Conceptual Model of an Intelligent Data Ecosystem for AI and Generative AI Skill Development in Higher Education

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Abstract. Artificial intelligence education is being reshaped by the widespread availability of generative AI (GenAI). Higher education programs, especially in computing, engineering, and applied informatics, must develop not only technical AI knowledge, programming, and data-analysis skills, but also students' ability to use AI assistants deliberately, verify generated outputs, disclose AI assistance, and reflect on human-AI collaboration. This paper proposes a conceptual model of an intelligent data ecosystem for AI and GenAI skill development in higher education. The model connects competency areas, learning activities, task modes, human-AI interaction events, learner traces, indicators, and feedback mechanisms. Its key contribution is an event-oriented and indicator-oriented structure that links GenAI interaction, verification, transparency, and responsible use to observable traces, candidate indicators, and validation sources. The model also distinguishes between different roles of GenAI in learning tasks, showing that the same trace can have different meanings depending on whether AI use is prohibited, allowed, or required. An illustrative implementation scenario demonstrates how the ecosystem can be introduced incrementally in a virtual learning environment and used as a reference structure for future learning analytics and empirical validation.

Keywords: AI education; GenAI literacy; learning analytics; data ecosystem; automated assessment; higher education; virtual learning environment.

1 Introduction

Artificial intelligence (AI) has become a central component of computing, engineering, and applied informatics education. Graduates are expected not only to understand AI concepts, but also to design, implement, evaluate, and responsibly use AI-based systems in professional contexts. This requirement is reinforced by the shift toward human-centered, collaborative forms of digital work, in which technical competence must be combined with critical judgment and responsible decision-making [1], [2].

The widespread availability of generative AI (GenAI) tools has further changed the conditions under which AI-related skills are developed and assessed. Because students can use AI assistants across explanation, coding, debugging, experimentation, and critique, AI education must address not only technical knowledge but also accountable human-AI collaboration [3], [4], [5], [6], [7].

This situation creates an **evidence problem for higher education**. Final artifacts, such as programs, reports, or trained models, are no longer sufficient indicators of competence, as they may result from independent work, productive AI-supported learning, unverified AI-generated output, or inappropriate outsourcing of the task. Meaningful assessment therefore requires data structures that connect outcomes with interpretable process traces, including attempts, revisions, executions, validation actions, and reflections.

Although virtual learning environments and learning management systems already collect many digital traces, these traces often remain fragmented. Quiz attempts, programming submissions, notebook executions, feedback requests, and AI-use declarations are usually stored as separate records rather than as evidence linked to specific AI competencies. This setting limits their value for learning analytics, teacher support, and curriculum improvement, especially when GenAI use becomes part of the learning process.

This paper proposes a conceptual model of an intelligent data ecosystem for AI and GenAI skill development in higher education. The model links competency areas, learning activities, task modes, human-AI interaction events, observable learner traces, indicators, and feedback mechanisms. Its purpose is not to present a complete adaptive learning system or a predictive model, but to define a transferable structure for organizing educational data so that future learning analytics can be grounded in interpretable evidence.

The contribution of the paper is as follows:

- It defines a compact ecosystem model for representing AI and GenAI skill development as connected educational data.
- It proposes an event-oriented structure that links GenAI interaction, verification, transparency, and responsible use to observable traces, candidate indicators, and validation sources.
- It provides an illustrative implementation scenario showing how selected ecosystem elements can be introduced incrementally in a virtual learning environment that combines microlearning, automated programming assessment, notebook-based experimentation, GenAI-supported tasks, and student reflection.

2 AI Competence, GenAI Use, and Learning Analytics

Recent AI education literature treats AI competence as a multidimensional construct rather than a narrow technical skill [8], [9]. It includes conceptual understanding, data and model work, practical application, ethical awareness, and higher-order reasoning [10], [11]. This broader view is also reflected in recent competency frameworks, which connect AI knowledge and skills with human agency, safe use, values, and responsible citizenship [2], [3]. In the European context, the Artificial Intelligence Act further underscores the importance of AI literacy beyond specialist AI development, as providers and deployers of AI systems are expected to ensure users have an appropriate level of AI-related understanding [12], [5].

