. Although useful, such designs provide limited information about *how* students interacted with multimedia resources. Two students spending fifteen minutes in the same lesson may demonstrate substantially different learning behaviors. One may strategically replay difficult explanations, manipulate simulation parameters, compare representations, correct erroneous responses, and subsequently solve a transfer problem. Another may rapidly click through the material while spending a similar amount of total time.

The resulting research problem is therefore not simply whether multimedia improves achievement. A more consequential question is: **which patterns of interactive multimedia behavior indicate genuine conceptual development, for which students, and under what instructional conditions?**

Research Gap

A significant gap exists at the intersection of multimedia learning, secondary education, and interpretable learning analytics. Existing research has established extensive theoretical foundations for multimedia instruction and has separately developed methods for analyzing educational trace data. However, these strands remain insufficiently integrated when the target construct is *conceptual understanding* rather than general achievement, completion, engagement, or prediction of academic performance.

Three methodological limitations are particularly important.

First, multimedia effectiveness is frequently represented by aggregate variables such as total usage time, frequency of platform access, or post-test achievement. Such measures conceal the temporal structure of student interaction. A learner's sequence of *view* → *manipulate* → *error* → *revisit* → *compare* → *correct* may contain substantially more evidence of conceptual restructuring than total time-on-task.

Second, interactive multimedia research often treats learners as relatively homogeneous. Prior knowledge, cognitive load, digital familiarity, and self-regulation can alter how students benefit from interactive content. The same animation or simulation may provide productive scaffolding for one learner while creating unnecessary processing demands for another.

Third, many predictive educational-AI models emphasize classification accuracy without providing sufficiently interpretable explanations of why particular learners are classified as demonstrating strong or weak understanding. In school environments, interpretability is critical because predictions may influence instructional intervention. A useful model should therefore identify actionable behavioral evidence rather than generate opaque risk labels.

The present study addresses this gap by proposing a **Conceptual Interaction Sequence Analytics (CISA) framework**, in which multimedia-learning events are modeled as temporally ordered behavioral sequences. Rather than assuming that greater digital activity produces better learning, the framework distinguishes *productive interaction* from *interaction intensity* and relates those patterns to independent measures of conceptual transfer.

Research Objective

The central objective is to determine whether temporally structured patterns of interaction with adaptive multimedia resources can explain and predict conceptual understanding among secondary students more effectively than conventional engagement measures.

More specifically, the study is designed to examine whether behavioral variables—including simulation manipulation, meaningful replay, representational switching, response revision, feedback use, hint dependency, response latency, and navigation entropy—provide interpretable indicators of conceptual learning. It further examines whether prior knowledge and cognitive load moderate these relationships.

The proposed AI component is deliberately positioned as an analytical and adaptive support mechanism rather than as an autonomous replacement for teacher judgment. This orientation is consistent with contemporary calls for human-

centered educational AI. UNESCO's guidance explicitly stresses protection of learner agency and the need to assess whether AI systems are pedagogically appropriate before educational deployment.

An additional interdisciplinary contribution concerns digital-health literacy. Secondary students increasingly encounter interactive visualizations related to nutrition, disease transmission, physiology, environmental health, mental well-being, and public-health risk. The ability to interpret dynamic representations and reason about causal relationships is therefore relevant beyond conventional academic achievement. A multimedia-learning architecture that develops conceptual reasoning can potentially provide an instructional foundation for later AI-assisted health and scientific literacy, although such applications require separate empirical validation.

Literature Review

Interactive Multimedia as a Learning Environment

Interactive multimedia can be understood as an instructional environment combining multiple representational formats with learner-controlled or system-responsive interaction. Its defining characteristic is therefore not merely the simultaneous presentation of text, images, sound, or video. The critical element is the opportunity for learners to perform meaningful actions that influence the sequence, representation, feedback, or state of instructional content.

