CHAPTER 1

AI-DRIVEN PSEUDO-LEARNING IN HIGHER EDUCATION: DETECTION, PREVENTION AND DEVELOPMENT OF DIGITAL RESILIENCE IN DATA-DRIVEN LEARNING ENVIRONMENTS

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INTRODUCTION

The rapid integration of generative artificial intelligence (GenAI) into the higher education landscape has marked the beginning of a new era, where the accessibility of knowledge is no longer a limiting factor. However, alongside undeniable positive aspects – such as personalized learning, automation of routine tasks, and the ability to instantaneously process vast datasets – a sharp systemic contradiction arises. Artificial intelligence, intended to serve as a «cognitive enhancer», is increasingly being transformed into a tool for the imitation of intellectual activity, giving rise to the phenomenon of AI-driven pseudo-learning.

A key problem of the modern digital transformation in education is the formation of an «illusion of knowledge». By delegating complex analytical and creative tasks to algorithms, students achieve flawless results without undergoing the necessary cognitive journey. As noted by Gimpel, Hall, and Decker[1], this creates an effect of «cognitive passivity», where the speed of obtaining an answer replaces the depth of understanding. In data-driven environments, education faces the risk of «human exclusion» from the process of critical thinking, leading to total AI-dependency and the loss of academic authenticity.

The problem of learning imitation in the context of digitalization is within the focus of many domestic and foreign scholars. Specifically, the issues of information hygiene and the gap between self-assessed skills and the actual state of digital tool proficiency have been investigated by Yu. Rudenko,

[1] Gimpel H., Hall K., Decker S. Uncovering the Illusion of Knowledge: A Study on AI-assisted Pseudo-learning. *Computers and Education: Artificial Intelligence*. 2024. Vol. 6. P. 100198. DOI: 10.1016/j.caeai.2024.100198

M. Drushliak, and O. Semenikhina[2]. Questions of digital resilience and the adaptation of educational systems to AI challenges have been analyzed by N. Morze and L. Varchenko-Trotsenko, as well as S. Seufert, J. Guggemos, and M. Sailer. The ethics and systemic risks of using LLM models in education are examined in the works of E. Kasneci and O. Zawacki-Richter. Furthermore, the «black box» problem and the necessity of Explainable AI (XAI) to prevent pseudo-knowledge are emphasized by German researchers H. Fischer, C.Helbig, and H. Kilian.

The aim of this research is to develop a methodological model for detecting and overcoming pseudo-learning in intelligent educational environments by fostering the digital resilience of users and implementing learning analytics tools.

This work attempts to answer the fundamental question: *«Will education work at all in the AI era?»* by proposing a transition from passive adaptation to the active design of resilient

1. Phenomenology of AI-driven Pseudo-Learning

The modern paradigm of digital education is rooted in the idea of maximizing ease of access to information. However, as R. Luckin[3] argues, this very ease becomes a primary cognitive barrier, giving rise to the «pseudo-learning trap». At the core of this phenomenon lies a specific psychological effect: receiving a structured, grammatically correct, and logically sound response from Generative AI instantaneously creates a false sense of competence in the student–a phenomenon known as the illusion of explanatory depth.

According to H. Gimpel, K. Hall, and S. Decker[4], a user who receives a ready-made intellectual product without the preliminary stage of data searching and filtering subconsciously attributes the algorithm's cognitive efforts to themselves. This leads to a distorted self-assessment of skills, which records a significant gap between the subjective confidence of youth in their information literacy and their actual proficiency.

In the context of AI-driven environments, a fundamental gap widens between two types of knowledge:

[2] Rudenko Y. et al. Development of Youth Information Hygiene Skills: The Gap Between the Self-Assessment and Real State. *E-Learning and Enhancing Soft Skills*. Springer, Cham, 2025. P. 89–104. DOI: 10.1007/978-3-031-82243-8_5

[3] Luckin R. Towards AI-augmented Human Intelligence: Beyond the Pseudo-Learning Trap. *International Journal of Artificial Intelligence in Education*. 2024. Vol. 34. P. 12–25. DOI: 10.1007/s40593-023-00382-x

[4] Gimpel H., Hall K., Decker S. Uncovering the Illusion of Knowledge: A Study on AI-assisted Pseudo-learning. *Computers and Education: Artificial Intelligence*. 2024. Vol. 6. P. 100198. DOI: 10.1016/j.caeai.2024.100198

- Declarative knowledge («knowing what») – facts, concepts, and definitions that AI generates instantly.
- Procedural understanding («knowing how») – the ability to apply information, analyze connections, and synthesize new meanings, which must emerge directly within the learner.

