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From Data Skills to Critical Data Agency: An Interdisciplinary Framework for Data Science and Critical Data Literacy in Higher Education

Dr Neha Paliwal

HOD (Computer Science Department)
Shri Mahaveer College, Jaipur

Abstract: *The rapid expansion of datafication, artificial intelligence (AI), machine learning, learning analytics and generative AI has transformed the competencies expected from higher-education students. Conventional data-literacy education frequently emphasizes the ability to collect, process, visualize and analyse data, whereas contemporary digital environments also require learners to understand how data are produced, selected, interpreted and embedded within social, cultural, political and economic systems. This study develops an interdisciplinary framework for moving from conventional data skills towards* ***critical data agency*** *in higher education. The research builds on an interdisciplinary higher-education course that brought together students from computer science and media education through problem-based and project-based learning. The original educational intervention combined theoretical discussions of data, power, context and algorithms with practical work using Python, pandas, machine-learning models and publicly available datasets. A collaborative project further required students to investigate social-media data, hashtags, sentiment and geographical considerations. The present article reinterprets these source-grounded experiences through an updated conceptual framework incorporating contemporary AI-literacy and digital-education developments. A design-oriented qualitative synthesis was employed. The source case was reconstructed and thematically analysed across technical, algorithmic, contextual, ethical, collaborative and reflective dimensions. Contemporary literature and international policy frameworks were then used to extend the conceptual interpretation. The analysis identifies six interdependent capabilities: problem framing, data and computational practice, algorithmic reasoning, contextual and ethical inquiry, interdisciplinary collaboration, and communication-oriented data agency. The study proposes an integrated curriculum model, a four-level critical data literacy maturity framework and an assessment architecture for higher education. The article argues that data literacy should no longer be treated as a narrowly technical competency. Instead, students should learn to* ***interpret, question, create and act*** *with data while understanding the assumptions, power relations and consequences embedded within data-driven systems.*

Keywords: critical data literacy; data science education; higher education; artificial intelligence literacy; data ethics; algorithmic literacy; interdisciplinary learning; problem-based learning; data agency; generative AI

1. Introduction

Data have become a central component of contemporary social, educational, economic and technological systems. Digital platforms continuously generate, collect, classify and analyse information about human activities. Algorithms increasingly participate in recommendation, classification, prediction, assessment and decision-making processes. Consequently, students entering professional and civic environments require more than the ability to operate software or interpret numerical outputs.

The challenge is particularly significant in higher education. Students may learn statistical analysis, programming, visualization and machine-learning techniques while receiving comparatively less attention to the social and political conditions through which data are generated. The source study underlying this article explicitly identifies data as connected with power, emphasizes the importance of context, and highlights the fundamental relationship between data and computational systems.

Critical Data Studies provides an important conceptual foundation for addressing this problem. From this perspective, data are not neutral representations of reality. They are produced through particular technological, institutional and social arrangements. Questions concerning who collects data, why they are collected, which categories are selected, whose experiences are excluded and how algorithms transform datasets therefore become educational questions as well as technical questions.

The educational problem is intensified by the emergence of generative AI. Contemporary students increasingly interact with systems capable of generating text, code, images and analytical suggestions. UNESCO's AI Competency Framework for Students identifies 12 competencies across four dimensions—human-centred mindset, ethics of AI, AI techniques and applications, and AI system design—and organizes development into understanding, application and creation.

Similarly, the OECD Digital Education Outlook 2026 emphasizes that generative AI can support learning when guided by pedagogical objectives, but simply outsourcing

cognitive tasks to general-purpose AI may improve task performance without producing corresponding learning gains. These developments indicate a need to reconsider what data literacy should mean in higher education. The central argument of this article is that **technical data literacy and critical data literacy should not be treated as competing alternatives**. Technical competence enables students to inspect, manipulate and test data, while critical competence enables them to question the origins, assumptions, limitations and consequences of those data practices. The article therefore proposes a transition: **Data skills → Data literacy → Critical data literacy → Critical data agency** Critical data agency is understood here as the capacity to use technical and conceptual knowledge to interpret data, question data-driven systems, communicate uncertainty and participate responsibly in decisions involving data and AI.

