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ARTIFICIAL INTELLIGENCE-BASED ADAPTIVE LEARNING AND INTELLIGENT DIAGNOSTIC TECHNOLOGIES

Ilbayev Shukhrat Oktamovich

Head of Cycle, Military Security and Defense University
of the Republic of Uzbekistan

Abstract

This article analyzes the theoretical and conceptual foundations, architectural design, and strategic role of artificial intelligence-based adaptive learning and intelligent diagnostic technologies within the contemporary educational ecosystem. Adaptive learning systems are characterized as intelligent pedagogical frameworks that compute a learner's distinct cognitive attributes, knowledge baseline, mastery velocity, and psychological state in real-time to automatically calibrate the instructional cycle. The paper elucidates the critical roles of Learning Analytics, Educational Data Mining, Machine Learning, and Deep Learning technologies in optimizing adaptive instruction. Furthermore, it scientifically substantiates the pedagogical and psychological capacities of intelligent diagnostic architectures, highlighting the prospective horizons of their deployment within higher education and specialized military training institutions.

Keywords: Adaptive learning, artificial intelligence, digital learning environment, intelligent diagnostics, Learning Analytics, Educational Data Mining, cognitive load, military pedagogy, cadet, individualized learning trajectory, ITS frameworks, stress resilience, hyper-personalization, military educational technologies.

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Introduction

The global transformation and informatization processes of the international educational space task Higher Military Educational Institutions (HMEIs) with fundamentally upgrading the quality of future officer corps training. Under contemporary conditions, the digitalization of military education implies not merely converting traditional instructional materials into electronic formats (digitization), but signifies a total architectural and conceptual restructuring of the learning environment.

Worldwide digital transformation processes are introducing radical shifts into the higher military education system, necessitating a comprehensive review of the methodology for training future officers. Because contemporary military operations demand competencies in rapid decision-making within complex information environments, cognitive flexibility, analytical reasoning, and proficiency with digital technologies, the traditional instructional model anchored in the "one-size-fits-all" paradigm is reaching its functional limits.

The current dynamics of digital transformation introduce profound structural changes into the higher military education framework, mandating a rigorous re-examination of training methodologies for the officer corps. Given that modern military operations necessitate rapid decision-making under complex information constraints, alongside cognitive agility, analytical thinking, and advanced digital literacy, the legacy instructional model based on uniform standards has exhausted its functional utility.

There are significant individual variances among cadets enrolled in higher military educational institutions regarding their baseline knowledge levels, information absorption velocities, psychological resilience, and cognitive styles. Consequently, an instructional process conducted under a unified methodology and fixed pacing risks decelerating the intellectual growth of high-ability cadets, while simultaneously inducing academic deficiencies and motivational decline in struggling learners.

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Today, adaptive learning technologies are being extensively deployed not only across civilian higher education institutions but also within military, engineering, and specialized educational systems. Particularly within the military educational ecosystem—where high stress levels and split-second decision-making are paramount—intelligent diagnostic frameworks are emerging as highly effective mechanisms for assessing cadets' psychological resilience, cognitive adaptability, and operational thinking.

Adaptive Learning is an intelligent pedagogical approach that automatically calibrates the instructional process based on the individual characteristics, knowledge baseline, and mastery velocity of the learner. The primary objective of this technology is to engineer an optimal learning environment tailored to each unique student.

Adaptive systems are anchored by three foundational components:

- **The student model** (Student Model)
- **The domain model** (Domain Model)
- **The adaptation engine** (Adaptation Engine)

The structural integration of these components enables the system to continuously monitor the user's knowledge state and dynamically generate individualized instructional recommendations.

In scientific and pedagogical literature, the digital learning environment (DLE) is characterized as an integrated cyber-pedagogical system. This framework facilitates information-communication interaction among educational participants, manages instructional content, and tracks learner performance in real-time.