The crux of the problem is that procedural understanding is impossible without effortful processing. As J. Richter and K. Scheiter[5] point out, the cognitive durability of knowledge is directly proportional to the energy expended on its acquisition. When a student delegates the «thinking» stage to artificial intelligence, they bypass critical phases of encoding information into long-term memory.

In this context, pseudo-learning is defined as the process of absorbing or transmitting AI-generated outputs where the formal presence of an answer is not accompanied by an internal cognitive transformation of the subject.

The absence of effort leads to several negative consequences:

- The «Fluid Knowledge» effect: Information that has not been critically processed is subject to immediate passive forgetting.
- Cognitive Passivity: The development of a habit of relying on external intellectual resources, which reduces neuroplasticity and the capacity for concentration.
- Inability to Transfer Knowledge: A student may successfully pass an AI-generated test but find themselves entirely incapable of applying this «knowledge» in non-standard situations or practical cases where an algorithmic answer is unavailable.

Thus, the accessibility of GenAI transforms learning from an active process of knowledge construction into a passive process of content consumption. As emphasized by S. Seufert et al.[6] without the purposeful development of digital resilience, education risks turning into a mechanical manipulation of symbols devoid of real intellectual experience.

The transformation of artificial intelligence from a supporting tool into an indispensable element of intellectual labor has led to a phenomenon researchers describe as an «external cognitive prosthesis». As M. Bearman and R. Ajjawi[7]

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5 Richter J., Scheiter K. Pseudo-learning vs. Deep Learning: Detecting Cognitive Passivity in AI-supported Environments. *Educational Psychology Review*. 2025. Vol. 37, No. 1. P. 56–78. DOI: 10.1007/s10648-024-09881-4

6 Seufert S., Guggemos J., Sailer M. Digital Resilience in Higher Education: Navigating the Risks of AI-Dependency. *European* Journal *of Education*. 2024. Vol. 59, No. 2. P. 201–219. DOI: 10.1111/ejed.12644

7 Bearman M., Ajjawi R. Learning to work with the black box: Pedagogy for a world with artificial intelligence. *British Journal of Educational Technology*. 2023. Vol. 54, No. 5. P. 1160–1173. DOI: 10.1111/bjet.13337

argue, the problem lies not in the technology itself, but in the gradual delegation of core thinking functions to algorithms, leading to systemic AI-dependency. In this context, «cognitive prosthetics» becomes a risk because, instead of expanding human capabilities, it causes the atrophy of natural analytical skills.

One of the most critical systemic risks is the development of automation bias. This is a cognitive bias where an individual tends to trust AI decisions or assertions implicitly, ignoring their own judgment or contradictory facts. According to S. Becker[8], in the educational process, this manifests as students' refusal to verify generated content; they perceive a grammatically perfect AI response as a priori true. Such intellectual submissiveness blocks the development of fact-checking skills, which form the foundation of information hygiene, as discussed by B. Stamov and S. Handschuh[9].

The systemic delegation of cognitive tasks to AI triggers the degradation of the following fundamental skills:

– Information Synthesis: The ability to independently assemble disparate data into a coherent logical structure. When AI automatically generates conclusions, the student loses the ability to see interconnections between complex phenomena.

– Argumentation and Reflection: The capacity to construct and defend one's own position. As noted by E. R. Mollick and L. Mollick[10], using AI as a «thought generator» deprives the individual of the need for internal dialogue and the search for counterarguments, which are critical for academic discussion.

– Critical Source Evaluation: In environments where AI synthesizes answers without clear attribution (or with hallucinated references), the user loses the habit of consulting primary sources.

Research by Yu. Rudenko and colleagues[11] emphasizes that the formation of cybersecurity and information hygiene skills directly depends on the capacity for critical analysis of the digital environment. However, AI-dependency creates an effect of «intellectual laziness», where the complexity of a task is perceived as an undesirable barrier rather than an opportunity for development.