Generative AI extends this competence model. Students need to understand not only AI concepts and model behavior, but also the conditions under which AI assistants can be used productively and responsibly. This need includes formulating prompts, providing relevant context, recognizing hallucinations or bias, verifying generated text or code, and disclosing AI assistance when required. Guidance on GenAI in education emphasizes a human-centered approach, privacy protection, pedagogically appropriate integration, and institutional validation of tools [4], [13]. Related European guidance for research and higher education similarly emphasizes reliability, honesty, accountability, and transparent disclosure [6].

For higher education, GenAI should therefore be treated not only as a tool used during learning, but also as a competence area that intersects with technical skills, critical evaluation, ethics, and academic integrity. GenAI tools are particularly influential in programming, data science, and AI-related courses, where students work with code, data, experiments, and iterative problem solving. Large language models can generate code fragments, explain compiler or runtime errors, suggest tests, create examples, and support debugging [14], [15], [16].

In these domains, prompting is not only a communication skill but part of practical problem formulation. Students need to describe the task, specify constraints, provide relevant context, request explanations or tests, and compare alternative outputs. The educational issue is therefore not merely whether students use GenAI, but whether they can formulate tasks, evaluate outputs, revise suggestions, and justify the role of AI assistance in the learning process [17].

However, the same tools can also undermine learning when students accept generated outputs without understanding, testing, or revising them. This issue makes verification, human revision, and transparent declaration central evidence dimensions in GenAI-supported programming, data science, and AI learning tasks [18], [19].

Learning analytics and educational data mining provide methods for interpreting digital traces of learning activity [20], [21], including progress, difficulty, engagement [22], and possible support needs [23]. In AI education, such traces cannot be limited to correctness and final scores. They also need to capture experimentation, debugging, validation, reflection, and collaboration. GenAI further extends this evidence space by adding prompt iterations, AI-generated suggestions, human edits, output verification, source checking, and responsible-use declarations.

The central challenge is interpretability. A log entry is not, by itself, educational evidence. It becomes meaningful only when it is linked to the learning activity, the competency context, the task rules, and the sequence of learner actions. For example, repeated code submissions may indicate guessing, persistent difficulty, or productive debugging depending on timing, error patterns, and test results. Similarly, multiple prompts may reflect confusion, iterative refinement, or purposeful exploration depending on prompt quality, generated outputs, and subsequent validation steps.

Together, these strands of research show that AI competence, GenAI-supported learning, and learning analytics are closely connected, but they are often discussed separately. AI competence frameworks define what should be developed; GenAI education research discusses human-AI interaction; and learning analytics provides methods for analyzing digital traces. Less attention has been paid to a compact data ecosystem that connects these elements into a unified structure for AI and GenAI skill development. This situation motivates the proposed model.

3 Data Ecosystem for AI and GenAI Skill Development

The proposed approach treats AI and GenAI skill development as an ecosystem of connected educational data. The unit of analysis is not a single grade or final submission, but a structured collection of traces produced while learners interact with content, code, data, models, peers, teachers, and AI assistants. This approach is especially relevant for GenAI-supported learning and rests on four assumptions:

- AI and GenAI competencies are multidimensional and cannot be evaluated only through traditional tests or final artifacts.
- Learning activities should produce interpretable traces that can be linked to competencies and task contexts.
- GenAI use should be treated as a learning process that can be reflected on, documented, and verified, rather than just a risk to be detected.
- Data collection should be proportionate, transparent, and privacy-aware, especially when prompts, outputs, or student reflections may contain sensitive information.

The data ecosystem must therefore support two complementary views:

- competence-oriented: what evidence indicates that a student understands AI concepts, can build or evaluate a model, or can reason about limitations and ethical implications?
- process-oriented: how did the student arrive at the solution, what role did GenAI play, and how were generated outputs checked, modified, or rejected?

Both views are needed to support AI-ready graduates while preserving meaningful assessment rules.

A compact implementation does not require collecting every possible learner event. Instead, it should define a transferable data structure that can be instantiated across different learning scenarios and educational platforms. The initial objective is therefore not exhaustive data collection, but a stable and interpretable structure for capturing educationally meaningful traces. After pilot validation, this core model can be extended with teacher dashboards, recommendation mechanisms, or more advanced learning analytics models.

In a GenAI-enabled ecosystem, tasks must also be distinguished by the permitted role of AI assistance. Some activities may prohibit GenAI use to protect independent understanding, others may allow it for explanation or debugging, and professional simulations may require it as part of an authentic workflow (Table 1). These task modes are essential because the same trace, such as a correct answer or a code submission, has a different meaning depending on whether GenAI use was prohibited, allowed, or required.