Within a specialized military training environment, the DLE diverges significantly from conventional civilian higher education institutions across the following institutional and sectoral parameters:

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- **High Regulation and Security:** Stringent demands for instructional content confidentiality, strict information security protocols, and the necessity of operating within localized internal networks (Intranets).
- **Temporal Deficits and Intensity:** Since cadets' daily routines encompass not only academic hours but also rigorous service and operational readiness obligations, the DLE must deliver highly compressed, targeted information packets via microlearning strategies.
- **Complex Competency-Based Approach:** Cadets are required to concurrently acquire theoretical (academic) and tactical-specialized (practical) knowledge assets. The DLE must seamlessly unify these twin components through immersive simulations and virtual training setups.

In contemporary military pedagogy, the role of the DLE has evolved from a passive information dispenser (content repository) to an active instrument of pedagogical management. This architecture is powered fundamentally by **Learning Analytics and Educational Data Mining**.

Scientific research substantiates that the DLE executes the following critical didactic functionalities:

1. **Proactivity:** Preemptively forecasting potential educational crises (underachievement states) in cadets and deploying early diagnostic intervention.
2. **Hypermediality:** Fusing linear text, audio, 3D modeling, and tactical simulations into a single cohesive logical chain.
3. **Asynchronous Interaction:** Ensuring autonomous knowledge acquisition dictated entirely by the cadet's individual intellectual pacing.

Within higher military educational institutions, cadets' baseline knowledge levels, cognitive faculties, and absorption velocities vary significantly. However, the traditional instructional system operates on a "**one-size-fits-all**" framework, which stalls the development of high-ability cadets while causing underachieving learners to accumulate academic deficiencies and drop out. Implementing AI-driven diagnostics and adaptive methodologies within digital environments

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enables the high-quality training of future officers within highly compressed timeframes.

Because the baseline knowledge, information processing speeds, psychological resilience, and cognitive styles of enrolled cadets vary markedly, an instructional process conducted under a uniform methodology and uniform pacing risks slowing the intellectual trajectory of talented individuals while inducing academic debt and motivational decay among slower learners.

As an effective resolution to this systemic bottleneck, the integration of AI-based intelligent diagnostics and adaptive learning technologies into the military educational ecosystem is emerging as a critical vector of scientific and practical inquiry. Adaptive learning architectures process a cadet's unique knowledge levels, learning dynamics, and cognitive attributes in real-time, automatically formulating tailored instructional content, assignments, and pedagogical strategies.

The current generation of cadets entering higher military institutions (**Generation Z** and **Generation Alpha**) exhibits a strong preference for visualized, dynamic, and interactive information processing modalities. The traditional, uniformalized lecture-seminar structure fails to respect these individual cohort characteristics. Consequently, the environment becomes monotonous for high-velocity learners while overwhelming reproductive thinkers, leading to severe academic debt.

Therefore, implementing intelligent diagnostic systems that capture a cadet's actual knowledge boundaries and deploying adaptive instructional methods that dynamically recalibrate learning paths stands as a paramount vector for safeguarding modern national security and enhancing institutional human capital. Under the conditions of modernizing the higher military education system, implementing technologies that adapt to the individual cognitive characteristics of learners has emerged as one of the paramount priorities of pedagogical science. Adaptive Learning is a digital-pedagogical technology that automatically calibrates the substance, complexity tier, and presentation modality of

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instructional materials in real-time, based on the learner's current knowledge baseline, psychophysiological state, and mastery dynamics.

Intelligent diagnostics is a contemporary pedagogical-analytical system designed for the comprehensive evaluation of a learner's knowledge baseline, cognitive attributes, psychological state, and mastery dynamics through artificial intelligence and learning analytics algorithms. This approach diverges fundamentally from traditional testing and evaluation methods, enabling the analysis of the intrinsic mechanisms of the learning process rather than merely recording summative outcomes.

While student assessment in traditional diagnostic systems is predominantly limited to standardized test results or summative performance indices, intelligent diagnostics continuously monitors the learner's entire educational activity in real-time to generate an individualized learning profile. Consequently, this technology serves as a pivotal component of modern adaptive learning architectures.

