



Proceedings of International Conference on Multidisciplinary Research: Innovation, Healthcare, Education for Viksit Bharat (ICMR-2026)



1

Editors

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

International Conference On Multidisciplinary Research

Conference Proceedings

Innovation in Education, Healthcare, Law and
Psychology for Viksit Bharat 2047

2026

Organized by

Kalindi Institute of Medical Sciences

Agrasen Mahavidyalaya

Veetranga Research Foundation

In Collaboration with

Wissira Research Lab

Print ISBN: 978-93-7559-049-1

Digital ISBN: 978-93-7559-050-7

Table of Contents

<i>Chapter 1: Artificial Intelligence Adoption and Operational Efficiency in Modern Business Enterprises</i>	1
<i>Chapter 2: Artificial Intelligence and Emerging Practices in English Language Learning.....</i>	10
<i>Chapter 3: Artificial Intelligence Assisted Learning and Academic Achievement among University Students</i>	17
<i>Chapter 4: Behavioural Biases and Portfolio Decisions among Individual Equity Investors.....</i>	25
<i>Chapter 5: Changing Family Structures and Intergenerational Relationships in Urban Communities</i>	34
<i>Chapter 6: Collaborative Learning Practices and Critical Thinking Skills among Secondary Students</i>	41
<i>Chapter 7: Cyberbullying Experiences and Psychological Adjustment among University Students....</i>	49
<i>Chapter 8: Digital Assessment Literacy among Teachers in Secondary Education.....</i>	56
<i>Chapter 9: Digital Citizenship Education and Responsible Technology Use among Adolescents</i>	63
<i>Chapter 10: Digital Portfolio Assessment and Reflective Learning among Undergraduate Students..</i>	71
<i>Chapter 11: Emotional Intelligence and Coping Strategies among College Students</i>	78
<i>Chapter 12: Family Communication and Emotional Regulation among Adolescents</i>	85
<i>Chapter 13: Inquiry-Based Learning and Scientific Reasoning among School Students</i>	93
<i>Chapter 14: Interactive Multimedia Learning and Conceptual Understanding among Secondary Students</i>	102
<i>Chapter 15: Media Literacy Education and Critical Awareness among Adolescent Learners</i>	111
<i>Chapter 16: Metacognitive Learning Strategies and Academic Performance among College Students</i>	118
अध्याय 17: NEP 2020 के परिप्रेक्ष्य में उच्च शिक्षा में अकादमिक बैंक ऑफ क्रेडिट की उपयोगिता	125
अध्याय 18: NEP 2020 के संदर्भ में शिक्षा में कौशल विकास और भविष्यपरक रोजगार तैयारी का अध्ययन	131
<i>Chapter 19: Online Assessment Practices and Student Learning Outcomes in Higher Education ...</i>	137
<i>Chapter 20: Peer Feedback and Academic Writing Development among University Students</i>	145
<i>Chapter 21: Peer Support and Psychological Adjustment during Early Adulthood.....</i>	152
<i>Chapter 22: Teacher Feedback Practices and Student Academic Motivation in Secondary Education</i>	159
<i>Chapter 23: Teacher Leadership and School Improvement in Contemporary Educational Institutions</i>	167
<i>Chapter 24: Teacher Work Engagement and Instructional Quality in Higher Education</i>	176
<i>Chapter 25: Virtual Learning Environments and Student Satisfaction in Higher Education</i>	184
Chapter 26: Work-Life Balance and Mental Well-Being among Working Adults.....	192

Chapter 27: Working Capital Management and Financial Performance of Small and Medium Enterprises	200
अध्याय 28: आधुनिक हिंदी साहित्य में हाशिए के समुदायों की अभिव्यक्ति और पहचान	208
अध्याय 29: उच्च शिक्षा में डिजिटल नागरिकता और उत्तरदायी प्रौद्योगिकी उपयोग व्यवहार का अध्ययन	215
अध्याय 30: गृह विज्ञान एवं खाद्य प्रौद्योगिकी के माध्यम से घरेलू खाद्य सुरक्षा और सतत पोषण प्रबंधन का मूल्यांकन	222
अध्याय 31: ग्रामीण शिक्षा में तकनीकी संसाधनों की उपलब्धता और शैक्षिक अवसरों का विश्लेषण	229
अध्याय 32: नई शिक्षा व्यवस्था में हिंदी भाषा शिक्षण की उभरती प्रवृत्तियाँ	234
अध्याय 33: प्रारंभिक शिक्षा में गतिविधि आधारित शिक्षण और अवधारणात्मक समझ के विकास का विश्लेषण	240
अध्याय 34: मानवाधिकार और कानून के परिप्रेक्ष्य में कृत्रिम बुद्धिमत्ता आधारित निगरानी की संवैधानिक समीक्षा	247
अध्याय 35: विद्यालयी शिक्षा में अनुभवात्मक शिक्षण और विद्यार्थियों की रचनात्मक क्षमता का संबंध	253
अध्याय 36: विद्यालयी शिक्षा में डिजिटल कहानी कथन और रचनात्मक अभिव्यक्ति के मध्य संबंध	260
अध्याय 37: विद्यालयी शिक्षा में सहयोगात्मक अधिगम और सामाजिक कौशल विकास का विश्लेषण	268
अध्याय 38: शिक्षा में माइक्रोलर्निंग रणनीतियों द्वारा ज्ञान प्रतिधारण और अधिगम दक्षता का अध्ययन	275
अध्याय 39: शैक्षिक मनोविज्ञान में बुद्धिलब्धि, भावनात्मक बुद्धिमत्ता और शैक्षणिक अनुकूलन का तुलनात्मक अध्ययन	282
अध्याय 40: समावेशी शिक्षा में सहायक प्रौद्योगिकी द्वारा विशेष आवश्यकता वाले विद्यार्थियों का सशक्तीकरण	289