2. Research Problem and Knowledge Gap

Existing educational approaches often separate technical and critical competencies. Programming may be taught within computer science, data ethics within humanities or social sciences, and media literacy within communication-oriented programmes. Such disciplinary separation can make it difficult for students to understand the complete data lifecycle.

The source case demonstrates the potential of interdisciplinary education to address this separation. Students from computer science and media education worked together and encountered both technical and critical dimensions of data science. The course combined theoretical discussion with hands-on programming and collaborative project work.

However, the original educational experience also identified several unresolved challenges:

1. critical data literacy is conceptually complex;
2. students have different levels of technical preparation;
3. interdisciplinary work requires flexible teaching arrangements;
4. authentic data projects can become technically demanding;
5. critical reflection must remain connected to practical data work;
6. small experimental courses are difficult to scale across institutions.

Recent AI-literacy research reinforces this problem. A 2025 review of AI-literacy frameworks found recurring emphasis on technical knowledge, ethics, social responsibility, critical thinking, collaboration and adaptability, while also identifying the need for stronger empirical validation and attention to equity.

A further review published in 2026 proposes seven dimensions of AI literacy in higher education, including technical, applicational, critical-thinking, ethical, social, integrational and legal dimensions.

Thus, a research gap remains between:

- technical data-science education,
- critical data studies,
- interdisciplinary pedagogy,
- AI literacy,
- and assessable student competencies.

This article addresses this gap by synthesizing these dimensions into an integrated higher-education framework.

3. Research Objectives

The study has four objectives:

O1. To identify the competencies required for moving from basic data literacy towards critical data agency.

O2. To analyse the pedagogical lessons emerging from an interdisciplinary data-science course.

O3. To integrate critical data literacy with contemporary AI-literacy requirements.

O4. To propose an assessment and curriculum framework suitable for higher-education institutions.

4. Research Questions

RQ1: What dimensions of competence are required to develop critical data literacy in higher education?

RQ2: What pedagogical lessons can be derived from interdisciplinary, problem-based data-science education?

RQ3: How can technical, contextual, ethical and algorithmic competencies be integrated into a single educational framework?

RQ4: How can higher education assess students' progression from data skills to critical data agency?

5. Review of Literature

5.1 Critical Data Studies and Data Literacy

Critical Data Studies challenges the assumption that data are objective or context-free. Data are created within social arrangements and subsequently interpreted through technical systems. Consequently, data literacy requires more than understanding numerical information.

The source study emphasizes three important propositions: data constitute a form of power, context becomes increasingly important with large datasets, and data and code are fundamentally connected.

This perspective is consistent with earlier critical scholarship concerning Big Data, algorithms, surveillance, data colonialism and algorithmic power.

Data literacy can therefore be conceptualized as a multidimensional competence involving:

- technical understanding;
- interpretation;
- contextual awareness;
- critical questioning;
- ethical reasoning;
- communication;
- and responsible action.

5.2 Data Science as an Interdisciplinary Field

Data science combines computational methods, statistics, domain knowledge and communication. Its interdisciplinary character makes it particularly suitable for problem-based learning.

The source course used programming not simply as an additional technical component but as a mechanism through which students could engage directly with data. Python and pandas were used to introduce data manipulation and computational thinking, while pair programming supported collaboration.

This suggests that technical skills can themselves become instruments of critical inquiry.

For example, cleaning a dataset can generate questions such as:

- Why are certain observations missing?
- Who defined the categories?
- What assumptions were used during transformation?
- Does preprocessing alter the meaning of the original data?

Thus, coding can become a form of epistemological investigation rather than merely software training.

5.3 Problem-Based Learning

Problem-based learning places problems rather than academic disciplines at the centre of learning. The source course used problem-based and project-based learning to connect data science methods with authentic questions.

