2.4. ARTIFICIAL INTELLIGENCE AS A TOOL FOR ANALYTICAL SUPPORT OF QUALITY ASSURANCE SYSTEMS BASED ON INTERNATIONAL AND NATIONAL ASSESSMENTS

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The study substantiates the conceptual foundations for utilising artificial intelligence (AI) to provide analytical support for educational quality assurance systems, a task of critical importance amidst global digitalisation and escalating demands for institutional efficiency. It explores the potential of neural networks and Data Mining techniques for the in-depth processing of results from international (PISA, TIMSS) and national monitoring assessments, such as Ukraine's External Independent Evaluation (ZNO) and National Multi-Subject Test (NMT). Findings indicate that modern AI toolsets enable not only the automated detection of latent correlations but also the prediction of academic risks and the scenario-based modelling of educational reform impacts using Big Data. Particular emphasis is placed on the transition from static statistics to dynamic predictive analytics, which provides stakeholders with an objective basis for strategic planning and managerial decision-making. The study concludes that the integration of intelligent systems facilitates personalised learning and optimises managerial processes, thereby enhancing the overall competitiveness of national education on the global stage.

Keywords: *artificial intelligence, educational quality assurance, international and national assessment systems, predictive analytics, Big Data, managerial decision-making*

The contemporary paradigm of educational quality assurance necessitates a transition from fragmentary assessments toward comprehensive ecosystems, where artificial intelligence (AI) serves as the core analytical engine. The theoretical framework for this transformation is rooted in the theory of digital transformation in education, which comprises five sequential stages: from comprehensive data collection to continuous process improvement driven by acquired insights. In contrast to previous technological waves that merely automated existing administrative tasks, AI possesses the potential to fundamentally reshape how institutions gather, analyse, and synthesise complex data regarding instructional quality (Warren et al., 2026). This shift is facilitated by the capacity of algorithms to process unstructured datasets and identify patterns that remain inaccessible to traditional statistical methods. Integrating AI into the quality assurance system must be a measured process, encompassing infrastructure readiness assessments, strategic planning, pilot implementation, scaling, and continuous performance monitoring via key performance indicators (KPIs). Such a systemic approach ensures that the technology is not merely deployed for the sake of innovation but becomes an effective instrument for enhancing institutional accountability and transparency (International Association for Quality Assurance in Pre-Tertiary and Higher Education, 2025).

A vital aspect of this conceptual justification is the shift toward proactive management, wherein real-time data allow for the identification of issues before they reach a critical threshold. The application of machine learning to monitor learner progress enables the automated tracking of compliance with accreditation standards (Campbell, 2025). This is particularly pertinent given the increasing variability of educational trajectories, where adaptive platforms dynamically adjust content and task difficulty based on student performance. Furthermore, the implementation of AI redefines the role of accreditation bodies: they are transitioning from static periodic reviews to continuous monitoring via intelligent dashboards that aggregate data on academic performance, research activity, and administrative efficiency. Under these conditions, every participant in the educational process receives personalised feedback and recommendations for further development.

New opportunities for interpreting the results of large-scale assessments, such as PISA and TIMSS, are provided by Data Mining techniques and artificial neural networks (ANNs). Traditional analytical methods, such as hierarchical linear modelling (HLM), frequently encounter limitations when processing thousands of variables and non-linear relationships between them (Huang et al., 2024). AI-specifically deep learning algorithms– effectively processes multidimensional datasets that incorporate not only test scores but also socio-economic factors, educational environment characteristics, and teacher preparation levels. Data Mining methods enable the extraction of the most influential factors determining learner success, utilising approaches such as Random Forest, Support Vector Machines (SVM), and XGBoost (Bayirli et al., 2023).

The Organisation for Economic Co-operation and Development (OECD) has officially announced the introduction of a new innovative domain within the PISA 2029 cycle: “Media and Artificial Intelligence Literacy” (MAIL), which effectively codifies technological and media literacy as a foundational skill equivalent to reading, mathematics, or science (OECD, 2026). This decision reflects the urgent need to assess learners’ ability not merely to use digital tools, but to interact with them critically, recognise sophisticated AI-driven manipulations, understand the profound ethical implications of algorithmic social governance, and collaborate effectively with intelligent systems as cognitive partners (Finnegan, 2025). The introduction of the MAIL domain responds to a world where content production, social media participation, and political engagement are increasingly mediated by algorithms, requiring learners to evaluate the credibility, quality, and intent of any digital media. At the core of the MAIL domain lies a conceptual fusion of media literacy and AI literacy, reflecting the current state of the digital ecosystem where these two concepts have become inseparable. Media literacy in this context is viewed as the capacity to access, analyse, evaluate, create, and interact responsibly with information across various formats, allowing learners to question sources, identify bias, and communicate ethically (Wong, n.d.).