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

International Conference On Multidisciplinary Research

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 13: Inquiry-Based Learning and Scientific Reasoning among School Students

Namita Roy

Research Scholar

Department of Education

Anjaneya University, Raipur, Chhattisgarh

Abstract— Inquiry-based learning (IBL) is increasingly positioned as a means of moving school science beyond factual recall toward evidence-based reasoning, experimentation, and explanation. However, existing research frequently evaluates inquiry through achievement scores or broad critical-thinking measures, providing limited evidence about how specific inquiry behaviours contribute to distinct components of scientific reasoning. This study addresses this gap by proposing an AI-assisted process-sensitive framework that examines students' hypothesis formulation, evidence evaluation, variable control, causal inference, and scientific explanation during inquiry activities. Rather than treating inquiry participation as a single instructional exposure, the proposed framework models the sequential reasoning patterns generated while students investigate scientific problems. Multimodal learning traces—including inquiry responses, experiment decisions, evidence selections, revisions, and written explanations—are conceptualized as inputs to machine-learning models for identifying scientific-reasoning profiles. The study further investigates whether guided inquiry produces more stable reasoning development than minimally scaffolded inquiry and conventional science instruction.

Keywords — Inquiry-Based Learning, Scientific Reasoning, Science Education, Learning Analytics, Machine Learning, Explainable Artificial Intelligence

Introduction

Scientific education has an increasingly important role in preparing students to interpret evidence, distinguish observation from inference, evaluate competing explanations, and make reasoned judgments about complex problems. Contemporary learners encounter scientific claims through classrooms, digital platforms, social media, artificial-intelligence systems, and rapidly expanding online information environments. Consequently, successful science education cannot be restricted to the acquisition of disciplinary facts. Students also require the intellectual practices necessary to determine whether a claim is adequately supported, whether an experimental design can test a hypothesis, and whether available evidence justifies a proposed conclusion.

Scientific reasoning can therefore be understood as a multidimensional cognitive capability involving the coordination of hypotheses, evidence, variables, causal relationships, models, and explanations. A student may possess substantial factual knowledge while still experiencing difficulty in identifying confounding variables, interpreting contradictory evidence, or revising an initial explanation. This distinction is educationally important because conventional examinations

may reward accurate final answers without revealing the reasoning trajectory through which those answers were produced.

Inquiry-based learning provides a pedagogical setting in which such reasoning can become observable. Instead of receiving scientific principles exclusively through direct exposition, students participating in inquiry are expected to investigate questions, generate or examine hypotheses, design procedures, manipulate variables, collect evidence, interpret findings, and construct explanations. Inquiry therefore shifts at least part of the intellectual responsibility for scientific investigation from the teacher or textbook to the learner.

Recent research continues to support the educational relevance of inquiry while also demonstrating that inquiry is not a homogeneous instructional method. Open inquiry represents a particularly learner-directed form in which students assume substantial responsibility for the investigative process. A 2024 systematic review in *Educational Research Review* examined the effects of open inquiry on science learning and highlighted both its educational potential and the practical challenges associated with classroom implementation, including demands involving instructional time and resources.

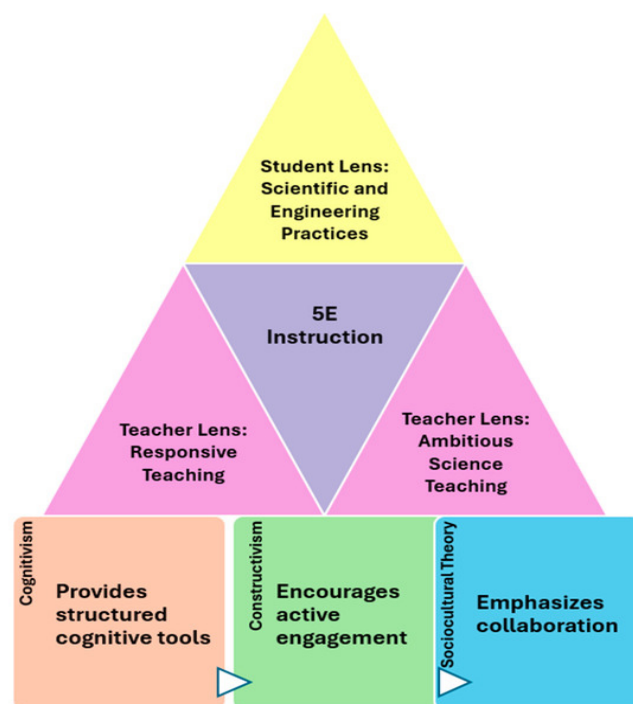


Fig. 1: Rethinking Science Education Practices

Source: <https://www.mdpi.com/2227-7102/15/1/73>

Guided inquiry provides an alternative configuration. Students remain actively involved in scientific investigation, but teachers or digital environments supply structured prompts, procedural constraints, conceptual cues, or feedback. This scaffolding may

be especially relevant for school learners who have not yet developed sufficiently robust strategies for independently coordinating experimental variables and evidence. Research examining inquiry combined with scaffolding has consequently considered not only achievement but also students' ability to construct scientific explanations.