Table 1. GenAI task modes and corresponding data rules.

Task mode	Role of GenAI	Data rule and assessment focus
Unaided competence task	GenAI use is not allowed or is limited to accessibility support.	Collect standard learning traces; assess independent understanding and performance.
GenAI-supported learning task	GenAI may be used for explanation, debugging, brainstorming, or examples.	Collect AI-use purpose, prompt summaries, and verification evidence; assess productive use and learning process.
Human-AI collaboration task	GenAI use is required as part of the activity design.	Assess prompt quality, iteration, comparison of alternatives, human revision, and final justification.
Responsible-AI reflection task	GenAI output or an AI-related scenario becomes an object of critique.	Assess identification of bias, hallucination, privacy risks, transparency, and limitations.
Summative restricted task	GenAI rules depend on the intended learning outcome.	Store the task policy and student declaration; interpret traces only against explicit assessment rules.

This distinction also supports academic integrity. The ecosystem does not need to rely primarily on AI-generated text detectors, whose reliability and fairness remain contested. Instead, it interprets AI use against explicit task rules and links allowed assistance to verification evidence and human revision.

The proposed ecosystem is organized into six layers: competency, learning activity, human-AI interaction, data trace, evidence and indicator, and feedback. Its key extension is the human-AI interaction layer (Table 2), which captures GenAI use during the learning process and links it to verification, transparency, and responsible-use evidence.

Table 2. Conceptual layers of the proposed AI and GenAI data ecosystem.

Layer	Purpose	GenAI-specific extension
Competency layer	Defines what should be developed and monitored.	Includes GenAI interaction, verification, disclosure, and responsible AI use.
Learning activity layer	Defines where evidence can be produced.	Includes GenAI-supported programming, notebook, writing, reflection, and project tasks.
Human-AI interaction layer	Represents how learners use AI assistants during tasks.	Captures prompts, revisions, outputs, human edits, validation actions, and AI-use declarations.
Data trace layer	Stores observable learner and system events.	Stores metadata-rich events; sensitive prompts may be summarized, hashed, or stored only with consent.
Evidence and indicator layer	Transforms traces into interpretable learning evidence.	Uses indicators such as prompt refinement, output verification, source checking, and correction quality.
Feedback layer	Provides information for teachers, learners, and curriculum designers.	Supports guidance on productive GenAI use, not only academic-integrity warnings.

The minimal data-object structure of the proposed ecosystem is centered on the learning activity. Each activity is contextualized by the learner, course, and competency tags and may generate repeated attempts, executions, GenAI interactions, validation events, submissions, assessment results, reflections, feedback events, and artifact references. This structure keeps the model process-oriented while allowing GenAI interaction to be represented through structured metadata rather than full prompt-output logs.

An event-oriented structure represents heterogeneous learning activities in a common format. Each event should include a timestamp, learner identifier, activity identifier, event type, competency tags, result status, artifact reference, and contextual metadata (Table 3).

For GenAI-related events, metadata may describe the purpose of AI use, the tool category, the prompt type, the output type, the student action after the output, and the validation method. This allows the ecosystem to connect GenAI use with learning evidence rather than treating it as external noise.

Table 3. Minimal event types for a GenAI-aware educational data ecosystem.

Event type	Generated by	Potential indicator
answer_submission	Microlearning or quiz task.	Concept mastery, repeated misconceptions, and readiness for applied activity.
code_submission	Automated programming assignment.	Implementation success, debugging progress, and error persistence.
notebook_cell_run	Notebook-style AI or data task.	Experimentation sequence, parameter exploration, model workflow.
model_evaluation	Model-building task.	Evaluation awareness, metric interpretation, validation, and data use.
GenAI_prompt_event	AI assistant interaction.	Prompt specificity, task decomposition, context quality.
GenAI_output_use	Use of generated text, code, explanation, or design.	Type of AI support, reliance level, and human editing behavior.
validation_event	Testing, source checking, code execution, metric comparison, or teacher review.	Verification behavior, hallucination detection, and correction quality.
AI_use_declaration	Student declaration or platform-supported disclosure.	Transparency, responsible use, and alignment with task rules.
reflection_submission	Ethics or higher-order thinking task.	Critical reflection, reasoning about limitations, fairness, privacy, and accountability.