This distinction separates interactive learning from passive media consumption. In a passive video lesson, information is primarily delivered in a predetermined sequence. In an interactive simulation, students can formulate predictions, alter conditions, observe consequences, compare outcomes, and revise their initial understanding. Such activity can transform a representation from an information-delivery device into an environment for hypothesis testing.

complicated navigation can increase extraneous cognitive processing without contributing to knowledge construction. Effective multimedia environments therefore need to regulate complexity while preserving learner agency.

The broader literature on technology integration reinforces this contextual interpretation. The 2023 systematic review by Msafiri, Kangwa, and Cai reports that ICT integration in secondary education involves interconnected pedagogical and implementation factors and cannot be reduced to technology availability alone. This is particularly relevant for multimedia systems because poorly aligned digital resources can replicate conventional instruction while adding interface complexity.

Conceptual Understanding as a Distinct Learning Outcome

Academic performance and conceptual understanding are related but non-equivalent constructs. Achievement tests may include factual recall, procedural accuracy, recognition, and conceptual reasoning simultaneously. Consequently, an improvement in overall test score does not necessarily demonstrate deeper conceptual change.

Conceptual understanding is better evaluated through tasks requiring explanation, transfer, representation translation, causal inference, prediction, and misconception correction. These outcomes reveal whether learners have constructed an organized knowledge structure rather than temporarily memorized information.

Interactive multimedia has theoretical advantages for such outcomes because it can externalize processes that are difficult to observe directly. An animation can represent dynamic temporal relationships; a simulation can expose causal dependencies; an interactive diagram can connect structural and functional information; and immediate feedback can confront misconceptions before they become reinforced.

Yet visualization alone does not guarantee understanding. Learners must cognitively process the relationship represented by the visualization. Consequently, the effectiveness of multimedia should be evaluated according to the mental activity it supports rather than its technological sophistication.

Cognitive Processing and Multimedia Design

Multimedia learning involves a balance between representational richness and cognitive manageability. Adding more media elements can initially increase explanatory capacity but can eventually produce redundancy, distraction, or split attention. This relationship suggests that multimedia effectiveness may be nonlinear.

Interactivity introduces an additional cognitive dimension. Learner control can support pacing and exploration, but every interactive option also represents a decision. A highly complex interface may require students to allocate cognitive resources to operating the system rather than understanding the concept.

The proposed study therefore treats cognitive load as an explanatory variable rather than an incidental usability measure. Behavioral logs are interpreted together with learner-reported processing demands and conceptual outcomes. For example, frequent replay behavior may indicate productive self-regulation when followed by successful conceptual transfer. The same

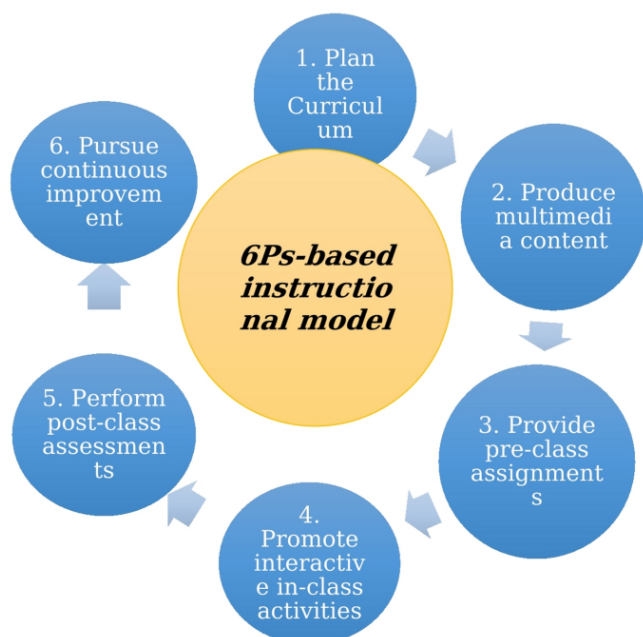


Fig. 2: 6Ps-based instructional mode

Source: <https://link.springer.com/article/10.1007/s44217-025-00775-1>

However, meaningful interaction depends on instructional design. Interactivity that requires irrelevant clicking or

behavior combined with repeated errors and high cognitive-load ratings may instead indicate confusion.