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[8] Becker S. Künstliche Intelligenz in der Hochschullehre: Zwischen Effizienzsteigerung und dem Risiko des Kompetenzverlusts. *Zeitschrift für Hochschulentwicklung*. 2024. Jg. 19, Nr. 1. S. 21–39. DOI: 10.3217/zfhe-19-01/02

[9] Stamov B., Handschuh S. Information Hygiene and AI: Detecting Synthetic Content in Student Submissions. *Communications in Computer and Information Science*. 2023. Vol. 1876. S. 312–326. DOI: 10.1007/978-3-031-43401-3_22

[10] Mollick E. R., Mollick L. Assigning AI: Seven Approaches for Students, with a Focus on Critical Thinking. *SSRN Electronic Journal*. 2023. P. 1–45. DOI: 10.2139/ssrn.4475995

[11] Rudenko Y. et al. Development of Youth Information Hygiene Skills: The Gap Between the Self-Assessment and Real State. *E-Learning and Enhancing Soft Skills*. Springer, Cham, 2025. P. 89–104. DOI: 10.1007/978-3-031-82243-8_5

In summary, digital delegation creates an illusion of efficiency, behind which lies the progressive atrophy of analytical abilities. While traditional education was built on overcoming intellectual resistance, AI-driven education–oriented toward minimizing effort–risks raising a generation of users capable of operating tools but unable to understand the logic of their work or the consequences of the results obtained. As N. Pinkwart[12] warns, without conscious resistance to this trend, human agency in decision-making may be permanently replaced by algorithmic conclusions.

Pseudo-learning becomes a systemic effect characterized by cognitive passivity and the imitation of activity within the «Student – AI – Instructor» triangle. In this context, pseudo-learning ceases to be merely an individual student's problem, taking on the signs of institutional degradation. As M. Bearman and R. Ajjawi[13] observe, we are witnessing the formation of an «educational theater», where technologies are used not to deepen understanding but to maintain the formal procedures of the academic process.

A central element of this section is the analysis of the diffusion of responsibility within the «Student – AI – Instructor» triangle:

1. The Student (Input-imitation): Uses generative models to quickly create essays, solve problems, or write code. The goal is not to master a competency but to close a formal knowledge deficit (deadline) with minimal time expenditure.
2. Artificial Intelligence (Mediator): Acts as a neutral content generator that optimizes the student's request, creating a product that externally meets academic standards but lacks intellectual subjectivity.
3. The Instructor (Output-imitation): Under excessive workload, increasingly delegates the verification and grading of work to automated systems (AI detectors, plagiarism checkers, or LLM models for peer review).

This creates a «circle of zero learning»: an algorithm writes a paper for an algorithm that grades it, while the human capital of both parties remains disengaged. This phenomenon is described by Y. K. Dwivedi et al.[14] as a crisis of academic authenticity, where the value of learning as a process is negated by the speed of obtaining a result.

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[12] Pinkwart N. Künstliche Intelligenz und Bildung: Von der algorithmischen Analyse zur Förderung menschlicher Urteilskraft. *Informatik Spektrum*. 2024. Bd. 47. S. 88–96. DOI: 10.1007/s00287-024-01532-w

[13] Bearman M., Ajjawi R. Learning to work with the black box: Pedagogy for a world with artificial intelligence. *British Journal of Educational Technology*. 2023. Vol. 54, No. 5. P. 1160–1173. DOI: 10.1111/bjet.13337

[14] Dwivedi Y. K. et al. «So what if AI wrote it?» The character, challenges, and opportunities of generative AI. *International Journal of Information Management*. 2023. Vol. 71. P. 102642. DOI: 10.1016/j.ijinfomgt.2023.102642

Within this methodology, the term «empty learning» is proposed, characterized by:

- Formalism of Metrics: High grades and successful course completion despite the student's actual inability to replicate the logic of a solution without network access.
- Syntactic Literacy vs. Semantic Emptiness: Assignments look professional but contain no unique authorial insights or critical reflection.
- Loss of Agency: The student stops being the «author» of their knowledge, becoming merely a «prompt-operator», which contradicts the classical goal of higher education.

The systemic effect of such an approach is devastating: real human capital development trends toward zero despite positive success statistics. As O. Zawacki-Richter[15] notes, if the educational system does not shift its focus from «outcome verification» to «process monitoring», it risks turning into a mechanism for issuing diplomas without corresponding competencies.

In light of this, there is a necessity to implement Learning Analytics, as mentioned by Yu. Rudenko and colleagues[16], not merely for performance tracking but for detecting anomalies in user behavior that indicate imitative activity. Only by dismantling this «imitation triangle» is a return to authentic learning in data-driven environments possible.