The ecosystem should distinguish between GenAI use and responsible GenAI use. The aim is not to penalize every AI interaction, but to identify whether AI assistance supports learning. These indicators should not be interpreted mechanically. Many prompt revisions, for example, may indicate either confusion or productive refinement. Similarly, a high level of AI assistance may be appropriate in a human-AI collaboration task but inappropriate in an unaided competence task. Each indicator must therefore be interpreted in relation to task mode, competency tags, and teacher expectations.

To make this interpretation transferable, the event structure must be complemented by an operationalization layer. Table 4 illustrates how selected GenAI-related constructs can be connected to observable evidence, candidate indicators, and validation sources. This layer is not intended to standardize one universal scoring procedure, but to clarify what should be captured automatically, what should be declared or submitted by students, and what should be interpreted through instructor-defined rubrics.

Table 4. Examples of GenAI-related indicator operationalization and validation sources.

Construct	Observable evidence	Example indicator	Validation source
Prompt formulation	GenAI_prompt_event	prompt specificity, contextualization, task decomposition	instructor rubric, prompt-quality checklist
Verification behavior	validation_event	proportion of AI outputs tested, source-checked, or compared with task constraints	test results, code execution logs, instructor judgment
Human revision	GenAI_output_use and artifact revision	extent and quality of student modification after AI output	artifact comparison, teacher assessment
Transparent disclosure	AI_use_declaration	completeness and consistency of AI-use declaration with task mode	task policy alignment, declaration rubric
Critical and ethical reflection	reflection_submission	identification of limitations, bias, privacy risks, hallucination, or accountability issues	reflection rubric, qualitative teacher assessment

These indicators should be treated as candidate evidence. Their validity depends on triangulation with learning outcomes, instructor judgments, student feedback, and rubric-based assessment of selected artifacts or reflections. This approach is particularly important for higher-order constructs such as ethical awareness, critical reasoning, and responsible AI use, where metadata can identify relevant learning events but cannot replace qualitative interpretation.

Together, the task-mode structure, event schema, and operationalization layer define the operational core of the ecosystem and prepare its implementation in a virtual learning environment.

4 Illustrative Implementation Scenario

The proposed ecosystem can be instantiated in a virtual learning environment that supports microlearning, automated programming assessment, notebook-style AI experimentation, GenAI-supported tasks, and educational data collection. A Priscilla-like environment provides a suitable example because it already combines programming education, microlearning, automated assessment, and Jupyter-like AI learning activities [24], [25]. The scenario illustrates incremental implementation rather than a complete platform redesign.

1. In the first stage, the environment can collect traditional learning traces, such as microlearning answers, attempts, time indicators, programming submissions, test results, runtime errors, notebook cell executions, model metrics, and feedback requests. These traces support baseline indicators of conceptual stability, debugging progress, experimentation breadth, and evaluation awareness.
2. In the second stage, GenAI-supported activities can be added. A task may explicitly allow students to use GenAI for explanation, brainstorming, code generation,

debugging, critique, or model interpretation. Instead of treating this use as hidden or uncontrolled, the environment can require a lightweight AI-use record. This record may include the purpose of assistance, prompt category or summary, type of generated output, student modifications, verification steps, and final reflection.

Depending on platform capacity, evidence in this second stage can be collected through three implementation modes:

- In an integrated logging mode, selected events are captured automatically when the AI assistant is embedded in the learning environment.
- In a structured self-reporting mode, students document AI use, verification steps, and reflections when using external GenAI tools.
- In a hybrid mode, minimal metadata are combined with selected verification evidence, such as tests, source checks, code executions, or submitted reflections (Fig. 1).

Across these modes, the same operationalization logic should guide what is captured automatically, what is provided through student declaration, and what is assessed through rubric-based interpretation.

The scenario also shows how one activity can combine outcome traces, process traces, GenAI interaction records, and validation evidence according to the assigned task mode. This avoids treating all traces as equally relevant and preserves the interpretive link between the competency, the activity context, and the permitted role of AI assistance.