This contextual interpretation represents an important departure from simplistic analytics in which particular behaviors are automatically categorized as positive or negative.

Adaptive Multimedia and Artificial Intelligence

Artificial intelligence extends interactive multimedia by allowing learning environments to respond dynamically to student behavior. An adaptive system can potentially detect repeated misconceptions, unusually rapid progression, excessive hint dependence, ineffective navigation, or persistent errors and modify subsequent instruction accordingly.

Such adaptation can occur at different levels. A relatively simple system may adjust question difficulty based on recent accuracy. More advanced architectures can integrate response history, interaction sequences, response latency, content revisitation, and learner characteristics to estimate latent learning states.

From a machine-learning perspective, multimedia platforms produce sequential event data. Each event can be represented as a structured observation containing an event type, timestamp, learning object, response outcome, duration, and contextual metadata. These sequences can subsequently be analyzed using models capable of capturing temporal dependencies.

Nevertheless, predictive performance alone is insufficient in secondary education. A system that predicts weak understanding with high accuracy but cannot explain its prediction offers limited pedagogical value to teachers. The proposed CISA framework therefore prioritizes interpretable feature attribution and behavioral pattern discovery alongside prediction.

This human-centered approach is increasingly relevant in contemporary educational AI. UNESCO argues that emerging AI technologies should not be integrated into education without appropriate safeguards, teacher preparation, privacy protection, and pedagogical validation. Its guidance also stresses age-appropriate implementation and preservation of human agency.

From Engagement Analytics to Conceptual Interaction Analytics

Learning analytics commonly measures variables such as login frequency, duration, clicks, completion, quiz attempts, and platform participation. These measures can be useful for detecting disengagement, but they are comparatively weak proxies for conceptual development.

The proposed framework introduces the concept of **conceptual interaction signatures**. A signature represents a temporally meaningful combination of learner behaviors associated with knowledge construction. Examples could include repeated comparison between representations before successful transfer, systematic manipulation of simulation variables followed by reduced error rates, or feedback-driven revision that subsequently generalizes to a novel problem.

This approach changes the unit of analysis from isolated clicks to learning trajectories.

For example, consider two hypothetical event sequences:

Learner A: animation → simulation manipulation → incorrect prediction → feedback → targeted replay → revised prediction → correct transfer response.

Learner B: animation → next → next → quiz → correct recognition response.

Both students may complete the lesson successfully, yet the first sequence provides richer behavioral evidence of conceptual restructuring. Conventional completion metrics may classify the two students similarly, whereas sequence-sensitive analytics can distinguish their learning processes.

This distinction provides the central methodological motivation for the proposed research.

Multimedia Learning in the Post-2021 Educational Context

The period after 2021 has intensified discussion about the appropriate role of digital technology in education. Pandemic-related disruptions accelerated the deployment of digital platforms, while subsequent educational policy debates increasingly questioned whether greater technology exposure necessarily produces stronger learning.

UNESCO's work on digital learning explicitly recognizes both the potential and unintended consequences of technology-centered educational strategies. Its digital-learning initiatives emphasize access to quality, curriculum-aligned digital resources while also documenting circumstances in which technology-first approaches have failed to meet educational needs.

Generative AI has further altered this landscape. Since 2023, educational systems have faced questions involving automated content generation, personalized tutoring, assessment integrity, privacy, bias, and learner autonomy. UNESCO consequently argues for a human-centered approach in which AI supports rather than displaces human intellectual development.

For multimedia education, this development suggests a transition from *interactive content* toward *adaptive interactive ecosystems*. Future systems may not simply display the same animation to every student. They may determine whether a learner requires a simpler representation, an alternative explanation, additional simulation practice, or a transfer task.