To complete the analysis of the first chapter, it is necessary to consider how leading European educational systems are adapting to AI challenges. The German-speaking scientific community (DACH: Germany, Austria, Switzerland) is currently among the most reflective on this issue, emphasizing ethics and the preservation of human agency.

2. International and Domestic Experience in Countering Pseudo-Learning: Strategies for Digital Adaptation and Resilience

Modern higher education is in a state of global search for a balance between technological efficiency and the preservation of the cognitive autonomy of the learner. An analysis of the experiences of European countries and Ukraine allows for the identification of key vectors in the transformation of educational systems in response to the challenges of AI-driven imitation.

European Experience: Ethics and «Digitaler Humanismus» Leading European educational systems (notably Germany, Switzerland, and the United

[15] Zawacki-Richter O., Marín V. I., Bond M. Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education*. 2020. Vol. 16, No. 39. P. 1–27. DOI: 10.1186/s41239-019-0171-0

[16] Rudenko Y. et al. Development of Youth Information Hygiene Skills: The Gap Between the Self-Assessment and Real State. *E-Learning and Enhancing Soft Skills*. Springer, Cham, 2025. P. 89–104. DOI: 10.1007/978-3-031-82243-8_5

Kingdom) demonstrate a transition from attempts to ban AI to the development of comprehensive «AI competence» frameworks (KI-Kompetenz).

- In the German-Swiss model, emphasis is placed on «productive failure» (S. Seufert, S. Becker), where tasks are designed such that AI provides only superficial answers, forcing the student to engage in a critical confrontation with the algorithm[17] .
- The British model (R. Luckin) focuses on the transparency of the «cognitive path», requiring students to demonstrate their query history and reflect on every step of their interaction with AI, making the learning process visible and resilient to imitation.
- The Ukrainian model for forming digital resilience is unique, as it is built under conditions of extreme digitalization and constant information threats. Research by Yu. Rudenko, M. Drushliak, O. Semenikhina, and other domestic scholars emphasizes that in Ukraine, digital resilience is viewed not merely as an academic skill but as the foundation of information hygiene.
- A distinctive feature of the Ukrainian approach is bridging the gap between students' high self-assessment of digital skills and their actual vulnerability to the «illusion of knowledge».
- The use of mathematical modeling methods (e.g., the Saaty method) for choosing learning strategies allows Ukrainian researchers to create precise tools for detecting anomalies in user behavior.

Synthesis of Approaches and Conclusion on the Necessity of the Model A comparative analysis of global and domestic practices suggests that despite a high level of theoretical understanding of the problem, education still lacks an integrated toolkit that allows for the objective measurement and prompt correction of the level of pseudo-learning in real-time.

The justified necessity for developing an original methodological model (DRI and PLR) arises from the following factors:

1. Subjectivity of Existing Metrics: Most modern approaches rely on student self-reports or manual instructor verification, which is inefficient in the context of mass education. An automated tool based on Learning Analytics is required.
2. The Need for Prevention: Traditional methods (plagiarism detection) only identify the result of imitation. Our model aims to detect the *process* of AI-dependency formation at the early stage of the «illusion of knowledge».
3. Resilience as a Target Indicator: Defining the Digital Resilience Index (DRI) will allow for a shift in focus from controlling the student to developing their internal mechanisms of protection against cognitive degradation.

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[17] Seufert S., Guggemos J., Sailer M. Digital Resilience in Higher Education: Navigating the Risks of AI-Dependency. *European Journal of Education*. 2024. Vol. 59, No. 2. P. 201–219. DOI: 10.1111/ejed.12644

Thus, the development of a methodological model for detecting and overcoming pseudo-learning is a critically necessary step to ensure the viability of higher education in the age of artificial intelligence. It is not merely a control tool but a strategic architecture for preserving human capital within intelligent educational environments.

3. Methodological Architecture for the Detection and Prevention of Pseudo-Learning

The transition from a conceptual analysis of AI-related risks to the practical management of the educational process requires a clear parameterization of the core research variables. Building upon the risks of cognitive degradation and imitative learning identified in Chapter 1, this section proposes an instrumental model designed to translate these threats into the domain of measurable risks and counter-strategies.

According to our methodology, evaluating the effectiveness of learning in AI-driven environments is based on monitoring two integral indicators: the cognitive passivity threat indicator, Pseudo-Learning Risk (PLR), and the indicator of a subject's capacity for critical resistance and adaptation – the Digital Resilience Index (DRI).

