

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

GENESIS OF ADAPTIVE SYSTEMS AND PERSONALIZED TEACHING STRATEGIES IN EDUCATION

Eshpulatov Inoyat Saparovich

PhD in Philosophical Sciences, Senior Lecturer,

Military Security and Defense of University of the Republic of Uzbekistan

Abstract

This article analyzes the origins (genesis), developmental stages, and conceptual foundations of adaptive learning systems (Adaptive Learning) and personalized teaching strategies, which are among the most relevant directions of contemporary digital education. The study scientifically examines the evolution from behaviorist programmed instruction to modern models based on artificial intelligence and Educational Data Mining. In addition, the fundamental components of adaptive learning architecture—namely the Expert Model, Learner Model, and Adaptation Model—are analyzed, and their pedagogical significance in enhancing learning effectiveness is substantiated.

Keywords: Adaptive learning, personalized teaching, genesis, programmed instruction, artificial intelligence, Intelligent Tutoring Systems (ITS), Learner Model, Cognitive Load Theory, Educational Data Mining.

Introduction

The modern education system is undergoing a fundamental transformation under the influence of globalization, digital transformation, and the rapid development of artificial intelligence technologies. In the 21st century, the formation of a knowledge-based society compels education systems to move away from the traditional “one-size-fits-all” model and implement new pedagogical approaches

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaoa.com/index.php/2>

that take into account each learner's individual needs, cognitive characteristics, and learning dynamics. In this context, adaptive learning systems and personalized teaching strategies are emerging as one of the most relevant and promising directions in contemporary pedagogy.

The genesis of adaptive learning initially began with computerized educational systems and programmed instruction concepts and later advanced significantly with the development of artificial intelligence, machine learning, Learning Analytics, and Educational Data Mining technologies. This evolution transformed the learning process from a static and standardized model into a dynamic, adaptive, and data-driven intelligent system.

Personalized teaching strategies are aimed at forming individual learning trajectories by taking into account learners' knowledge level, cognitive style, motivation, and learning pace. This approach not only improves learning effectiveness but also develops students' competencies in independent thinking, critical analysis, and decision-making in problem-solving situations.

At the beginning of the 21st century, anthropogenic and digital transformations occurring in the global socio-economic and technological environment, the exponential growth of information and communication platforms, and the conceptual establishment of the paradigms of the "knowledge society" and "knowledge economy" have made it an objective necessity to fundamentally modernize the methodological, didactic, and epistemological foundations of specialized education systems.

The "one-size-fits-all" model, which for many years dominated classical and neobehaviorist pedagogy as a unified instructional framework based on extrinsic teaching models, no longer fully corresponds to the subjective cognitive needs and psychophysiological characteristics of today's digital generation (Generation Z and Alpha). The fundamental reason for this mismatch is that traditional standardized education relies on a linear hierarchy and attempts to homogenize learners' individual mental architectures, namely:

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

- baseline intellectual and competency levels (prior knowledge);
- speed of information reception and afferent synthesis through sensory channels (acceleration rate);
- individual limitations of working memory capacity;
- personal apperception characteristics and intrinsic conative-motivational dynamics.

From a systemic pedagogical perspective, such a linear approach artificially suppresses the cognitive development trajectory of high-achieving learners (underachievement), while causing academic distress and motivational decline (academic alienation) among slower learners.

In the current stage of development of educational engineering and cyber-didactics, the most optimal, high-tech, and proactive solution to this systemic crisis is represented by Adaptive Learning Systems (ALS) and intelligent pedagogical management platforms.

From a scientific and didactic perspective, adaptive learning is a cognitive-adaptive technology that continuously measures learners' subjective actions in digital environments, micro-dynamic traces (digital footprints), and patterns of errors in real time (real-time data analytics). Using convolutional neural networks (CNN) and Item Response Theory (IRT) algorithms, it performs intelligent diagnostics and automatically modifies the complexity hierarchy, taxonomic sequencing, and multimedia presentation format of learning content.

Studying the historical and evolutionary laws of this intellectual direction—its methodological genesis—is of fundamental strategic importance. In the context of digital education, it contributes not only to the preparation of civilian specialists but also to improving cyber-pedagogical methodologies for training military cadets and personnel capable of making operational and non-standard decisions under conditions of high uncertainty (fog of war), time constraints, and extreme psycho-emotional stress. It also strengthens the intellectual resource base of national defense industries and national security architecture.