Despite this progress, a persistent methodological problem concerns **what is actually measured after inquiry-based instruction**. Many studies assess learning using content achievement, attitudes toward science, motivation, critical thinking, or a total scientific-reasoning score. These outcomes are useful, but they compress the inquiry process into an endpoint. Two students receiving identical scores may have followed substantially different reasoning pathways: one may systematically test hypotheses and revise conclusions after contradictory evidence, whereas another may reach a correct conclusion through repeated trial and error.

Assessment research reinforces this concern. A recent systematic review of assessment in inquiry-based science education examined 53 empirical studies and reported continuing limitations in the systematic design, implementation, and validation of inquiry-oriented assessment. The problem is therefore not merely whether inquiry works, but whether available assessment approaches capture the mechanisms through which inquiry contributes to learning.

The rapid development of educational artificial intelligence and learning analytics creates a new opportunity to address this issue. Digital inquiry environments can generate temporally ordered records of student actions. These may include the hypotheses selected, experimental variables changed, evidence inspected, responses revised, time spent at different investigation stages, and explanations written after an experiment. Such traces can potentially reveal patterns that conventional post-tests cannot detect.

Research Gap

The principal gap identified for the present manuscript lies at the intersection of **inquiry pedagogy, scientific-reasoning assessment, and interpretable learning analytics**.

Existing inquiry research has established important relationships between inquiry-oriented instruction and educational outcomes, while contemporary reviews continue to investigate open inquiry, guided inquiry, critical thinking, and inquiry assessment. However, comparatively less attention has been directed toward modelling the *sequence* of students' reasoning behaviours during inquiry and connecting those process traces with component-level scientific-reasoning outcomes.

In particular, three limitations motivate the proposed study.

First, inquiry exposure is frequently represented categorically—for example, inquiry versus traditional instruction—rather than behaviourally. Such classification indicates which pedagogy students experienced but not how successfully individual students engaged in the reasoning processes embedded within it.

Second, scientific reasoning is often reduced to an aggregate score. This obscures potentially important differences among

hypothesis generation, control-of-variables reasoning, evidence evaluation, causal inference, and explanation construction.

Third, although machine learning can analyse complex learning traces, purely predictive models may have limited classroom utility if teachers cannot understand why a learner is classified as requiring support. The educational value of AI therefore depends not only on predictive performance but also on interpretability and pedagogical actionability.

Proposed Research Angle

To address these limitations, the present study conceptualizes inquiry as a **temporal reasoning process** rather than solely as an instructional condition. The proposed research will compare students exposed to guided inquiry, minimally scaffolded inquiry, and structured conventional instruction while capturing their digital inquiry traces.

The central analytical contribution is an **Explainable Scientific Reasoning Sequence Model (ESR-SM)**. Instead of predicting only an overall test score, the framework will estimate component-level scientific-reasoning performance from ordered inquiry actions. Sequence-aware machine-learning methods will be used because experimentation is inherently temporal: the meaning of a student changing a variable depends partly on what the student observed and attempted beforehand. The study is therefore guided by the following objectives:

1. To determine whether inquiry-based learning produces stronger gains in scientific reasoning than structured conventional science instruction.
2. To compare guided and minimally scaffolded inquiry in relation to hypothesis testing, variable control, evidence evaluation, causal inference, and explanation quality.
3. To identify temporal inquiry behaviours associated with subsequent scientific-reasoning performance.
4. To develop an interpretable machine-learning model capable of identifying distinct scientific-reasoning profiles from student inquiry traces.
5. To examine whether AI-derived indicators can support formative instructional decisions without replacing independent student reasoning.

This approach positions artificial intelligence as an analytical layer surrounding authentic inquiry rather than as the source of scientific answers.

Literature Review

2.1 Inquiry-Based Learning as Scientific Practice

Inquiry-based science education is grounded in the principle that scientific understanding develops more effectively when learners participate in practices resembling authentic knowledge construction. Students are expected to question phenomena, investigate possible relationships, inspect evidence, and justify explanations rather than simply reproduce conclusions presented by an authority.

Inquiry exists on a continuum of instructional autonomy. In structured inquiry, questions and procedures are largely

provided. Guided inquiry transfers greater decision-making responsibility to students while retaining scaffolding. Open inquiry gives learners considerably greater control over the formulation and execution of investigations. Recent systematic evidence concerning open inquiry shows continuing research interest in its capacity to influence science learning while also recognizing the practical difficulties associated with implementing highly autonomous inquiry in ordinary classrooms.