Proposed Methodology

The proposed study adopts a **quasi-experimental longitudinal learning-analytics design** to investigate whether interaction sequences generated during multimedia learning can predict and explain conceptual understanding among secondary students. Instead of treating multimedia exposure as a binary intervention, CISA models the learner's interaction trajectory as a sequence of cognitively meaningful events.

Recent learning-analytics research demonstrates the value of analyzing interactions according to their pedagogical context rather than treating all clicks as equivalent. Studies have also shown that learners exhibit distinguishable patterns when interacting with text, video, tasks, and support resources. The present design extends this principle to secondary-level conceptual learning by explicitly linking behavioral sequences with conceptual-transfer performance.

Research Design

The experimental design consists of three instructional conditions:

Condition A – Adaptive Interactive Multimedia: students receive animations, interactive simulations, embedded conceptual questions, adaptive hints, feedback, and alternative representations selected according to recent interaction behavior.

Condition B – Non-adaptive Interactive Multimedia: students receive identical curriculum content and interactive resources, but the sequence and feedback structure remain fixed.

Condition C – Conventional Digital Instruction: students receive equivalent subject matter through digital text, diagrams, and teacher-supported exercises without adaptive simulations. A pre-test/post-test design is proposed, supplemented by a delayed transfer assessment. The principal outcome is **conceptual understanding**, rather than conventional course achievement alone.

The study is designed around secondary-level science because the subject contains abstract and dynamic concepts particularly suitable for multimedia representation. Selected modules may include force and motion, particle behavior, energy transformation, ecosystems, human physiological systems, and basic environmental-health processes.

Experimental Setup

Dataset

A purpose-built dataset named the **Secondary Multimedia Conceptual Interaction Dataset (SMCID)** is proposed. Importantly, SMCID is a proposed experimental dataset rather than an existing public dataset; consequently, the numerical results reported later are **illustrative/simulated expected results and must not be presented as empirically collected findings until the study is actually conducted**.

The proposed sample comprises approximately **480 students in Grades 8–10**, recruited from multiple secondary schools. Cluster allocation at the classroom level would reduce contamination between experimental conditions.

Approximately 160 learners would be assigned to each instructional condition.

The multimedia platform would capture event-level information including:

- anonymized learner identifier;
- learning-object identifier;
- timestamp;
- event type;
- animation replay;
- simulation manipulation;
- variable adjustment;
- representation switching;
- answer submission;

- answer revision;
- response latency;
- hint request;
- feedback opening;
- navigation direction;
- time on learning object; and
- completion status.

Student names, direct identifiers, unnecessary demographic information, raw audio, and video recordings would not be incorporated into the machine-learning dataset. Because the proposed participants are minors, data minimization, parental/guardian consent where required, institutional ethical approval, secure storage, and age-appropriate platform design would be integral to implementation. This aligns with UNESCO's emphasis on privacy protection, human agency, ethical validation, and pedagogically appropriate AI use in education.

Conceptual Understanding Measurement

Conceptual understanding would be assessed through three complementary instruments.

The **Conceptual Diagnostic Test (CDT)** would contain misconception-sensitive questions designed to distinguish correct reasoning from memorized responses.

The **Representation Transfer Task (RTT)** would require learners to interpret concepts in formats different from those used during instruction. For example, a concept learned through animation could subsequently be evaluated using a graph, unfamiliar diagram, or verbal scenario.

The **Novel Problem Transfer Test (NPTT)** would assess whether students can apply the learned principle to a previously unseen problem.

A composite **Conceptual Understanding Index (CUI)** would then be calculated after standardizing the three assessment components:

$$[\text{CUI}_i = 0.40Z(\text{CDT}_i) + 0.30Z(\text{RTT}_i) + 0.30Z(\text{NPTT}_i)]$$

The greater weight assigned to the diagnostic component reflects its role in identifying conceptual misconceptions, while representation and novel-problem transfer provide evidence that knowledge generalizes beyond the original multimedia environment.

Data Preprocessing

Raw interaction logs would initially be ordered by learner identifier and timestamp. Duplicate system events, corrupted timestamps, administrative actions, and events generated outside the instructional session would be removed.