Pseudo-Learning Risk is defined as the probability that a student achieves a formal learning outcome (a completed task) without a corresponding cognitive transformation. Unlike static plagiarism detection methods, PLR is a dynamic metric based on the analysis of the «digital footprint» (learning analytics).

The key parameters for calculating PLR are:

1. Temporal Anomaly (T): The ratio of the time spent by the student on the task t_{fact} to the normative time t_{norm} required for a human to independently process such an amount of information. An anomalous reduction in time $T \to 0$ serves as the primary marker of uncritical delegation of functions to AI.
2. Structural Monotonicity (S): An indicator of the monotonicity of modifications. In authentic learning, the text creation graph is iterative (pauses, deletions, rephrasing). In pseudo-learning, «block insertion» (copy-pasting) is observed, recorded as low structural variability.
3. Semantic Consistency Gap (C): The discrepancy between the semantic complexity of the output and the student's prior cognitive profile.

Mathematically, the risk of pseudo-learning can be represented as a function:

$$PLR = f(T, S, C)$$

where a high PLR value indicates the imitation of activity and the formation of the «illusion of knowledge» as described by H. Gimpel[18].

The Digital Resilience Index (DRI) serves as an indicator of student agency. It measures the level of «critical engagement» and the information hygiene of the user. To objectify the DRI, we distinguish three levels of resilience:

- Reactive (Basic): The ability to identify obvious errors and AI «hallucinations».
- Proactive (Technological): Proficiency in prompt engineering for data verification and structuring one's own ideas rather than replacing them.
- Transformational (Cognitive): The ability to synthesize new knowledge based on a critical evaluation of algorithmic recommendations.

DRI parameters include:

- Verification Rate (V): The number of external links and sources cited by the student to verify AI claims.
- Argumentation Depth (A): The proportion of original text containing critical analysis or refutation of AI proposals.
- Methodological Awareness (M): The ability to justify the choice of a specific AI tool for solving a subtask.

The central hypothesis of the model's construction is the assertion of an inverse relationship between these indicators: an increase in DRI leads to an automatic decrease in PLR. This creates the foundation for a validation model where the instructor evaluates not only the «correctness» of the answer but also the «quality of the cognitive path».

As emphasized by Yu. Rudenko and colleagues[19] , using such integrated indicators allows for overcoming the limitations of traditional assessment. Implementing PLR and DRI into the learning process provides the instructor with an objective picture: whether the student is an active researcher or merely a «data operator» captive to algorithmic recommendations.

This parameterization serves as the basis for designing the architecture of an analytical module capable of processing data for large groups of students (100+). To transition from theoretical measurement to practical monitoring in large cohorts (80–100 people), the architecture of the analytical module must be based on objective «digital footprint» metrics. The prototype module is envisioned as an analytical superstructure that integrates with cloud environments and visualizes learning dynamics.

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[18] Gimpel H., Hall K., Decker S. Uncovering the Illusion of Knowledge: A Study on AI-assisted Pseudo-learning. *Computers and Education: Artificial Intelligence*. 2024. Vol. 6. P. 100198. DOI: 10.1016/j.caeai.2024.100198

[19] Rudenko Y. et al. Development of Youth Information Hygiene Skills: The Gap Between the Self-Assessment and Real State. *E-Learning and Enhancing Soft Skills*. Springer, Cham, 2025. P. 89–104. DOI: 10.1007/978-3-031-82243-8_5

The structural and logical construction of the module consists of four levels that ensure the transformation of raw data into strategic decisions for the instructor.

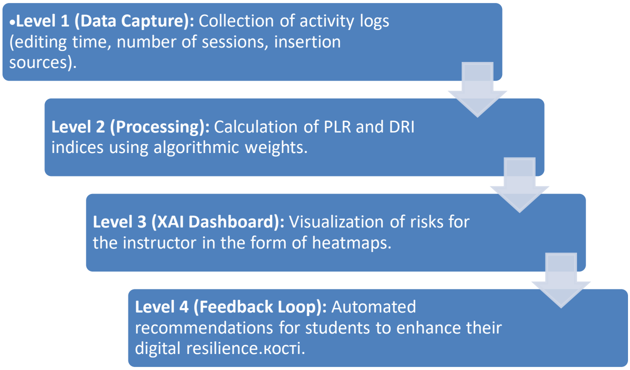

Fig. 1. Architectural diagram of the module

The central component of the analytical module is the formula for determining the intensity of cognitive contribution (I_{cog}), which enables the identification of pseudo-learning. If the obtained result significantly exceeds the individual capacity of the student within a short period, the system flags it as a high PLR Risk.