Such approaches are particularly useful for data education because real-world datasets are rarely perfect. Students encounter missing observations, ambiguous categories, inconsistent structures and contextual limitations.

These imperfections become pedagogical resources.

Instead of presenting students with perfectly cleaned datasets, educators can ask students to document how the dataset was constructed and how their own decisions influence the analytical outcome.

5.4 AI Literacy and Higher Education

The emergence of generative AI makes the integration of technical and critical literacy increasingly important.

UNESCO's framework positions students not only as AI users but also as responsible participants and potential co-creators. Its competency architecture connects technical knowledge with human-centred thinking and ethics.

Recent research similarly identifies critical thinking, ethical reasoning, social responsibility and technical competence as interconnected components of AI literacy.

Therefore, contemporary data literacy should include the ability to question AI-generated outputs rather than simply produce them.

5.5 Generative AI and the Changing Meaning of Learning

The educational environment has changed substantially since the original course was conducted in 2019–2020.

Students can now obtain generated code, explanations, summaries and analytical suggestions through general-purpose AI systems. This creates both opportunities and risks.

The OECD's 2026 analysis indicates that GenAI may enhance performance on tasks without necessarily producing equivalent learning when cognitive work is outsourced. It

recommends human-centred and pedagogically purposeful uses of AI.

This reinforces the central argument of the present study: students need sufficient underlying data and computational knowledge to evaluate AI-generated outputs.

6. Research Methodology

6.1 Research Design

This study adopts a **design-oriented qualitative synthesis**.

It does not claim to be a new experimental study. Instead, it reconstructs and analytically extends the educational case presented in the supplied source material.

The methodology contains three layers:

Layer 1: Source-case reconstruction

The educational intervention was examined with attention to:

- participants;
- curriculum structure;
- learning activities;
- technologies;
- project organization;
- interdisciplinary collaboration;
- reported challenges;
- and conclusions.

The source describes a higher-education course involving students from media education and computer science, with a workload of approximately four to six hours per week.

Layer 2: Thematic analysis

The source was reorganized into six analytical dimensions:

1. technical competence;
2. algorithmic reasoning;
3. contextual understanding;
4. ethical awareness;
5. interdisciplinary collaboration;
6. reflection and agency.

Layer 3: Contemporary contextualization

The framework was compared with recent developments in AI literacy and digital education, particularly UNESCO's 2024 AI competency framework and OECD's 2026 Digital Education Outlook.

No new student-level quantitative results were invented. The numerical information reported in this article comes only from the source material. The proposed percentages in the assessment framework are recommendations for curriculum design rather than empirical findings.

7. Source Educational Case

The source course was organized into three broad components.

Stage 1: Theoretical orientation

Students examined education, data science and societal challenges. Discussions included:

- data and power;
- context and meaning;
- algorithms;
- algorithmic thinking;
- digital data practices.

Stage 2: Technical and machine-learning practice

Students learned Python and pandas and subsequently worked with basic machine-learning concepts and models. The course used publicly available datasets, including the Titanic dataset. Students experimented with Logistic Regression, K-Nearest Neighbour and Naïve Bayes.

Importantly, the technical work was accompanied by discussion of missing data, interpolation and gender-related patterns.

Stage 3: Collaborative project

Students participated in a joint project examining winter, Christmas, cultural themes and emotions expressed through social-media hashtags during December 2019 to mid-January 2020. The project explored questions involving hashtags, sentiment, geography, weather and organizational social-media activity.

This structure provides the empirical foundation for the conceptual framework proposed below.

8. Findings

8.1 Finding 1: Technical Competence and Critical Inquiry Are Complementary

The case indicates that technical learning can support critical thinking.

Students who manipulate data directly are able to see that analytical outputs depend on decisions concerning:

- variable selection;
- data cleaning;
- missing observations;
- model selection;
- visualization;
- and interpretation.

Therefore, technical skills should not be isolated from critical reflection.