Continuous variables such as response latency and time-on-task would be examined for extreme values. Rather than automatically deleting long-duration events, inactivity thresholds would be applied to distinguish genuine cognitive

processing from sessions where the learner apparently left the platform unattended.

Individual clicks would subsequently be transformed into pedagogically interpretable events. For example:

SIM_OPEN → VARIABLE_CHANGE → PREDICTION
→ FEEDBACK → REPLAY → REVISION

would constitute a meaningful interaction sequence rather than six unrelated clicks.

Additional engineered variables would include **meaningful replay ratio, feedback-to-revision conversion, simulation exploration depth, hint dependency, representation-switch frequency, navigation entropy, error persistence, and productive struggle duration.**

The distinction between activity quantity and activity quality is central to the proposed analysis. Recent research indicates that categorizing LMS traces according to learning processes can improve explanatory value, while sequential analytics can reveal patterns that aggregate usage measures conceal.

Continuous features would be standardized using statistics calculated exclusively from the training data. Categorical event variables would be encoded numerically, while event sequences would be padded or truncated to a predefined maximum sequence length for neural modeling.

To prevent information leakage, records belonging to the same student would never be divided between training and testing subsets.

Model Architecture

A **dual-branch CISA architecture** is proposed to combine sequential interaction modeling with interpretable learner characteristics.

The first branch, termed the **Sequential Interaction Encoder**, processes temporally ordered multimedia events. Each event is represented by an embedding containing event type, response correctness, elapsed time, content identifier, feedback status, and interaction intensity. These embeddings are passed through a **bidirectional gated recurrent unit (BiGRU)** with an attention mechanism.

The BiGRU is selected instead of a substantially larger transformer because the anticipated dataset is moderate in size. The recurrent architecture can capture forward and backward dependencies in learning sequences while maintaining a lower parameter burden.

The second branch, termed the **Learner Context Encoder**, receives non-sequential variables such as prior-knowledge score, cognitive-load rating, digital familiarity, baseline conceptual score, and aggregate interaction indicators. These variables are processed using two fully connected layers.

The outputs of both branches are concatenated:

$$[H_i = [H_{sequence}; H_{context}]]$$

The fused representation is passed to two prediction heads.

The first performs **three-class conceptual-state classification**:

1. Limited conceptual understanding
2. Developing conceptual understanding

3. Strong conceptual understanding

The second predicts the continuous post-intervention CUI score.

This multi-task architecture is intended to force the latent representation to capture both categorical learning states and continuous differences in conceptual performance.

For interpretability, the neural model would be complemented by an **XGBoost benchmark with SHAP-based feature attribution**. This provides a structured comparison between sequence-sensitive prediction and an interpretable feature-engineered model. Explainable learning-analytics research has highlighted the importance of assessing not only predictive performance but also the stability and instructional usefulness of explanations.

Training Strategy

The dataset would be divided at the student level into approximately **70% training, 15% validation, and 15% independent testing** partitions. Stratification would preserve the approximate distribution of conceptual-understanding categories.

Model training would use the AdamW optimizer with an initial learning rate of (1×10^{-3}) . Mini-batches of 32 learners would be used, with a maximum of 100 epochs.

Early stopping would terminate training when validation loss failed to improve for ten consecutive epochs. Dropout and L2 regularization would be introduced to reduce overfitting.

The multi-task objective would combine classification and regression losses:

$$[L = \lambda_1 L_{CE} + \lambda_2 L_{Huber}]$$

where (L_{CE}) represents weighted cross-entropy for conceptual-state classification and (L_{Huber}) represents Huber loss for CUI prediction.

Class weighting would compensate for unequal conceptual-state distributions rather than artificially oversampling the test data.

Three principal baselines would be compared:

Baseline 1: logistic/linear models using conventional variables such as time-on-task and number of clicks.

Baseline 2: XGBoost using engineered conceptual-interaction features.