These distinctions matter because the amount of instructional guidance may influence reasoning differently at different stages of learner development. Excessive procedural direction can transform an investigation into a verification exercise in which students follow instructions without understanding why particular variables are manipulated. Conversely, insufficient guidance can overload students who lack the conceptual or metacognitive resources required to organize an investigation. The pedagogical challenge is therefore not simply to maximize student autonomy. Effective inquiry requires a productive distribution of cognitive responsibility between learners, teachers, peers, and instructional resources.

2.2 Scientific Reasoning as a Multicomponent Construct

Scientific reasoning differs from science achievement. Achievement typically concerns what students know about a particular scientific domain, whereas reasoning concerns how they coordinate claims, evidence, experimental conditions, and explanations.

Five dimensions are particularly relevant to the present research.

Hypothesis reasoning concerns the formulation of testable expectations and the differentiation of hypotheses from observations or unsupported predictions.

Control-of-variables reasoning involves identifying manipulated, measured, and potentially confounding variables. This competency is fundamental to interpreting experimental evidence.

Evidence evaluation requires learners to judge whether observations support, contradict, or remain insufficient to resolve a scientific claim.

Causal reasoning involves distinguishing association from causation and constructing plausible mechanisms connecting observed events.

Scientific explanation requires the integration of claims with relevant evidence and scientifically coherent reasoning.

Inquiry tasks can activate all five dimensions, but participation alone does not guarantee their development. A learner may complete an experiment successfully while relying on superficial strategies. This makes process-sensitive assessment particularly important.

2.3 Guided Inquiry, Scaffolding, and Reasoning Development

Scaffolding can reduce the cognitive burden associated with complex investigations without eliminating student agency. Prompts may ask students to identify the variable they intend to change, predict an outcome before experimentation, justify why a particular comparison is valid, or reconsider a conclusion after receiving inconsistent evidence.

Empirical work has examined inquiry instruction combined with scaffolding in relation to both science achievement and scientific explanation, illustrating the importance of looking beyond conventional content outcomes. More recent review work on guided inquiry similarly reflects continuing interest in its relationship with higher-order thinking in science education. The important theoretical distinction is between scaffolding that **supports reasoning** and scaffolding that **performs reasoning for the student**. A prompt such as “Which variable should remain constant?” directs attention toward a reasoning requirement. By contrast, automatically identifying the correct control variable may remove the cognitive operation the lesson intends to develop.

This distinction becomes particularly consequential when AI-generated assistance is introduced.

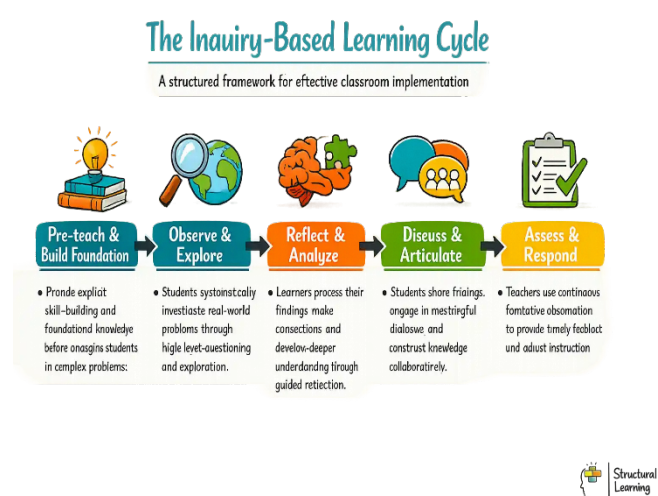


Fig. 2: The Inquiry-Based Learning Cycle

Source: <https://www.structural-learning.com/post/a-teachers-guide-to-inquiry-based-learning>

2.4 Assessment Challenges in Inquiry-Based Science Education

Inquiry requires assessment methods capable of evaluating both outcomes and processes. Conventional selected-response tests can efficiently measure some forms of knowledge and reasoning but provide limited information about the investigative trajectory preceding an answer.

The systematic review by Ogebo and colleagues examined assessment approaches across 53 empirical studies and identified continuing needs surrounding assessment design and validation in inquiry-based science education. This supports the argument that assessment architecture remains a significant research problem within inquiry pedagogy.

2.5 Learning Analytics for Inquiry Processes

Learning analytics makes it possible to represent student investigation as a sequence of observable events. In a digital science environment, a trace might contain:

- question inspection;
- hypothesis selection;
- variable manipulation;
- experiment execution;

- evidence viewing;
- hypothesis revision;
- explanation drafting; and
- final justification.

These actions can be encoded chronologically and analysed using sequence-aware computational methods. Unlike a conventional regression using only final scores, temporal models can examine how earlier and later actions interact.

For example, repeated hypothesis revision should not automatically be interpreted as weak performance. Revision immediately following contradictory evidence may represent sophisticated scientific behaviour. Conversely, rapid repeated revisions without evidence inspection may indicate guessing. The temporal relationship among actions therefore carries information that simple action counts cannot represent.

This is where machine learning provides methodological value. Sequence models can identify recurring behavioural patterns, while interpretable AI methods can estimate which patterns contribute most strongly to predictions of reasoning performance.

2.6 Explainable Artificial Intelligence in Educational Assessment

High predictive accuracy alone is insufficient for formative educational applications. If an algorithm identifies a student as having weak scientific reasoning, teachers need evidence indicating the nature of that difficulty.