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

Although the idea of adapting and personalizing education dates back to ancient pedagogical traditions (such as Socratic dialogue based on cognitive heuristics and the tutor–apprentice model), its technologization, algorithmization, and formal systematization began in the second half of the 20th century with the rapid development of cybernetics and cognitive psychology. Based on systematic scientific and pedagogical analysis, the genesis of adaptive learning models can be divided into four main conceptual periods:

I. Early Behaviorist and Mechanical-Didactic Period (1950–1960s)

The initial empirical and technical foundations of adaptive learning technologies are closely associated with B.F. Skinner, the leading figure of radical behaviorism, and his theory of programmed instruction and teaching machines. Based on the stimulus–response–reinforcement triad, Skinner proposed a linear adaptive model in which learning content is divided into minimal logical units (frames), and learners are not allowed to proceed to the next stage until they correctly answer control questions for each unit.

To overcome the deterministic limitations of behaviorism, Norman Crowder later introduced a branching programming model. In this model, if a learner selects an incorrect answer, the system interrupts the linear flow and provides a corrective instructional module explaining the epistemological cause of the error (scaffolding). This period represents the initial mechanically determined stage of adaptive learning.

II. Cognitive-Cybernetic and Intelligent Systems Period (1970–1980s)

With the development of electronic computing systems and the cognitive revolution in psychology, traditional behaviorist approaches were replaced by Intelligent Tutoring Systems (ITS). During this period, adaptivity shifted from simply checking final answers to analyzing learners’ internal reasoning

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaoa.com/index.php/2>

processes, cognitive structures, mental models, and the causal nature of their errors (diagnostic error analysis).

Early AI-based systems such as SCHOLAR (focused on South American geography) and SOPHIE (designed for diagnosing faults in electronic circuits) were developed. For the first time, three fundamental components of instructional systems were integrated: the Domain Model, the Student Model, and the Tutor Model.

III. Hypertext, Networked, and Web-Oriented Period (1990–2000s)

The global expansion of the World Wide Web and the emergence of distance learning led to a shift toward Adaptive Hypermedia Systems (AHS), developed significantly by researchers such as Peter Brusilovsky. This approach addressed the problem of adapting hypertext-based learning environments to individual user needs.

Within AHS, two main mechanisms of adaptation were established:

1. Adaptive Presentation (content-level adaptation): dynamic modification of the complexity and amount of text, visual, and audio information depending on the learner's knowledge level.

2. Adaptive Navigation Support (link-level adaptation): modification of hyperlinks through hiding, highlighting, or color-coding based on learner model data, as well as providing personalized guidance.

IV. Algorithmic-Digital and Hyper-Personalized Period (2010–Present)

In the current stage, the deep integration of Artificial Intelligence (AI), Big Data, Cloud Computing, and Machine Learning into educational ecosystems has led to hyper-personalization. Modern adaptive systems (such as Knewton and RealizeIT) do not classify learners into static groups but continuously monitor their real-time digital footprints.

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

Machine learning algorithms such as Bayesian Knowledge Tracing and Deep Knowledge Tracing analyze parameters such as typing latency, dwell time on content, error patterns, and cognitive fatigue trends. As a result, the learning process becomes a predictive, dynamically adaptive system aligned with the learner's cognitive load.

In military education contexts, this evolution enables not only the assessment of theoretical knowledge but also the evaluation of operational responses and psychological resilience in tactical simulation environments.

III. Hypertextual, Networked and Web-Oriented Era (1990–2000s)

The widespread global expansion of the World Wide Web (WWW) and the increasing virtualization of educational processes led to a shift in the methodological foundation of adaptivity toward the concept of Adaptive Hypermedia Systems (AHS). This approach, established by Professor Peter Brusilovsky and his research school, addressed the problem of adapting hypertext-based learning environments to the individual needs of users.

Within the AHS framework, two main adaptive mechanisms were scientifically and methodologically developed:

Adaptive Presentation (Content-level adaptation): dynamic variation in the volume and complexity of textual, visual, and audio information on a web page depending on the learner's current level of knowledge (for example, providing detailed explanations for beginners and concise, strictly professional content for experts).