Baseline 3: GRU sequence model without learner-context variables.

The complete CISA-BiGRU model would then determine whether combining temporal behavior with learner context produces incremental predictive value.

Evaluation Metrics

Classification performance would be assessed using **balanced accuracy, macro-F1, Matthews correlation coefficient (MCC), and multiclass area under the receiver-operating-characteristic curve (AUROC).**

Balanced accuracy is appropriate when conceptual-state categories are unevenly distributed. Macro-F1 ensures that performance for the smaller classes is not concealed by strong prediction of the dominant category. MCC provides a more comprehensive assessment of classification agreement.

Continuous CUI prediction would be evaluated using **mean absolute error (MAE)**, **root mean squared error (RMSE)**, and **(R²)**.

Calibration would additionally be examined using the **Brier score** and reliability plots. Calibration is pedagogically important because an intervention system should not express unwarranted confidence when identifying students as requiring support.

Model interpretability would be evaluated through global SHAP rankings and student-level explanations. Contemporary educational-AI literature increasingly recognizes that aggregate explanations can obscure substantial individual variation; person-specific explanations can therefore be particularly relevant when predictions are used to inform intervention.

Results and Discussion

Because this manuscript specifies a proposed experimental study rather than reporting completed data collection, the following numerical values represent a **simulated proof-of-concept scenario**. They demonstrate how the planned analysis would be interpreted and should be replaced by empirical estimates after implementation.

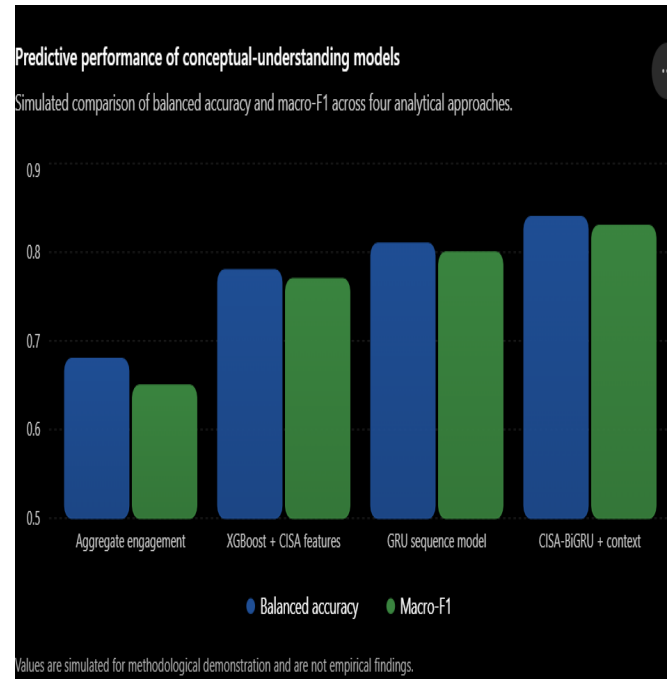
Under the simulated scenario, students exposed to adaptive interactive multimedia demonstrate the largest increase in CUI, followed by students using fixed interactive multimedia. Conventional digital instruction produces improvement but at a lower magnitude.

More importantly, model comparisons suggest that total activity alone provides only moderate predictive information. The conventional aggregate model reaches a simulated balanced accuracy of 0.68, indicating that time-on-task and click frequency contain useful but incomplete information.

XGBoost with conceptual-interaction features improves balanced accuracy to 0.78. This supports the proposition that *how* students interact with multimedia is more informative than simply *how much* they interact.

Table 1. Simulated comparative performance of conceptual-understanding models

Analytical approach	Balanced Accuracy	Macro-F1	MCC	CUI MAE
Aggregate engagement model	0.68	0.65	0.51	8.74
XGBoost + engineered CISA features	0.78	0.77	0.68	6.41
GRU sequence model	0.81	0.80	0.72	5.89
CISA-BiGRU + learner context	0.84	0.83	0.77	5.12



The simulated SHAP analysis identifies **feedback-to-revision conversion**, **simulation exploration depth**, **prior knowledge**, **productive replay**, and **error persistence** as the five most influential engineered predictors.