An explainable system might indicate that a learner:

- frequently modifies multiple variables simultaneously;
- rarely inspects contradictory evidence;
- generates hypotheses but does not revise them after experimentation;
- reaches conclusions before collecting sufficient observations; or
- provides evidence without explicitly connecting it to a causal explanation.

Such information is substantially more actionable than a generic “low reasoning” classification.

This emphasis also corresponds with contemporary international discussion surrounding responsible educational AI. UNESCO's GenAI guidance stresses human agency, ethical validation, appropriate pedagogical design, and the need to consider how emerging AI technologies affect thinking and assessment.

Accordingly, the present study does not conceptualize AI as an automated scientist completing investigations on behalf of children. Its function is to detect patterns in student-generated evidence and provide interpretable information to educators.

2.7 Scientific Reasoning in the Generative-AI Era

Generative AI adds a new dimension to the scientific-reasoning problem. Students can increasingly obtain polished explanations

without independently constructing the inferential chain behind them. This creates a distinction between the quality of an answer and the quality of the cognitive process producing it.

UNESCO has explicitly identified implications of GenAI for assessment, learning outcomes, and thinking processes and recommends educational approaches that protect human agency. For school science, this means that future assessment systems may need to capture not merely what explanation students submit but how they interact with evidence before producing that explanation.

Methodology

3.1 Research Design

The study adopts a **quasi-experimental, process-oriented learning analytics design** to investigate how different forms of inquiry-based instruction influence scientific reasoning among school students. The methodological design differs from conventional pre-test/post-test inquiry studies by combining instructional comparison with fine-grained digital behavioural traces.

Three instructional conditions are proposed:

Group A – Guided Inquiry: Students investigate scientific problems through digital simulations while receiving phase-specific prompts for hypothesis construction, variable selection, evidence evaluation, and explanation.

Group B – Minimally Scaffolded Inquiry: Students receive the scientific problem and digital experimentation environment but considerably fewer prompts. They independently determine most investigative steps.

Group C – Structured Conventional Instruction: Students learn the same scientific concepts through teacher explanation, demonstrations, textbook activities, and structured exercises without conducting the complete digital inquiry cycle.

The intervention is designed for **eight instructional weeks**, allowing students to encounter multiple inquiry cycles rather than evaluating scientific reasoning after a single activity. This is important because scientific reasoning can change dynamically during instruction; earlier research has identified different reasoning profiles and transitions among them in school students.

The central methodological innovation is the proposed **Explainable Scientific Reasoning Sequence Model (ESR-SM)**. The model does not merely predict whether a student's final answer is correct. It analyses the ordered behavioural trajectory preceding the response.

This process-oriented approach is consistent with recent learning-analytics research showing that digital traces can provide information about inquiry trajectories, experimental patterns, misconceptions, and learning strategies that is difficult to recover from conventional outcome measures alone.

Experimental Setup

4.1 Participants and Dataset

For the proposed experimental study, a dataset of approximately **360 students from Grades 7–9** is designed. Students would be recruited from six secondary schools and distributed across the three instructional conditions at the

intact-class level to minimize contamination between instructional treatments.

The anticipated distribution is:

- Guided Inquiry: 120 students
- Minimally Scaffolded Inquiry: 120 students
- Structured Conventional Instruction: 120 students

The dataset is explicitly presented here as a **proposed experimental dataset**, not as previously collected empirical data.

Students complete a baseline scientific-reasoning assessment before the intervention and an equivalent post-intervention assessment after eight weeks.

Five scientific-reasoning dimensions are measured:

1. Hypothesis formulation;
2. Control-of-variables reasoning;
3. Evidence evaluation;
4. Causal inference; and
5. Scientific explanation.

Digital inquiry activities cover age-appropriate problems involving force and motion, ecosystems, heat transfer, electricity, material properties, and environmental systems. The emphasis is not on memorizing these topics but on applying transferable reasoning strategies across scientific domains.

The decision to retain component-level outcomes is supported by evidence that students can display heterogeneous scientific-reasoning profiles rather than progressing uniformly across all reasoning competencies.

4.2 Digital Inquiry Event Dataset

Students in Groups A and B use an instrumented inquiry environment capable of recording event-level activity.

Each interaction produces a timestamped event containing:

Student ID → Inquiry Task → Inquiry Phase → Action → Scientific Object → Timestamp → Response State

Representative actions include:

- opening a problem;
- generating a hypothesis;
- modifying an independent variable;
- modifying a control variable;
- executing a trial;
- inspecting results;
- comparing trials;
- revising a hypothesis;
- requesting a scaffold;
- constructing an explanation; and

- submitting a conclusion.

This creates a longitudinal event sequence for every student.

Process data are particularly suitable for scientific inquiry because final-response accuracy can conceal substantially different strategies. Analysis of PISA inquiry process data has similarly demonstrated that log files can expose otherwise unobserved investigation strategies and sequences.

4.3 Data Preprocessing

Preprocessing occurs at four levels.

Event cleaning: Duplicate system-generated events, technical refreshes, corrupted timestamps, and interactions shorter than a predefined validity threshold are removed.