Proposition 1:

Critical data literacy is strengthened when students learn technical procedures and simultaneously interrogate the assumptions behind those procedures.

8.2 Finding 2: Imperfect Data Can Become a Pedagogical Resource

Traditional teaching often gives students clean datasets. Real-world data are considerably more complex.

The source case's discussion of missing information and interpolation illustrates how data imperfections can stimulate methodological reflection.

Rather than treating imperfect data exclusively as errors, educators can use them to teach:

- provenance;
- uncertainty;
- bias;
- representation;
- methodological choice;
- and responsible interpretation.

8.3 Finding 3: Interdisciplinary Teams Distribute Expertise

The combination of computer science and media education created complementary forms of expertise.

Computer-science students could contribute computational knowledge, while media-education students could contribute perspectives concerning communication, society and interpretation.

The source therefore demonstrates that interdisciplinary collaboration can make data science less technically isolated and more socially contextualized.

8.4 Finding 4: Ethical Reflection Must Occur Throughout the Data Lifecycle

Ethics should not be confined to a final lecture.

Ethical questions emerge during:

Data collection → Data cleaning → Analysis → Modelling → Interpretation → Communication → Decision

For example, questions of privacy can emerge during collection, bias during preprocessing and fairness during model evaluation.

This finding is particularly important in the era of generative AI, where data provenance, model behaviour and generated outputs create additional ethical questions.

8.5 Finding 5: Critical Data Literacy Requires Agency

The ultimate educational objective should not be merely knowing that algorithms can be biased.

Students should be able to:

1. identify a problem;
2. inspect available evidence;
3. analyse data;
4. identify limitations;
5. question assumptions;
6. communicate uncertainty;
7. propose responsible action.

This represents a movement from **awareness to agency**.

9. Proposed Integrated Critical Data Literacy Framework

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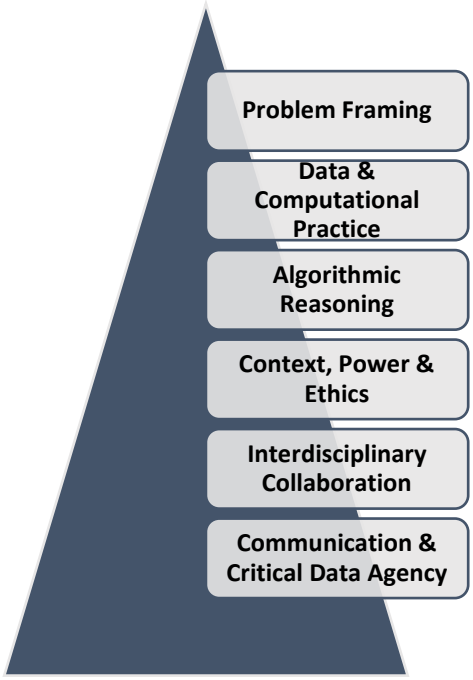


Figure 1. Integrated Critical Data Literacy Framework

The proposed framework contains six interconnected competency domains:

The six dimensions converge in the overall outcome:

CRITICAL DATA AGENCY

Interpret → Question → Create → Act

10. Competency Architecture

Table 1. Competency Architecture for Critical Data Literacy

Dimension	Core Capability	Learning Evidence	Critical Question
Problem framing	Define meaningful data problems	Problem statement	Whose problem is being defined?
Data & computation	Collect, clean, analyse and document data	Notebook/pipeline	What transformations changed the data?
Algorithmic reasoning	Understand models and limitations	Model comparison	What does the model fail to capture?
Context & power	Interpret data socially and institutionally	Context memo	Who produced and controls the data?
Ethics & governance	Identify risks and responsibilities	Ethics checklist	Who could be harmed?
Communication & agency	Communicate findings and implications	Report/presentation	What action is justified by the evidence?