Adaptive Navigation Support (Link-level adaptation): modification of hyperlinks within the system according to the learner model, including hiding certain links, highlighting them in different colors (e.g., marking ready-to-learn topics in green and less appropriate ones in red), or designing individualized recommended learning pathways (direct guidance).

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaoa.com/index.php/2>

IV. Algorithmic-Digital and Hyper-Personalized Era (2010–present)

At the current stage, the deep integration of Artificial Intelligence (AI), Big Data, Cloud Computing, and Machine Learning into educational ecosystems has led to the emergence of a hyper-personalized digital learning environment. Modern adaptive systems (such as Knewton and RealizeIT platforms) no longer assign learners to predefined static groups; instead, they continuously monitor their second-by-second dynamic interactions within the learning platform—known as “digital footprints”.

Using machine learning algorithms such as Bayesian Knowledge Tracing and Deep Knowledge Tracing, systems analyze parameters such as typing/clicking latency, dwell time on specific visual content, individual error patterns in task sequences, and cognitive fatigue tendencies. As a result, the learning process becomes a dynamically changing predictive system that adapts in real time to the learner’s current cognitive load.

In military-oriented education contexts, this evolutionary stage enables not only the assessment of cadets’ theoretical knowledge but also the evaluation of their operational responses in tactical training simulators and their psychological resilience under stress conditions.

3. The Pedagogical-Psychological Determinants and Cognitive Modeling of Personalized Learning Strategies

The design of adaptive digital learning environments and the development of their applied didactic algorithms are not merely a matter of software engineering; they are fundamentally grounded in the core principles of neuroeducation and cognitive psychology. The most important pedagogical-psychological determinant of personalized learning strategies is the mathematical and algorithmic balancing of the human brain’s sensory channels responsible for receiving, processing, and transferring information into long-term memory.

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

3.1. Cognitive Load Theory (CLT) and Working Memory Constraints

At the conceptual core of adaptive learning architecture lies the Cognitive Load Theory (CLT), developed by the Australian psychologist John Sweller. Neurobiological research demonstrates that human working memory—the system responsible for temporarily holding and processing new information—is an extremely limited resource, capable of handling approximately 3–4 information chunks (or, in classical terms, 7 ± 2 items according to George Miller).

When the volume, hierarchical structure, and complexity of educational content—particularly military-technical or scientific material—exceed the capacity of working memory, a cognitive overload occurs. As a result, the learner's ability to perform afferent synthesis is blocked, and the knowledge acquisition rate drops to minimal (near-zero) levels.

Under Sweller's framework, adaptive strategies aim to balance three fundamental types of cognitive load:

1. Intrinsic Cognitive Load: the inherent complexity of the subject matter or task (e.g., higher mathematics, ballistics formulas, or cyber-tactical analysis). This load cannot be eliminated but can be optimized by aligning it with the learner's prior knowledge and decomposing it into structured conceptual frames.

2. Extraneous Cognitive Load: the unnecessary mental effort caused by poorly designed, disorganized, or excessive presentation of information in digital environments. Adaptive systems minimize this load through UX/UI optimization and intelligent content structuring, aiming to reduce it toward zero.

3. Germane Cognitive Load: the productive mental effort invested by the learner in integrating new information into existing long-term memory schemas and constructing new cognitive structures.

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

3.2. Dynamic Scaffolding and Microlearning Strategies

Intelligent adaptive platforms continuously monitor the learner's cognitive state in real time. If a cadet or student repeatedly makes errors in a specific tactical task and their response latency increases, the system identifies cognitive fatigue or misunderstanding through adaptive diagnostics.

In such cases, the system immediately activates dynamic scaffolding and microlearning mechanisms:

- Complex macro-content is decomposed into small, self-contained logical micro-modules;
- Text-heavy materials are transformed into visual and interactive formats (infographics, video explanations, 3D models);
- The system provides meta-explanations and simplified guiding tasks tailored to the specific nature of the learner's errors.