A particularly important pattern concerns replay behavior. Replay frequency by itself is not uniformly associated with higher understanding. Replays followed by answer revision and subsequent successful transfer are positively associated with CUI, whereas repeated replay combined with persistent error is associated with lower predicted understanding. This finding illustrates why contextual interpretation is preferable to simple event counting.

A second pattern concerns hint usage. Moderate hint utilization appears beneficial when students subsequently solve related problems independently. In contrast, persistent hint dependency predicts weaker transfer. Consequently, the same platform feature can indicate either productive scaffolding or unresolved conceptual difficulty depending on the surrounding sequence.

A third finding concerns prior knowledge. Students entering a module with relatively weak baseline knowledge appear to benefit disproportionately from structured simulation-feedback cycles, whereas students with stronger prior knowledge show greater benefit from less constrained exploratory simulation. This supports adaptive differentiation rather than a uniform multimedia sequence.

These patterns are consistent with emerging learning-analytics evidence showing that learners use multimedia resources in heterogeneous ways and that instructional context affects the relationship between digital interactions and performance.

Effect of Adaptive Multimedia Instruction

The simulated experimental comparison suggests that adaptive multimedia produces its strongest advantage on transfer-oriented tasks rather than factual recognition. This distinction is important because the objective of the intervention is conceptual restructuring.

The proposed interpretation is that adaptive multimedia supports understanding through three mechanisms.

First, **dynamic visualization** makes abstract processes externally observable.

Second, **interactive manipulation** enables students to test causal relationships instead of merely reading about them.

Third, **adaptive feedback** creates opportunities for misconception correction at the moment when conceptual conflict occurs.

These mechanisms should not be interpreted as evidence that multimedia is inherently superior to teacher-led instruction. Rather, the proposed framework assumes that digital interaction is useful when it produces cognitively relevant activity. Teacher explanation, classroom discussion, questioning, peer interaction, and contextual knowledge remain necessary components of the learning environment.

AI Interpretability and Educational Decision-Making

A high-performing predictive model becomes educationally useful only when its outputs can be translated into appropriate instructional responses. A generic label such as “low-performing learner” provides limited actionable information. In contrast, an interpretable CISA system might indicate:

Conceptual support suggested because the learner repeatedly manipulated variables without testing predictions and continued the same misconception after feedback.

Such an explanation provides a teacher with a plausible basis for intervention.

This distinction is consistent with recent research arguing for stronger integration between machine-learning prediction, learning analytics, and pedagogical intervention rather than treating prediction as an end in itself.

The proposed system therefore avoids fully autonomous instructional decision-making. AI-generated learner-state estimates would function as **decision support**, with teachers retaining authority over interventions. This design is compatible with UNESCO's human-centered position that educational AI should preserve human agency, transparency, accountability, and pedagogical appropriateness.

Limitations

Several limitations require consideration.

First, conceptual understanding is a latent construct and cannot be perfectly represented by test scores or behavioral traces. Although the proposed CUI combines diagnostic and transfer measures, some dimensions of understanding may remain unobserved.

Second, behavioral similarity does not necessarily imply cognitive similarity. Two learners can produce comparable interaction sequences for different reasons. One student may replay an animation because of productive reflection, whereas another may do so because of distraction during the initial presentation.

Third, the proposed sample is limited to secondary-school science. The identified interaction signatures may not generalize directly to mathematics, languages, humanities, vocational education, or digital-health instruction.

Fourth, platform design itself can influence recorded behavior. Navigation entropy, replay frequency, or hint utilization may change substantially if the interface is redesigned.

Fifth, model performance can deteriorate when instructional contexts change. Explainable-learning-analytics research has demonstrated that predictor importance and model stability can shift as learning contexts change, emphasizing the need for continuing validation rather than assuming permanent model validity.