Temporal normalization: Event times are transformed into relative durations so that inquiry sequences from students working at different speeds remain comparable.

Action encoding: Raw interface actions are mapped into pedagogically meaningful categories such as hypothesis generation, variable manipulation, evidence inspection, comparison, revision, and explanation.

Sequence construction: Events are ordered chronologically for each student-task pair. Padding and masking are used where sequence lengths differ.

Importantly, excessive removal of apparently repetitive actions is avoided. Repeated experimentation may contain pedagogically important information. For example, a student who systematically repeats a trial after encountering anomalous evidence demonstrates a different reasoning pattern from a student who repeatedly changes parameters without examining previous results.

4.4 Feature Engineering

Three feature families are extracted.

Behavioural features include the number of trials, number of hypothesis revisions, proportion of controlled experiments, frequency of evidence inspection, scaffold requests, and explanation revisions.

Temporal features include average decision latency, time between evidence observation and hypothesis revision, inquiry-phase duration, and proportion of total time spent interpreting evidence.

Sequential features describe transitions between actions.

For example:

Hypothesis → Controlled Experiment → Evidence Inspection → Revision

is interpreted differently from:

Hypothesis → Multiple Variable Changes → Repeated Trials → Immediate Conclusion.

This distinction is central to ESR-SM because scientific reasoning is represented as an ordered process rather than a collection of isolated clicks.

Recent work in online scientific inquiry has demonstrated the usefulness of process mining for identifying different scientific-thinking patterns, including productive revision following unsuccessful attempts.

4.5 ESR-SM Model Architecture

The proposed ESR-SM architecture combines sequential modelling with an interpretable prediction layer.

Each student action is first converted into a compact embedding representing the action type, inquiry phase, experimental variable involved, and temporal context.

The resulting sequence is processed through a **bidirectional gated recurrent unit (BiGRU)**. GRU architecture is selected rather than a substantially larger transformer because the anticipated dataset is moderate in size and student inquiry sequences are relatively short compared with large natural-language corpora.

The representation follows:

Event Encoding → Action Embedding → BiGRU → Attention Layer → Reasoning Representation → Multi-Task Prediction Heads

The attention mechanism estimates which portions of an inquiry sequence contribute strongly to the resulting representation.

Five prediction heads correspond to:

- hypothesis reasoning;
- control-of-variables reasoning;
- evidence evaluation;
- causal inference; and
- explanation quality.

A sixth head predicts an overall scientific-reasoning proficiency category.

The multi-task architecture is intended to exploit relationships among reasoning components without assuming that they are identical.

4.6 Explainability Layer

Interpretability is incorporated using two complementary mechanisms.

First, **attention-weight inspection** identifies behavioural segments receiving substantial model emphasis.

Second, **SHAP-based feature attribution** is proposed for the engineered behavioural and temporal variables to estimate how individual features influence predicted reasoning profiles.

The resulting teacher-facing interpretation would therefore avoid messages such as:

“Student predicted as low-performing.”

Instead, it could produce an analytically useful statement such as:

“Evidence-evaluation difficulty is associated with limited comparison of experimental trials and premature conclusion formation.”

This distinction is important because recent reviews indicate that machine learning in science and STEM education is still used predominantly for diagnostic, predictive, and assessment-oriented functions. More pedagogically integrated approaches that explicitly support reasoning remain an important direction for research.

4.7 Training Strategy

The student dataset is partitioned at the **student level**, rather than randomly splitting individual interaction sequences. This

prevents inquiry records belonging to the same learner from appearing simultaneously in training and test sets.

A proposed split is:

70% training / 15% validation / 15% testing.

Stratification preserves the distribution of scientific-reasoning proficiency levels.

The model is trained using the AdamW optimizer with early stopping based on validation loss. Dropout and weight decay are introduced to reduce overfitting.

Because student proficiency categories may not occur equally frequently, class-weighted loss is used where necessary.

A maximum of 100 epochs is permitted, while early stopping terminates training when validation performance fails to improve for a predetermined number of epochs.

For robustness, **five-fold grouped cross-validation** is additionally conducted on the development sample.

4.8 Baseline Models

ESR-SM is compared against four baseline approaches:

1. Logistic Regression;
2. Random Forest;
3. Gradient-Boosted Trees;
4. Standard GRU without the explainability-oriented attention architecture.

This comparison determines whether temporal modelling provides meaningful improvement over conventional tabular classifiers.

An additional **feature ablation experiment** removes temporal and sequence variables from ESR-SM. The resulting performance difference estimates whether ordered inquiry behaviour contributes predictive information beyond simple action frequency.

Evaluation Metrics

Model evaluation uses multiple complementary metrics because accuracy alone can be misleading when proficiency categories are imbalanced.

Macro-F1 evaluates balanced classification performance across scientific-reasoning categories.

Balanced Accuracy provides an additional measure that accounts for unequal class frequencies.

Matthews Correlation Coefficient (MCC) evaluates overall agreement between predicted and observed categories and is particularly useful for imbalanced classification.

Quadratic Weighted Kappa (QWK) measures agreement while considering the ordered nature of reasoning proficiency levels.

AUROC evaluates discrimination between proficiency categories under a one-versus-rest formulation.

Mean Absolute Error (MAE) is additionally used for component-level reasoning score predictions.