Intelligent diagnostic systems systematically compute a complex matrix of the following core parameters:

- **1. Accuracy of Responses:** The system determines the degree of correctness of the learner's submitted answers. However, contemporary diagnostics is not confined to merely binary "correct" or "incorrect" classifications. Artificial intelligence algorithms isolate the exact knowledge component causing the bottleneck based on the nature, repetition frequency, and logical architecture of the errors. For instance, if a cadet consistently misapplies the same formula in a mathematical task, it indicates a structural lacuna in their conceptual knowledge. Thus, the system diagnoses the root cause of the error rather than just logging the failure.
- **2. Response Latency:** Response latency serves as a critical indicator reflecting the learner's cognitive processing speed. Prematurely rapid responses may denote impulsive decision-making, whereas excessively delayed responses point toward

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difficulties in information processing or a lack of conceptual confidence. Within a military educational ecosystem, this parameter is of paramount importance, as future officers must execute rapid and precise decisions under tight temporal constraints. Consequently, adaptive systems analyze response latency in tandem with qualitative mastery metrics.

• **3. Error Dynamics:** The intelligent diagnostic engine evaluates learner errors as a dynamic trajectory rather than a static metric. Algorithms track the longitudinal escalation or reduction in error counts, the complexity thresholds of those errors, and their repetitive tendencies. If the system detects a rising error trajectory within a specific topic, it automatically triggers supplementary explanations, simplified content blocks, or targeted remediation, thereby adjusting the learning cycle in real-time.

• **4. Motivational State:** Artificial intelligence systems possess the capacity to implicitly evaluate motivational states by computing the user's platform activity, task completion frequency, interaction density, and session durations. For example, a decline in login frequency, premature abandonment of assignments, or an overall deceleration of engagement can be interpreted as markers of a motivational crisis. In such scenarios, the adaptive platform deploys gamification elements or calibrated micro-learning strategies to restore engagement.

• **5. Stress Resilience:** In educational frameworks oriented toward military and high-stakes operations, assessing stress resilience possesses strategic value. Intelligent diagnostic systems analyze decision-making velocity, error distributions, and cognitive stability within simulated operational environments to isolate the learner's threshold of psychological endurance. For instance, a cadet's performance metrics within virtual training scenarios involving severe time constraints or emergency management model their operational reasoning and stress-under-fire efficiency.

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• **6. Attention Stability:** Within a digital learning environment, attentional persistence correlates directly with instructional efficiency. The system measures attention thresholds by tracking content consumption duration, cross-page navigation frequency, task interruptions, and interactive engagement metrics. If the underlying algorithm isolates an attention deficit, the system can dynamically modify the content modality, inject microlearning elements, or activate highly interactive tasks. Consequently, this intervention optimizes the cognitive load and augments knowledge retention rates.

Integrating the multi-parametric computation of these vectors yields the generation of the user's **Digital Learning Profile**. This profile serves as a highly dynamic model mirroring the student's mastery level, learning style taxonomy, psychological configuration, motivational baselines, and latent cognitive capacities.

The digital learning profile operates as the central command architecture of the adaptive learning system. Dictated entirely by this model, the system:

- maps customized learning trajectories;
- executes content selection parameters;
- optimizes instructional delivery strategies;
- generates predictive forecasting regarding the learner's prospective requirements.

As a result, the instructional cycle shifts from a standardized design into an individualized, predictive management ecosystem.

An evolutionary analysis of adaptive learning systems demonstrates that educational personalization is not merely a pedagogical trend, but the highest technological method of managing cognitive resources in the information age. Integrating this genesis into the cadet training framework establishes a methodological foundation for the precise intelligent diagnostics of future officers' intellectual potential.

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The dynamic assessment of cadets' knowledge baselines and the design of their personalized learning trajectories within higher military educational institutions is not merely a technical, algorithmic cycle. Its core is anchored in deep pedagogical-psychological and neurocognitive principles. Within a military training environment, intelligent diagnostics must evaluate not only the learner's acquired factual knowledge assets but also their underlying cognitive architecture.

Cognitive Load Theory, pioneered by the Australian educational psychologist John Sweller, constitutes the psychological foundation of the intelligent diagnostic framework. According to this paradigm, human short-term (working) memory possesses strictly constrained resource capacities, enabling it to process only a limited number of information packets (chunks) concurrently.

Within military instruction, cognitive load is composed of three discrete vectors:

1. **Intrinsic load:** The objective complexity of the military-technical subject matter being processed (e.g., ballistics computations or cybersecurity protocols).
2. **Extraneous load:** The redundant mental strain induced by poorly structured or overly complex content presentation formats within the digital environment.
3. **Germane load:** The productive mental energy expended by the cadet to integrate novel information assets into existing cognitive schemas stored within long-term memory.