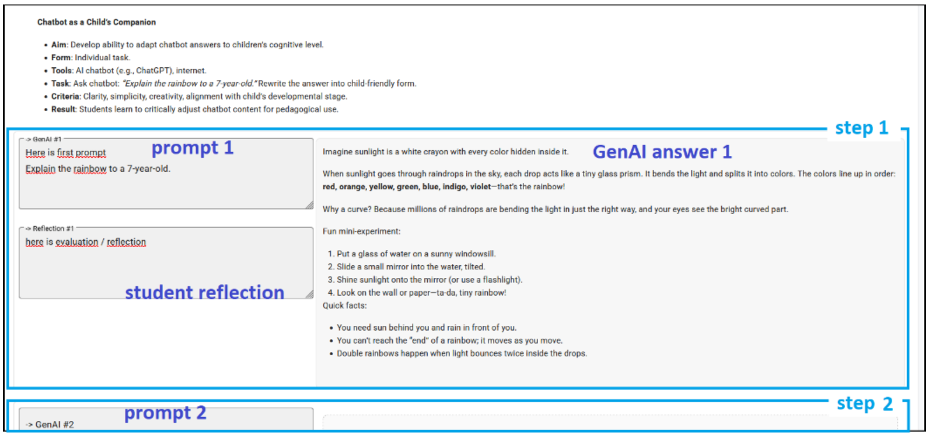

Fig. 1. Example of a Priscilla [25] GenAI-supported task in which students submit prompts, inspect chatbot answers, and record reflections across iterative steps.

The implementation should remain privacy-aware and proportionate. Full prompt and output logging is not required in every activity. In many cases, structured metadata, prompt summaries, declared AI-use purpose, verification actions, and student reflections are sufficient. Full logging should be reserved for activities that are pedagogically justified, transparent to students, and aligned with institutional rules. This design allows the ecosystem to support learning analytics and teacher feedback without disproportionate monitoring.

5 Discussion and Conclusion

The proposed model contributes a compact structure for organizing educational data in AI-focused higher education. Its main contribution is the connection of curriculum goals, task-mode rules, learner traces, GenAI interaction records, candidate indicators, and validation sources into a single interpretable structure. The model therefore supports a constructive interpretation of GenAI use: AI assistance is not treated only as an integrity risk, but as a learning process that can be documented, verified, reflected on, and interpreted against explicit assessment rules [3], [16], [19].

The model has several limitations:

- The model is conceptual and requires empirical validation in authentic courses. Pilot studies should examine whether indicators such as prompt refinement, output verification, human revision, transparency quality, and reflection depth correspond with learning outcomes, instructor judgments, student feedback, and rubric-based assessment of selected artifacts. Validation should also test whether the indicators remain interpretable across different task modes, course types, and platform configurations.
- GenAI traces are sensitive. Prompts and outputs may contain personal data, copyrighted content, confidential project information, or student misconceptions; therefore, data minimization and transparency are essential.
- Ethical awareness and higher-order thinking cannot be reduced to clickstream metrics. Metadata can identify relevant events, but the quality of reasoning, verification, disclosure, and ethical reflection requires rubrics, qualitative assessment, peer discussion, and instructor interpretation.
- The model does not address academic integrity on its own. It provides a structure for transparent GenAI-supported learning, but assessment design must still define when AI use is allowed, limited, or prohibited.

A further limitation concerns transferability. Institutions differ in their curriculum structures, platform maturity, policy environments, and teacher readiness. The model should therefore be treated as a reference architecture rather than a recommended implementation. A robotics program may add hardware and sensor events, a data-science program may expand notebook and dataset-processing traces, and a responsible-AI program may add more reflection and case-analysis data. The common requirement is that each trace be linked to a competency, an activity context, and an interpretive purpose.

The paper proposed a conceptual model of an intelligent data ecosystem for AI and GenAI skill development in higher education. The model connects competencies, learning activities, human-AI interaction events, data traces, indicators, and feedback mechanisms, with GenAI interaction, verification, transparency, and responsible use treated as observable parts of the learning process. The Priscilla-based scenario illustrates how the model can be introduced incrementally through microlearning, automated programming assessment, notebook-based AI tasks, GenAI-supported activities, and reflection. Future work will focus on pilot implementation, indicator validation, dashboard design, and the empirical evaluation of the model in authentic learning settings.

Acknowledgments

This work was supported by the *Science Grant Agency of the Ministry of Education of the Slovak Republic* under Grant 1/0667/25, by the *Nitra Cybersecurity Competence Center* under project No. 17R05-04-V01-00003, funded by *the Recovery and Resilience Plan of the Slovak Republic*, within the call 17R05-04-V01 – *Establishment of Cybersecurity Competence Centers*, and by the *European Commission under the ERASMUS+ Programme, KA220* under Grant 2024-1-SK01-KA220-HED-000249044.

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