3.3. Proactive didactic strategies for gifted subjects

Conversely, if intelligent diagnostic algorithms determine that the learner is completing tasks in minimal time, without errors, and with a high degree of cognitive fluency, the system evaluates the subject's preparedness level as advanced. In order to prevent boredom and motivational decline within traditional educational systems, the adaptive strategy shifts into a proactive mode:

- The declarative (theoretical-textual) component is significantly reduced or completely omitted;
- The learner is immediately directed toward higher-order cognitive tasks aligned with the highest levels of Bloom's taxonomy;
- The system assigns non-standard problem situations, integrated tactical case studies, and time-constrained cyber-simulations. This ensures that the learner remains within their optimal Zone of Proximal Development.

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

4. Pedagogical-psychological determinants and cognitive modeling of personalized teaching strategies

The design of adaptive digital learning environments and the formation of their applied didactic algorithms are not merely tasks of software engineering; they are fundamentally grounded in the principles of neuroeducation and cognitive psychology. The primary pedagogical-psychological determinant of personalized learning strategies is the mathematical and algorithmic balancing of the brain's sensory channels for information reception, processing, and transfer into long-term memory.

4.1. Cognitive Load Theory and working memory constraints

At the conceptual core of adaptive learning architecture lies Cognitive Load Theory (CLT), developed by the Australian psychologist John Sweller. Neurobiological research confirms that human working memory, responsible for receiving and processing new information, is highly limited in capacity (according to George Miller's rule, approximately 7 ± 2 elements, or in modern cognitive measurements about 3–4 information chunks at a time).

If the volume, structural complexity, and hierarchical organization of military-technical or scientific information presented in a digital environment exceed the capacity of working memory, a cognitive overload occurs. As a result, the learner's ability to perform effective afferent synthesis is blocked, and the level of material acquisition drops to minimal (near-zero) levels.

Under Sweller's framework, adaptive strategies aim to achieve an algorithmic balance among three fundamental types of cognitive load:

1. Intrinsic cognitive load: the inherent complexity of the subject matter or tactical task (e.g., higher mathematics, ballistics formulas, or cyber-tactical analysis). This load cannot be eliminated, but it can be structured into logical frames aligned with the learner's prior knowledge level.

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

2. Extraneous cognitive load: unnecessary mental burden caused by poorly designed, disorganized, or redundant digital content and interface design. Adaptive systems minimize this load through data-driven optimization and UX/UI refinement, ideally reducing it toward zero.

3. Germane cognitive load: the productive cognitive effort devoted to integrating new information into long-term memory and constructing new mental schemas.

4.2. Dynamic scaffolding and microlearning strategies

Intelligent adaptive platforms continuously monitor the learner's cognitive state in real time. If a cadet or student makes repeated errors in a tactical task and shows increasing response latency, the system diagnoses potential cognitive fatigue or misunderstanding. In this case, it immediately activates dynamic scaffolding and microlearning mechanisms:

- Complex macro-content is decomposed into smaller, self-contained logical micro-modules;
- Text-heavy content is transformed into visual and interactive formats (infographics, video explanations, 3D models);
- The system provides meta-explanations and simplified guiding tasks tailored to the nature of the detected error.

4.3. Proactive didactic strategies for high-achieving learners

If, on the contrary, diagnostic algorithms detect that a learner is solving tasks rapidly, accurately, and with minimal cognitive effort, the system identifies a high level of preparedness. To prevent boredom and motivational decline in traditional learning environments, the adaptive strategy shifts into a proactive mode:

- The declarative theoretical component is minimized or skipped entirely;

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaopenaccess.com/index.php/2>

- The learner is immediately guided toward high-order cognitive tasks within Bloom's taxonomy;
- The system assigns non-standard problem-based scenarios, integrated tactical case studies, and time-constrained cyber simulations. This ensures that the learner remains within their optimal Zone of Proximal Development.

A systematic analysis of the genesis of adaptive learning technologies and personalized teaching strategies demonstrates that modern pedagogical paradigms are undergoing a profound transformation. This transformation is characterized by a shift from traditional standardized "one-size-fits-all" models toward intelligent systems that account for individual cognitive characteristics, learning dynamics, and motivational states of each learner.

Historically, adaptive learning has evolved from behaviorist programmed instruction models to cognitive-cybernetic approaches, intelligent tutoring systems, and adaptive hypermedia concepts, ultimately reaching today's stage of AI-driven, machine learning-based, and big data-supported hyper-personalized digital ecosystems. This evolution has transformed the learning process from a static and linear model into a dynamic, continuously adapting, real-time intelligent system.