Intelligent diagnostic algorithms compute the cadet's "digital footprint" within the platform (such as response latency and item retry frequencies) to detect cognitive overload states, immediately simplifying content delivery modalities to mitigate extraneous load metrics.

Taxonomy of Individual Cognitive Styles. Pedagogical psychology has substantiated that learners diverge markedly in their modalities for absorbing and processing information. An intelligent diagnostic system must isolate the cadet's unique cognitive profile across the following dimensions:

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• **Field Dependency versus Field Independency:** Field-independent cadets possess the capacity to autonomously isolate systematic sub-components from highly complex tactical scenarios, requiring only macro-level directives. Conversely, field-dependent cadets demand detailed, hierarchically structured, step-by-step operational instructions.

• **Impulsivity versus Reflexivity:** Impulsive cadets execute rapid, high-velocity choices within digital simulators that are highly prone to critical errors. Reflexive cadets analyze data profiles exhaustively, yielding delayed yet structurally more precise solutions. The adaptive engine intervenes by systematically pacing down impulsive individuals while utilizing temporal constraints (time limits) to accelerate the decision-making velocity of reflexive learners.

The defining attribute of military pedagogy dictates that a future officer must execute sound decisions not merely under peaceful and comfortable classroom parameters, but also under conditions of extreme psychological stress, such as temporal deficits, threat alerts, and severe information scarcity.

Within a digital learning environment, the intelligent diagnostic model also evaluates the cadet's stress resilience coefficient. In tactical training simulators, the cadet's behavioral and cognitive reactions to unexpected operational disruptions, such as an artificial communication failure or abrupt modifications in enemy tactical maneuvers, serve as a clear index of their psychological stability.

Theoretical–methodological synthesis enables the formulation of the following fundamental conclusions:

1. Systemic Transformation: The digital learning environment within higher military educational institutions functions not merely as a technical interface, but as an intelligent ecosystem that manages the instructional cycle based on Data-Driven Education principles.

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2. Pedagogical and Technological Convergence: The genesis of adaptive learning environments proves that modern EdTech architectures have traversed an evolutionary path extending from behaviorist programmed instruction to AI-driven hyper-personalized designs. Its operational efficacy relies entirely on the systematic equilibrium maintained among the Expert, Learner, and Adaptation Models.

3. Cognitive Compatibility: Intelligent diagnostics yields authentic pedagogical–psychological value only when it moves beyond evaluating purely academic knowledge assets to account for the learner's working memory capacity, individual cognitive style, and stress resilience indices.

Intelligent diagnostics stands as the foundation of any adaptive learning environment. It transcends the mechanical grading of summative assessments, operating instead as a continuous system for digitally identifying a learner's interaction hierarchies, reasoning logic, and evolving mental models. While traditional diagnostics is inherently lagging and summative (occurring only at the conclusion of a semester or exam cycle), intelligent diagnostics is fundamentally predictive and continuous.

Through these continuous diagnostic workflows, the system engineers a **Digital Twin** or a highly dynamic student model of the learner.

This model encapsulates several critical variables:

- **Cognitive baseline:** The current depth of the learner's subject-matter mastery and foundational skill metrics.
- **Behavioral analytics:** High-resolution metrics mapping precise time-on-task, response latency, and sequential clicking profiles.
- **Cognitive style:** The preferred modalities for processing sensory input (visual, interactive, textual) alongside the student's tendency toward either impulsive or reflexive decision-making.