11. Curriculum Pipeline

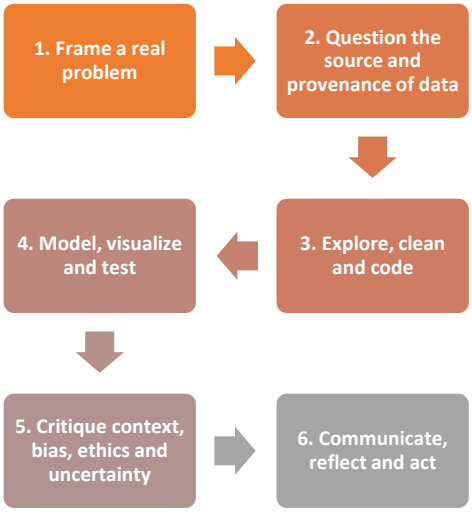


Figure 2. Six-Stage Curriculum Pipeline

Educational outcome

Technically capable + critically reflective + ethically responsible

This model extends the source course's problem-based structure while incorporating contemporary AI-literacy requirements.

12. Proposed Assessment Architecture

Assessment should evaluate both technical performance and critical reasoning.

Table 2. Proposed Assessment Model

Assessment Component	Weight
Authentic data project	30%
Data provenance and ethics portfolio	15%
Algorithm/model critique	15%
Data visualization and communication	15%
Reflective learning journal	15%
Peer/team contribution	10%
Total	**100%**

These percentages are **proposed curriculum-design values**, not validated empirical measurements.

The assessment model deliberately avoids making technical accuracy the only indicator of competence.

A student who produces an accurate model but cannot explain its assumptions, limitations or social implications should not automatically demonstrate advanced critical data literacy.

13. Critical Data Literacy Maturity Model

Table 3. Four-Level Maturity Model

Level	Capability	Evidence	Main Risk
Level 1: Foundational	Understand data, statistics and algorithms	Concept explanation	Passive consumption
Level 2: Operational	Collect, clean, analyse and visualize	Working project	Context blindness
Level 3: Critical	Question provenance, framing, bias and power	Audit/critique	Critique without technical competence
Level 4: Transformative	Use evidence for responsible action	Capstone/action proposal	Action without adequate evidence

The model is deliberately progressive rather than discipline-specific.

A computer science student may begin with strong operational competence but require further development in contextual and ethical reasoning. Conversely, a humanities or social-science student may have strong contextual understanding but require additional computational competence.

14. Discussion

The findings indicate that higher-education institutions should reconsider the conventional separation between technical data science and critical digital education.

The original course demonstrated that programming, machine learning and critical discussion can coexist within one educational environment. The source also emphasizes that the educational setting requires openness, trust, flexibility and interdisciplinary communication.

The proposed framework extends this insight in three ways.

14.1 From tools to practices

Curricula should avoid organizing learning exclusively around tools such as Python, Excel, visualization software or AI assistants.

Instead, tools should be embedded within practices:

Question → Investigate → Analyse → Critique → Communicate → Act

The tool is therefore subordinate to the intellectual problem.

14.2 From data literacy to AI-era literacy

AI systems increasingly mediate data analysis and knowledge production.

Students may use AI to generate code, explain algorithms or suggest interpretations. However, meaningful learning

requires students to retain the ability to inspect and evaluate these outputs.

UNESCO's framework similarly emphasizes critical judgement, ethical awareness and human-centred AI competence.

14.3 From individual skills to interdisciplinary capability

Complex data problems rarely belong to a single academic discipline.

A meaningful investigation may require:

- programming;
- statistics;
- domain knowledge;
- communication;
- ethics;
- policy;
- and social analysis.

Therefore, universities should create opportunities for students from different programmes to work together.

15. Implications for Higher Education

15.1 Curriculum Design

Institutions should introduce common foundational modules covering:

- data concepts;
- computational thinking;
- algorithms;
- AI fundamentals;
- data ethics;
- privacy;
- bias;
- critical evaluation;
- and communication.

Students can then specialize according to disciplinary requirements.

15.2 Faculty Development

Teachers require support to integrate technical and critical dimensions.