Leading global powers have already begun integrating AI competencies into national curricula, viewing this as a matter of economic survival and technological sovereignty. The United States, following a 2025 presidential executive order on "Advancing AI Education for American Youth", established a dedicated White House task force to develop online resources and foster public-private partnerships. Corporations such as Google, IBM, and NVIDIA have made significant commitments to train millions of learners and vocational educators in AI skills by 2028–2029, investing billions of dollars in the development of standards and infrastructure (The White House, 2025). In the US, the emphasis is placed on creating an "AI-ready workforce", which entails early access to technology and the integration of AI into courses on cybersecurity, programming, and general digital literacy.

South Korea's experience in 2025 has served as a serious warning to the international community regarding the dangers of overly rapid AI implementation without adequate infrastructure and teacher training. The ambitious "AI Digital Textbook Promotion Plan", which involved the rollout of 76 AI-powered digital textbooks for mathematics, English, and coding, effectively collapsed just four months after its launch (UNESCO, 2025). The programme faced sharp criticism due to technical glitches, AI-generated factual errors, and a significant increase in the workload for vocational educators who were forced to troubleshoot technical issues rather than teach. Parents initiated petitions against excessive screen time, fearing digital addiction and deteriorating child health, which led to these textbooks being downgraded from "primary" to "supplementary materials" (Securewithsaleh, 2025).

One of the most alarming findings of PISA 2022 was the widening gap between learners of different socio-economic statuses regarding access to digital resources. The lack of adequate devices and internet connectivity correlates directly with low academic performance; notably, learners from disadvantaged families and rural regions suffer most (Schleicher, 2024). In the age of AI, this divide risks becoming an "opportunity chasm", where those capable of using AI as an intellectual amplifier gain an exponential advantage over those who remain digitally isolated. Nevertheless, AI analytics also offer tools to address this issue (European Commission, 2024). The use of predictive algorithms allows teachers and institutional leaders to identify individuals at risk of "dropping out" of the educational process at an early stage by analysing data on attendance, grades, and online platform behaviour.

AI tools, such as AI graders or Socratic tutors, can scale quality education in regions lacking qualified teaching staff. In Brazil, an AI programme for essay assessment–trained on thousands of samples and verified by the national exam coordinator–enables teachers to devote more time to individual work with learners instead of routine syntax checks. In Italy, researchers utilise AI to minimise gender bias during mathematics course selection, providing educators with objective data for guidance (Table 2.5). Consequently, international assessments like PISA 2029 serve not only as a measure of success but as a compass for directing state investment into targeted support programmes for those most at risk of being left behind in the era of smart machines.

Table 2.5. Global Experience of AI Application for Ensuring Equality and Inclusivity in Education

AI Analytics Application Example	Geography / Project	Expected Impact on Educational Equality
Automated Essay Grading	Brazil (Scaled in gov schools)	Equal access to instant feedback for 1:1 learning.
Voice Recognition for Reading	South Africa (Facebook), India (Pratham)	Assessment of reading skills in local languages in remote regions.
Algorithms to Mitigate Gender Bias	Italy (STEM tracking)	Recommendations for STEM trajectories free from stereotypes.
Personalised Chatbots (Rori, Khanmigo)	Ghana, Canada, Nigeria	24/7 access to tutoring for socially vulnerable groups.

The link between learners' use of AI and the future competitiveness of national economies is becoming increasingly evident. Projections suggest that the global education market will reach at least 10 trillion USD by 2030, with digital education growing at an annual rate of 16.3% (Nartey, 2025). The AI segment in education demonstrates even more impressive dynamics: the CAGR is projected at 31.2–42.8%, and the market volume could exceed 41 billion USD by 2030 (HolonIQ, 2020). This growth is driven by the transition toward a lifelong learning model and a massive demand for the personalisation of the educational experience (Table 2.6).

For the 15-year-olds participating in PISA 2029, MAIL skills will determine their ability to integrate into a labor market where the automation of routine tasks is expected to release human capital for high-value-added activities. Already, over 75% of young people believe that AI will play a decisive role in their professional future. Countries demonstrating high MAIL 2029 scores will effectively declare the presence of the intellectual resources necessary to create and manage AI systems, acting as a magnet for investment. Conversely, economies with low levels of AI literacy risk chronic skills deficits and social instability due to the displacement of jobs by automation without the capacity for rapid worker retraining.