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2. Algorithmic and Mathematical Foundations of Intelligent Diagnostics

The artificial intelligence engine avoids subjective evaluations; it tracks and forecasts a learner's knowledge evolution using precise mathematical–statistical models. Currently, three primary algorithmic frameworks dominate the EdTech (educational technology) domain:

- **A. Bayesian Knowledge Tracing (BKT):** The Bayesian Knowledge Tracing framework computes the latent probability $P(L_t)$ that a learner has mastered a specific sub-skill or concept based on their sequential response history to each task.
 - It relies upon four fundamental parameters:
 1. $P(L_0)$ – the initial probability of the learner possessing the knowledge before instructional delivery begins;
 2. $P(T)$ – the transition probability of acquiring new knowledge (learning) during an instructional opportunity;
 3. $P(S)$ – the slip probability of committing an accidental error despite possessing the required knowledge;
 4. $P(G)$ – the guess probability of arriving at a correct response by chance without possessing the actual knowledge.
- **B. Deep Knowledge Tracing (DKT):** Operating on the architecture of Recurrent Neural Networks, specifically Long Short-Term Memory (LSTM) models, this framework analyzes the entire sequential chain of a learner's historical interactions on the platform. DKT enables the predictive forecasting of the highly non-linear and complex cognitive laws governing human knowledge acquisition with exceptional accuracy.
- **C. Item Response Theory (IRT):** Item Response Theory constitutes the mathematical foundation of computerized adaptive testing environments. It maintains a continuous equilibrium between an assessment item's objective difficulty coefficient and the learner's latent ability parameter (θ). As the student provides correct responses, the tasks become iteratively more complex;

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conversely, when an error occurs, the engine automatically routes back to simpler conceptual frames.

3. Alignment with Cognitive Load Theory (Didactic Function)

The foundational pedagogical objective of intelligent diagnostic technologies is the strategic management of a learner's mental exertion based on the tenets of Cognitive Load Theory, pioneered by John Sweller. Given that human working memory is a strictly constrained resource, the delivery of excessively dense or poorly structured information vectors induces cognitive overload, destabilizing knowledge retention thresholds.

When artificial intelligence algorithms detect indices of mental exhaustion or cognitive friction through interactive behavioral analytics, the platform instantaneously invokes dynamic scaffolding and microlearning protocols. Under these conditions, the macro-level content is partitioned into micro-logical modules, shifting dense textual overhead into visual–multimedia modalities. Conversely, when high-ability learners are diagnosed, the engine condenses declarative theoretical explanations and immediately directs them toward higher-order cognitive operations, such as complex problem-based case studies and immersive tactical simulations.

4. Pragmatic Value in Specialized and Higher Military Education Frameworks.

The deployment of these architectures within Higher Military Educational Institutions (HMEIs) holds profound strategic and innovative utility. Within the framework of qualifying future officers and military engineers, intelligent diagnostics functions as far more than an academic testing mechanism. It forms a high-resolution foundation for intelligent simulation complexes that compute cadets' operational and tactical decision-making velocities under intense psychological stress, acute temporal deficits, and simulated cyber or electronic warfare contexts (environments of radical uncertainty). Transitioning to a Data-

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Driven Education paradigm ensures that the operational readiness profile of each unique strategic asset is optimized to its highest latent potential.

The digital learning environment in the contemporary higher military training model is not a passive technical utility, but represents a management-driven pedagogical ecosystem. The continuous progression of adaptive instructional designs has completed an evolutionary path extending from behaviorist programmed modules to AI-driven, hyper-personalized environments. The definitive operational output of these configurations relies entirely on the cross-integration maintained among the expert model, the cadet profile matrix, and the underlying adaptation engines.

Intelligent diagnostics commands genuine pedagogical and military-practical value only when it moves beyond measuring explicit academic knowledge assets to account for a cadet's working memory thresholds, cognitive style taxonomy, psychological stability, and stress resilience indices. Moving forward, integrating AI-based adaptive platforms within higher military training frameworks will emerge as a definitive strategic factor for augmenting the intellectual capacity of the officer corps, optimizing instructional efficiency, and safeguarding national security through high-yield workforce qualification.

Ultimately, AI-driven adaptive learning and intelligent diagnostic technologies manifest not merely as automation mechanisms for the instructional cycle, but as a profound conceptual transformation of contemporary cyber-didactics. The functional convergence of advanced algorithmic models like BKT, DKT, and IRT frees instruction from standardized constraints, securing a dynamic, hyper-personalized learning path for every unique learner. Systematically deploying these architectures across higher education and specialized military academies optimizes valuable temporal resources, establishing a definitive methodological foundation for cultivating highly competitive professionals who possess elite cognitive capabilities and are capable of executing precise strategic decisions under extreme, non-linear environments.

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