To calculate this, we use the following normalized coefficient:

$$I_{cog} = \frac{\Delta V}{\Delta t\left(1 + Rsyn\right)}$$

ΔV – the volume of meaningfully significant text (number of characters/words);

Δt – the actual time spent in the document (active session);

$Rsyn$ – the indicator of syntactic complexity (determined via average sentence length and domain-specific terminology).

Where:

If $I_{cog} > I_{max}$ (where I_{max} is the upper limit of human productivity, typically 60–80 words/min for creative writing), the system signals the likely uncritical generation of content by AI.

For an instructor working with large groups without specialized IT training, the module offers a choice of tools depending on the type of learning activity (Table 1).

Table 1

Instrumental Base of the Analytical Module for Large Groups

Tool Type	Analytics Object	PLR Detection Method	Advantage for the Instructor (100+ students)
Cloud Docs (Google/MS)	Version history	Analysis of «block insertions» and pauses	Automatic video playback of the process (Draftback)
Version Control (GitHub)	Commit history	Frequency and content of iterative changes	Clear visualization of progress over time
Interactive Boards (Miro)	Spatial connections	Logic of mind map construction	Simultaneous monitoring of the entire group on one screen
Video Validation (Loom)	Meta-cognition	Express explanation of the cognitive path	Rapid verification of knowledge authenticity

The module prototype involves creating a control panel where each student is represented in a two-dimensional coordinate system: Pseudo-Learning Risk (PLR) – Digital Resilience (DRI).

This allows the instructor to instantly divide the flow into segments:

1. Autonomous Researchers (Low PLR, High DRI) – require minimal intervention.
2. Risk Group (High PLR, Low DRI) – require additional consultation and a review of task design.
3. Mechanical Performers (Low PLR, Low DRI) – students who work independently but exhibit low efficiency in using digital tools.

The implementation of such an analytical module ensures a transition from «outcome control» to «process management», which is the only effective way to preserve the quality of education in an environment of total access to artificial intelligence.

The final stage of the methodology is the re-engineering of educational design. If the analytical module identifies a problem, this section proposes strategies for its neutralization through the creation of AI-resilient tasks. The primary goal is to transform AI from an «answer generator» into a «tool for thinking», thereby increasing the student's Digital Resilience Index (DRI).

To minimize Pseudo-Learning Risk (PLR), it is proposed to shift the assessment focus from the final text to the stages of its creation. This is implemented through a system of «iterative drafts», where the instructor evaluates:

- The logic of prompt formulation (queries to the AI);
- Critical analysis of the initial (often imperfect) AI response;
- The process of integrating AI-generated content with the author's own arguments.

Such a design forces the student to undergo a stage of «effortful processing», which, as established in Section 1.1, is a mandatory condition for deep knowledge acquisition.

Within the framework of the project, a system of tasks has been developed aimed at fostering information hygiene and critical thinking (Table 2).

Table 2

Task Models for Neutralizing Pseudo-Learning

Method Name	Task Essence	Role of AI	Expected Outcome (DRI)
Hallucination Hunt	Identify 3 factual errors in an AI-generated text	Source of «raw» content	Verification and fact-checking skills
Socratic Dialogue	Conduct a discussion with the AI, where the student must convince the model of the opposite point of view	Opponent in discussion	Argumentation and critical thinking
Reflective Prompting	Describe why a specific query was chosen and how it evolved	Assistant	Metacognitive awareness
Synthesis of Contradictions	Force the AI to generate two polar opinions and write an original synthesis	Provider of alternatives	Synthesis and evaluation skills

A crucial aspect is the implementation of protocols for the responsible use of AI. Students must learn to perceive algorithms not as the ultimate truth, but as probabilistic statistical models. In practice, this is achieved through mandatory attribution:

1. Labeling AI content: A clear distinction between the author's original thought and the model's suggestions.
2. Declaration of limitations: The student must indicate which specific risks (bias, outdated data) they identified in the model used.

The developed methodological architecture, based on the PLR and DRI indices, allows for shifting the discourse on AI in education from the plane of «prohibit or allow» to the plane of «quality management». The prototype of the analytical module, combined with task re-engineering, creates conditions under which pseudo-learning becomes technically more difficult and less beneficial for the student than actual cognitive development.