Faculty development should include:

- data-literacy pedagogy;
- AI literacy;
- ethical data practices;
- project-based teaching;
- interdisciplinary assessment;
- and responsible use of generative AI.

15.3 Authentic Datasets

Students should work with datasets that retain some real-world complexity.

Instead of receiving perfectly prepared datasets, they should document:

- data sources;
- missing values;
- transformations;
- assumptions;
- limitations;
- and ethical concerns.

15.4 AI-Supported Learning

Generative AI can be used as a learning partner, but assignments should require students to explain and verify AI-generated outputs.

For example, students can be asked to:

1. generate code with an AI system;
2. inspect the code;
3. execute it;
4. identify errors;
5. compare the result with an independently developed solution;
6. document what the AI system got wrong.

This converts AI from a shortcut into an object of critical investigation.

The approach is consistent with the OECD's emphasis on pedagogically purposeful AI use.

16. Proposed Research Agenda

Table 4. Future Research Directions

Research Area	Proposed Investigation
Cross-institutional validation	Test the framework across universities
Assessment validation	Develop and statistically validate critical-data-literacy scales
AI-integrated learning	Examine responsible use of GenAI in data-science courses
Equity and inclusion	Study differences in access and prior computational experience
Longitudinal learning	Track development across multiple semesters
Institutional governance	Examine university policies for data and AI literacy
Interdisciplinary education	Compare disciplinary and mixed student teams

17. Limitations

Several limitations should be acknowledged.

First, the educational case on which this study is based was relatively small and context-specific. The source describes an interdisciplinary course rather than a large-scale controlled educational intervention.

Second, the present article does not introduce new participant-level quantitative data. The findings are therefore analytical and interpretive rather than causal.

Third, the proposed maturity model and assessment architecture have not yet undergone psychometric validation.

Fourth, AI technologies and educational policies are developing rapidly. Consequently, curriculum frameworks require periodic revision.

Finally, interdisciplinary concepts such as data literacy, AI literacy, computational literacy and critical literacy overlap in complex ways. The proposed framework should therefore be regarded as a conceptual integration rather than a definitive taxonomy.

18. Future Research

Future studies should test the proposed framework through multi-institutional empirical research.

A possible research programme could involve:

Phase 1: Framework development
↓
Phase 2: Expert validation
↓
Phase 3: Pilot implementation
↓
Phase 4: Development of assessment instruments
↓
Phase 5: Multi-university implementation
↓
Phase 6: Longitudinal evaluation

Future empirical studies could investigate whether integrated technical-critical curricula improve:

- data reasoning;
- algorithmic understanding;
- ethical decision-making;
- AI evaluation skills;
- interdisciplinary collaboration;
- and students' confidence in questioning data-driven systems.

19. Conclusion

The increasing importance of data and AI has changed the meaning of digital competence in higher education. Students need to understand not only how to process data but also how data are produced, framed, interpreted and used.

The interdisciplinary course examined in the source material demonstrates the educational value of combining critical discussion with programming, machine learning and collaborative project work. The experience shows that technical data-science activities can provide opportunities for critical reflection when they are deliberately embedded within broader questions of context, power, ethics and meaning.

This article extends that insight by proposing the concept of **critical data agency**. The proposed framework connects six capabilities: problem framing, computational practice, algorithmic reasoning, contextual and ethical inquiry, interdisciplinary collaboration, and communication.

The central implication is that higher education should move beyond a narrow model of data literacy based on software proficiency.

A more appropriate educational progression is:

Understand data → Work with data → Question data → Evaluate algorithms → Communicate uncertainty → Act responsibly

The emergence of generative AI makes this transition more urgent. Students increasingly need the ability to evaluate machine-generated outputs, understand underlying data and algorithms, recognize ethical implications and retain independent judgement. Contemporary international frameworks similarly emphasize the integration of technical knowledge with human-centred, ethical and critical capabilities. (UNESCO)

Thus, critical data literacy should be positioned not as an optional addition to data science education but as a core interdisciplinary capability for higher education.

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