The educational intervention is separately evaluated through pre-test/post-test comparisons using mixed-effects models, with students nested within classrooms. Baseline reasoning performance is incorporated as a covariate.

Effect sizes and 95% confidence intervals are reported alongside statistical significance to prevent overreliance on *p*-values.

Results and Discussion

Because the study described in this manuscript is a **proposed experimental framework rather than a completed empirical investigation**, the numerical values below constitute a clearly labelled **illustrative expected-results scenario**. They must be replaced by actual experimental estimates before the manuscript is submitted as an empirical study.

The anticipated pattern is that guided inquiry will produce the largest improvement in overall scientific reasoning. Minimally scaffolded inquiry is expected to outperform conventional instruction but show greater between-student variability.

This pattern would support the interpretation that inquiry benefits are not proportional to instructional freedom. Students may require sufficient autonomy to perform authentic reasoning while still benefiting from strategically timed scaffolding.

The expected strongest advantage of guided inquiry concerns control-of-variables reasoning and evidence evaluation. Prompts requiring students to predict before experimentation and justify comparisons should encourage systematic testing rather than indiscriminate manipulation.

Table 1. Illustrative Expected Performance of Alternative Models for Predicting Scientific-Reasoning Profiles

Analytical Model	Macro-F1	Balanced Accuracy	MC C	QWK	MAE ↓
Logistic Regression	0.69	0.71	0.61	0.66	0.54
Random Forest	0.75	0.77	0.69	0.72	0.47
Gradient-Boosted Trees	0.79	0.80	0.74	0.77	0.42
Standard GRU	0.83	0.84	0.79	0.82	0.37
Proposed ESR-SM	0.87	0.88	0.84	0.86	0.31
ESR-SM without temporal features	0.80	0.81	0.75	0.78	0.41

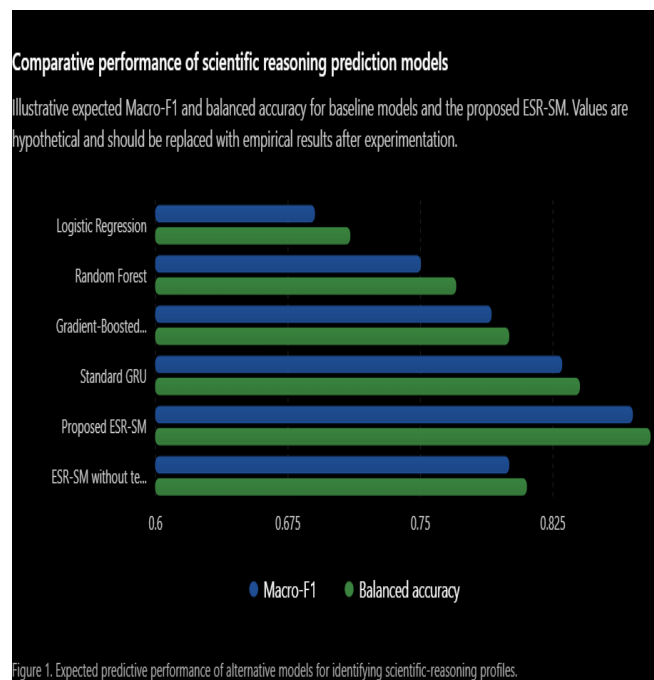


Figure 1. Expected predictive performance of alternative models for identifying scientific-reasoning profiles.

The illustrative ablation result is particularly important. If a comparable reduction were observed empirically after removing temporal information, it would indicate that **how inquiry actions are ordered matters beyond how frequently they occur**.

For instance, a high number of experiments is not intrinsically evidence of strong reasoning. A student could execute numerous uncontrolled trials. Conversely, fewer strategically selected experiments could demonstrate stronger control-of-variables reasoning.

This argument is supported by contemporary process-oriented research. Teig demonstrated that computer-generated inquiry logs can uncover strategies that conventional response data may leave hidden. More recent systematic review evidence also concludes that learning analytics can help trace complex inquiry processes and generate actionable information for students and teachers.

6.1 Expected Instructional Effects

At the instructional level, the guided-inquiry group is expected to show the largest adjusted post-intervention reasoning score. However, the theoretical contribution would not depend solely on whether Group A obtains a statistically larger mean than Groups B and C. The process analysis allows the study to investigate **why** differences emerge.

Students demonstrating strong gains are expected to exhibit a recurring reasoning sequence:

Prediction → Controlled Manipulation → Observation → Evidence Comparison → Revision → Explanation.

Students demonstrating weak gains may exhibit:

Unplanned Manipulation → Trial → New Manipulation → Trial → Conclusion

with comparatively little evidence comparison.

A third trajectory may contain productive failure:

Hypothesis → Test → Contradictory Evidence → Re-examination → Revised Hypothesis → Retest.

Such a trajectory is pedagogically significant because failure followed by evidence-responsive revision should not automatically be classified as poor performance. Recent process-mining research involving fifth-grade inquiry learners similarly identified revision after failure as a meaningful scientific-thinking pattern.

6.2 Educational Interpretation of the AI Model

The ESR-SM model is not intended to determine student grades autonomously.

Its more appropriate role is **formative diagnosis**.