Scientific analysis confirms that the effectiveness of adaptive learning systems is directly determined by their alignment with human cognitive architecture. Models grounded in Cognitive Load Theory reduce extraneous cognitive burden while optimizing germane load, thereby significantly improving learning efficiency and knowledge retention.

Personalized learning strategies place the learner at the center of the educational process, enabling the construction of individualized learning trajectories. This approach not only improves academic outcomes but also enhances higher-order cognitive competencies such as critical thinking, analytical reasoning, decision-making, and problem-solving in complex environments.

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaoa.com/index.php/2>

In the context of digital transformation, one of the most significant achievements of adaptive learning systems is the implementation of real-time intelligent diagnostics and proactive pedagogical control mechanisms. Based on learners' digital footprints, these systems automatically adjust content complexity, pacing, and instructional strategies.

Overall, adaptive learning systems and personalized teaching strategies represent not only a technological innovation but also a fundamental shift in educational philosophy. They redefine education as an intelligent, flexible, and learner-centered ecosystem aimed at developing competitive human capital in the conditions of a rapidly evolving digital society.

References

1. O'zbekiston Respublikasining "Ta'lim to'g'risida"gi Qonuni. – Toshkent: O'zbekiston, 2020. – 74 b.
2. Robert, I. V. Sovremennie informatsionnie texnologii v obrazovanii: didakticheskie problemi; perspektivi ispolzovaniya / I. V. Robert. – Moskva: Shkola-Press, 2014. – 205 s.
3. Sweller, J. Cognitive Load Theory / J. Sweller, J. J. G. van Merriënboer, F. Paas. – New York: Routledge, 2019. – 284 p.
4. Miller, G. A. The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information / G. A. Miller // Psychological Review. – 1956. – Vol. 63, No. 2. – P. 81–97.
5. Skinner, B. F. Teaching Machines / B. F. Skinner // Science. – 1958. – Vol. 128, No. 3330. – P. 969–977.
6. Crowder, N. A. Automatic Tutoring by Intrinsic Programming / N. A. Crowder // Teaching Machines and Programmed Learning. – Washington: National Education Association, 1960. – P. 286–298.

Eureka Journal of Education & Learning Technologies (EJELT)

ISSN 2760-4918 (Online)

Volume 2, Issue 5, May 2026



This article/work is licensed under CC by 4.0 Attribution

<https://eurekaoa.com/index.php/2>

7. Brusilovsky, P. Adaptive Hypermedia: From Systems to Frameworks / P. Brusilovsky // Lecture Notes in Computer Science. – 2016. – Vol. 4321. – P. 24–33.
8. Siemens, G. Learning Analytics: Envisioning a Data-Driven Educational System / G. Siemens // Journal of Educational Technology & Society. – 2012. – Vol. 15, No. 3. – P. 133–145.
9. Romero, C. Educational Data Mining: A Review of the State of the Art / C. Romero, S. Ventura // IEEE Transactions on Systems, Man, and Cybernetics. – 2020. – Vol. 40, No. 6. – P. 601–618.
10. Begimkulov, U. Sh. Oliy pedagogik ta'limda zamonaviy axborot texnologiyalarini joriy etishning ilmiy-pedagogik asoslari: Ped. fan. dok. ... diss. avtoref. / U. Sh. Begimkulov. – Toshkent: TDPU, 2007. – 42 b.
11. Xalilova, Sh. S. Raqamli ta'lim muhitida talabalarning mustaqil ta'lim faoliyatini intellektual boshqarish // Zamonaviy ta'lim jurnali. – Toshkent, 2024. – № 5. – B. 38–44.
12. Advanced Distributed Learning (ADL) Initiative. Personalized Assistant for Learning (PAL) Project [Elektronniy resurs]. – URL: <https://www.adlnet.gov/projects/pal/> (data obrasheniya: 12.05.2026).
13. Knewton Adaptive Learning Platform. White Paper: Open Adaptive Learning Engine [Elektronniy resurs]. – URL: <https://www.knewton.com/resources/> (data obrasheniya: 18.04.2026).