Table 2.6. Projected Performance Indicators and Technological Structure of the Global AI Education Market (2025–2030)

AI Education Market Indicator	2025 Value	2030 Projection	CAGR (2025–2030)
Global Market Volume (Solutions/Services)	~$6.90 billion	~$41.01 billion	42.83%
Dominant Region	North America (36–43%)	Asia-Pacific	Rapid growth rate in Asia
Key Segment by Technology	Machine Learning (64.7%)	Generative AI / NLP	Highest growth rate for GenAI
Digital Education Spending (Total)	~$404 billion	~$850 billion	16.3%

One of the most significant challenges for educational policy is the so-called "pedagogical paradox" of generative AI. OECD research published in the "Digital Education Outlook 2026' indicates that while the use of AI chatbots (such as ChatGPT, Gemini, or Claude) allows learners to complete tasks faster and demonstrate higher-quality results, this does not always lead to knowledge consolidation. Moreover, excessive reliance on AI creates a risk of "metacognitive laziness", wherein a learner ceases to exert effort for deep information processing, leading in the long term to the degradation of cognitive endurance, critical thinking, and the capacity for sustained concentration (dpa GmbH, 2026). To mitigate this risk, the OECD recommends using AI not as an "answer machine" but as a "Socratic tutor" that asks guiding questions, prompting the individual toward an independent conclusion (Widen, 2026).

The transition from retrospective analysis to predictive analytics constitutes a key stage in the evolution of quality assurance systems. Predictive models utilising data from Learning Management Systems (LMS) and Student Information Systems (SIS) allow for the identification of risk groups during the initial stages of the educational process. Instead of reacting to academic failure after the semester concludes, AI algorithms analyse behavioural indicators–system login times, forum activity, and the speed of completing interim tasks–to generate signals for early intervention (Bird, 2023). The use of advanced machine learning algorithms, such as XGBoost, is three times more effective at identifying at-risk learners than traditional reliance solely on grade point averages. This is because AI accounts for dynamic changes in learner behaviour rather than merely static input characteristics. These models can also be used to optimise resource planning: predicting the number of students requiring additional consultations or tutoring support allows educational institutions to allocate budgets and teacher workloads more efficiently. Furthermore, predictive analytics serves as the foundation for educational hyper-personalisation, where the system recommends individual learning materials or formats based on the learner's projected progress (Table 2.7).

Table 2.7. Functional Capabilities of Intelligent Analysis Systems

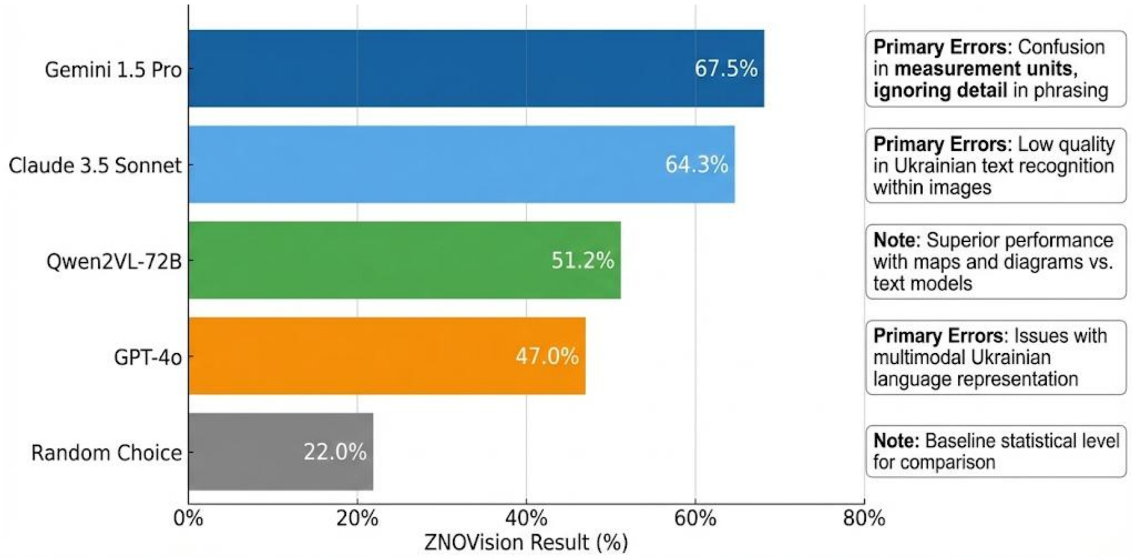
Application Scenario	Data for Analysis	Expected Result
Dropout Prediction	Attendance, LMS activity, socio-demographics	12–15% reduction in attrition
Early Warning	Interim tests, engagement in first 2 weeks	Timely tutoring support
Success Prediction	Previous grades, motivation, course difficulty	7–30% increase in performance
Resource Optimisation	Projected group sizes	Efficient staff and financial allocation