Suppose two students receive equivalent reasoning scores. ESR-SM may reveal that Student A has difficulty maintaining experimental controls, whereas Student B performs controlled experiments successfully but struggles to connect observations with causal explanations.

A single total score would recommend generic remediation.

Process-sensitive analytics could support differentiated intervention:

Student A: additional control-of-variables tasks.

Student B: claim–evidence–reasoning activities emphasizing causal justification.

This distinction represents a major practical advantage of combining inquiry pedagogy with explainable learning analytics.

6.3 Relationship with Recent Literature

The proposed results would extend recent research in three ways.

First, scientific reasoning is represented as dynamic rather than static. This is consistent with evidence that school students move between reasoning profiles during science instruction.

Second, digital process data are treated as substantive evidence of reasoning rather than merely engagement metadata. This builds on research demonstrating the capacity of inquiry log data to reveal otherwise invisible strategies.

Third, AI is positioned as a teacher-support mechanism. A 2025 systematic review found growing use of learning analytics for understanding and supporting inquiry processes while also identifying gaps in the practical integration of analytics into IBL. Recent literature also shows movement toward AI-supported inquiry environments. Research on technology-augmented scientific inquiry has begun examining learning analytics and AI as scaffolding mechanisms, reinforcing the need to investigate not only performance but the cognitive processes occurring within digitally supported inquiry.

Future Scope

Future studies should extend the framework longitudinally and determine whether inquiry-derived reasoning profiles predict subsequent achievement in biology, chemistry, physics, mathematics, or interdisciplinary STEM tasks.

A second direction involves **multimodal learning analytics**. Digital events could be integrated with students' written explanations, classroom discourse, diagrams, and experimental reports. Natural-language processing could examine whether changes in behavioural inquiry patterns correspond with increasingly sophisticated scientific argumentation.

A third direction involves adaptive scaffolding. Instead of providing identical prompts to every learner, future systems

could detect unproductive inquiry trajectories and deliver minimal, targeted support. Importantly, such systems should provide **metacognitive prompts rather than answers**.

For example:

“Which variable changed between these two trials?”

would preserve cognitive responsibility more effectively than:

“You changed temperature and concentration, so your experiment is uncontrolled.”

Future research should also evaluate model fairness across gender, socioeconomic background, school type, language group, and prior achievement. Recent reviews of machine learning in science and STEM education specifically identify the need for broader evaluation across diverse cultural, linguistic, and institutional settings.

Conclusion

This study proposes a process-sensitive framework for investigating the relationship between **inquiry-based learning and scientific reasoning among school students**. Its central premise is that the educational value of inquiry cannot be adequately understood from final achievement scores alone. Scientific reasoning develops through sequences of prediction, experimentation, evidence evaluation, revision, and explanation.

The proposed experimental design consequently compares guided inquiry, minimally scaffolded inquiry, and structured conventional instruction while recording students' digital investigation trajectories.

The **Explainable Scientific Reasoning Sequence Model (ESR-SM)** provides the computational component of the framework. By combining sequential behavioural modelling with component-level predictions and interpretable feature attribution, it is designed to distinguish productive inquiry strategies from superficially similar but scientifically weak patterns.

The expected theoretical contribution is therefore a transition from asking “**Does inquiry-based learning improve scientific reasoning?**” toward the more informative question: “**Which inquiry processes produce scientific-reasoning development, for which learners, and under what level of instructional guidance?**”

References

1. Chen, Z., & Klahr, D. (1999). All other things being equal: Acquisition and transfer of the control of variables strategy. *Child Development*, 70(5), 1098–1120.
2. Cho, K., et al. (2014). Learning phrase representations using RNN encoder–decoder for statistical machine translation. In *Proceedings of EMNLP 2014* (pp. 1724–1734).
3. Furtak, E. M., Seidel, T., Iverson, H., & Briggs, D. C. (2012). Experimental and quasi-experimental studies of inquiry-based science teaching: A meta-analysis. *Review of Educational Research*, 82(3), 300–329.
4. Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work. *Educational Psychologist*, 41(2), 75–86.

5. Lazonder, A. W., & Harmsen, R. (2016). Meta-analysis of inquiry-based learning: Effects of guidance. *Review of Educational Research*, 86(3), 681–718.
6. McNeill, K. L., & Krajcik, J. (2011). *Supporting grade 5–8 students in constructing explanations in science: The claim, evidence, and reasoning framework for talk and writing*. Pearson.
7. Minner, D. D., Levy, A. J., & Century, J. (2010). Inquiry-based science instruction—What is it and does it matter? *Journal of Research in Science Teaching*, 47(4), 474–496.
8. National Research Council. (2012). *A framework for K–12 science education: Practices, crosscutting concepts, and core ideas*. National Academies Press.
9. Pedaste, M., et al. (2015). Phases of inquiry-based learning: Definitions and the inquiry cycle. *Educational Research Review*, 14, 47–61.
10. Teig, N. (2024). Uncovering student strategies for solving scientific inquiry tasks: Insights from student process data in PISA. *Research in Science Education*, 54, 205–224. †
11. Zimmerman, C. (2007). The development of scientific thinking skills in elementary and middle school. *Developmental Review*, 27(2), 172–223.