The proposed model is scalable and can be integrated into the digital learning environments of universities as a tool for ensuring academic authenticity and forming a new elite of specialists capable of productive collaboration with artificial intelligence without losing human agency.

CONCLUSIONS

The monograph provides a theoretical generalization and proposes a new solution to the pressing scientific and applied problem of fostering digital resilience and information hygiene within the intelligent educational environments of higher education institutions, particularly under the active implementation of Big Data, learning analytics, and artificial intelligence.

An analysis of modern approaches to the digital transformation of education reveals that learning individualization based on Big Data is a key trend in higher education. Concurrently, it is proven that the increasing role of algorithmic systems is accompanied by risks of bias, over-automation of decision-making, and a decline in students' critical thinking.

It is substantiated that learning personalization in digital educational environments should be viewed not merely as a technological process of content adaptation, but as a complex pedagogical system encompassing the cognitive, behavioral, and ethical aspects of user interaction with data and algorithms.

Digital resilience is defined as an integral competence that ensures a student's ability to critically evaluate the outputs of intelligent systems, resist algorithmic distortions, and maintain decision-making autonomy within a digital environment.

The essence of information hygiene is revealed as a system of principles and practices for responsible data use, spanning technical, cognitive, behavioral, and institutional levels, serving as a necessary condition for the secure functioning of educational analytical systems.

A conceptual model of digital resilience is proposed, based on the integration of four components (cognitive, critical-analytical, behavioral, and ethical). This model functions within a closed-loop educational data processing cycle: from data collection to decision-making and feedback.

A methodology for evaluating digital resilience has been developed based on the integral Digital Resistance Index (DRI), which allows for the quantitative assessment of competence development and the tracking of its dynamics during the learning process.

A mechanism for integrating the model into higher education learning platforms is proposed, involving the use of LMS systems, Big Data analytics, visualization dashboards, Explainable AI (XAI), and interactive prompts to support decision-making and enhance students' critical thinking.

It is proven that the implementation of Explainable AI (XAI) and visualization tools in educational systems increases the transparency of algorithmic decisions, fosters user trust, and mitigates the risks of uncritical acceptance of system recommendations.

The expediency of applying the developed model in the fields of Smart Farming and Precision Agriculture is substantiated, where digital resilience acts as a critical competence for future agricultural specialists working with vast arrays of agro-data.

It is established that integrating digital resilience and information hygiene into higher education curricula ensures the formation of a new type of professional competence – the ability for critical interaction with intelligent systems in the context of the digital economy.

In conclusion, this monograph addresses the scientific and applied task of developing the conceptual and methodological foundations for fostering digital resilience in intelligent educational environments. The results are interdisciplinary, merging pedagogy, computer science, Big Data analytics, and digital agricultural technologies.

The proposed approaches create a theoretical and practical foundation for the further development of adaptive educational systems oriented toward the safe, ethical, and effective use of data, as well as the training of a new generation of specialists capable of critical engagement with digital technologies and intelligent systems.

SUMMARY

This monograph addresses the critical scientific and applied challenge of preserving human agency and cognitive autonomy in the era of Generative AI (GenAI) and Big Data. The research investigates the phenomenon of AI-driven pseudo-learning – a systemic contradiction where the accessibility of algorithmic answers leads to the «illusion of knowledge» and the atrophy of critical thinking skills.

The study introduces a novel methodological framework based on two integral indicators:

1. Pseudo-Learning Risk (PLR): A dynamic metric that detects cognitive passivity by analyzing digital footprints, temporal anomalies, and structural monotonicity in student work.
2. Digital Resilience Index (DRI): A measure of a learner's capacity for critical engagement, verification, and responsible interaction with intelligent systems.

The author proposes a prototype for an analytical module designed for large-scale educational cohorts. This module utilizes Explainable AI (XAI)

and visualization dashboards to transition from «outcome control» to «process management». Furthermore, the work provides practical strategies for educational re-engineering, offering a system of AI-resilient tasks (e.g., Socratic Dialogue, Hallucination Hunt) aimed at fostering information hygiene.

The findings are interdisciplinary, extending beyond general pedagogy into specialized fields such as Smart Farming and Precision Agriculture, where data-driven resilience is a vital professional competency. This monograph serves as a strategic architecture for higher education institutions seeking to integrate AI ethically while safeguarding the development of real human capital in the digital economy.

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