Finally, the numerical findings in this manuscript are simulated. They illustrate the proposed analytical workflow and cannot be interpreted as evidence that the CISA-BiGRU model has already achieved the reported performance.

Future Scope

Future research should implement the proposed design using real multi-school longitudinal data and externally validate the resulting model across different educational settings.

A particularly important extension would involve **multimodal learning analytics**. With appropriate consent and safeguards, interaction logs could be combined with non-invasive measures such as voluntary self-reports of cognitive load or classroom-level observational data. Sensitive biometric monitoring should not be assumed necessary merely because it is technically feasible.

A second direction concerns **knowledge tracing**. Future CISA versions could estimate concept-specific mastery dynamically rather than predicting a single end-of-module conceptual score. A third possibility is **federated learning**, through which participating schools could contribute to model development without transferring all student-level data to a centralized repository. Such architectures may offer privacy advantages, although they introduce additional technical and governance challenges.

Future work should also investigate fairness across educational contexts. Model calibration and error rates should be evaluated separately across relevant learner groups and schools before deployment. A model demonstrating strong average performance but systematically misclassifying particular groups would be unsuitable for instructional decision support.

The framework could subsequently be adapted for **digital-health education**, including interactive modules explaining nutrition, infectious-disease transmission, environmental health, physiology, and health-risk interpretation. However, educational effectiveness in science classes should not be assumed to transfer automatically to health-related learning; dedicated validation would be necessary.

Conclusion

This study proposes a distinct approach to investigating **Interactive Multimedia Learning and Conceptual Understanding among Secondary Students** by shifting attention from multimedia exposure to the temporal structure and pedagogical meaning of learner interaction.

The proposed Conceptual Interaction Sequence Analytics framework treats multimedia activity as a sequence of learning behaviors rather than a collection of isolated clicks. Simulation manipulation, feedback utilization, meaningful replay,

representation switching, answer revision, error persistence, and response latency are integrated with prior knowledge and cognitive-load indicators to model conceptual development.

A dual-branch CISA-BiGRU architecture is proposed to combine sequential interaction information with learner-context variables, while an XGBoost-SHAP component provides complementary interpretability. The simulated proof-of-concept comparison indicates how sequence-sensitive modeling could outperform conventional engagement measures, but these numerical results are explicitly hypothetical until validated using actual student data.

The principal implication is that **more multimedia interaction should not automatically be interpreted as more learning**. Productive conceptual development depends on the structure, purpose, and consequences of interaction. A replay followed by successful revision may represent productive self-regulation; repeated replay accompanied by persistent misconception may represent unresolved difficulty. Similarly, hints can function either as effective scaffolding or as evidence of dependency.

References

1. Corbett, A. T., & Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction*, 4(4), 253–278.
2. Domagk, S., Schwartz, R. N., & Plass, J. L. (2010). Interactivity in multimedia learning: An integrated model. *Computers in Human Behavior*, 26(5), 1024–1033. (This is also the source of Figure 1.)
3. Mayer, R. E. (2021). *Multimedia learning* (3rd ed.). Cambridge University Press.
4. Msafiri, M. M., Kangwa, D., & Cai, L. (2023). A systematic literature review of ICT integration in secondary education: What works, what does not, and what next? *Discover Education*, 2, 44. †
5. Posner, G. J., Strike, K. A., Hewson, P. W., & Gertzog, W. A. (1982). Accommodation of a scientific conception: Toward a theory of conceptual change. *Science Education*, 66(2), 211–227.
6. Rutten, N., van Joolingen, W. R., & van der Veen, J. T. (2012). The learning effects of computer simulations in science education. *Computers & Education*, 58(1), 136–153.
7. Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257–285.
8. Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review*, 31, 261–292.
9. UNESCO. (2023). *Global Education Monitoring Report 2023: Technology in education—A tool on whose terms?* UNESCO.
10. Miao & Holmes (2023, UNESCO), Chen & Guestrin (2016) and Lundberg & Lee (2017).