The Ukrainian educational system is currently actively seeking ways to integrate AI to enhance the reliability and objectivity of national assessments. The ZNOVision project represented the first large-scale attempt to test the capabilities of modern Large Language Models (LLMs) in solving ZNO and NMT tasks. The study revealed that although the models demonstrate a certain level of success (Gemini 1.5 Pro–67.5%, Claude 3.5–64.3%), they still face significant difficulties with the Ukrainian context, visual tasks, and specific terminology (Figure 2.3). This indicates the necessity of developing localised AI solutions trained on domestic educational content to ensure high analytical accuracy. The Ukrainian Center for Educational Quality Assessment (UCEQA) is considering the prospect of involving AI to grade open-ended NMT tasks, where the algorithm would act as a "third examiner" to minimise subjectivity and accelerate result processing (Lazurkevych, 2025).

In the Ukrainian context, burdened by the challenges of war, AI can also play a critical role in ensuring educational continuity through offline learning tools and the automated adaptation of materials for internally displaced learners. However, AI implementation in Ukraine remains fragmented and initiated primarily by individual institutions or educators, necessitating the development of a comprehensive state strategy and a strengthened regulatory framework (Hul et al., 2025). A vital aspect is also ethical oversight: learners and vocational educators in Ukraine demonstrate varying levels of trust in AI-driven monitoring of academic integrity, highlighting the need for a broad discourse on data transparency and security.

One of the most complex tasks for educational administrators is predicting the long-term consequences of reforms. AI provides tools for educational policy simulation, allowing for the evaluation of different intervention strategies before their practical implementation. Algorithmic models built on Big Data from national monitorings indicate that improving teacher training and expanding access to technological resources can increase learners' academic performance by 18% and reduce dropout rates by 12% (Guevara-Reyes et al., 2025).

Figure 2.3. Comparative Analysis of Multimodal AI Model Performance in National Assessment Visual Task Solving (ZNOVision)



Such simulations are based on an analysis of model stability and sensitivity to changes in input parameters, enabling the identification of the most critical leverage points. Modelling also helps address the issue of inequality: AI systems can simulate reform impacts separately for rural and urban schools, and for private and public institutions, allowing policymakers to develop more balanced solutions. The use of Deep Reinforcement Learning enables the automated discovery of optimal pathways for educational resource allocation to maximise the cumulative reward–knowledge quality and learner motivation (Zheng & Lu, 2026). For instance, the IDQN model in educational simulations demonstrated the ability to increase learning interest and performance by 27–34% through personalised material mastery recommendations. Thus, AI transforms educational policy from an intuitive process into an exact science, where every decision is supported by a numerical analysis of probable outcomes.

The study results provide grounds to assert that the contemporary paradigm of quality assurance is undergoing a fundamental transformation under the influence of AI, transitioning from a static retrospective monitoring model to dynamic predictive analytics. Findings prove that deep learning algorithms, particularly XGBoost and BPNN architectures, are significantly more effective at identifying non-linear correlations between socio-economic factors and learner success than classical linear modelling. This establishes an objective foundation for the transition toward proactive management, where the strategic decisions of ministries and institutional leaders are based on scenario modelling and digital twins of educational systems. In this context, the architecture of intelligent quality assurance must be viewed as a holistic ecosystem covering all stages of digital transformation: from automated Big Data collection to the creation of personalised value for every stakeholder. The global educational space, responding to digitalisation challenges, is effectively codifying technological literacy as a foundational skill, as evidenced by the introduction of the innovative "Media and Artificial Intelligence Literacy" (MAIL) domain in the PISA 2029 cycle. This decision marks the beginning of a new era of international competition for human capital quality, where the leadership of nations will be determined by their ability to integrate AI competencies into national curricula.

Consequently, technological transformation requires not only investment in soft and hard skills but also the formation of a social consensus and a culture of continuous professional development for vocational educators, who must become co-designers of intelligent educational tools. Addressing the "pedagogical paradox" of generative AI is of particular importance, where enhancing learners" short-term productivity via chatbots may be accompanied by the degradation of deep learning and cognitive endurance. To overcome the risk of "metacognitive laziness", it is necessary to transform the role of AI from an "answer machine" into a "Socratic tutor' that stimulates critical thinking and the independent pursuit of conclusions. Concurrently, intelligent analytics emerges as a powerful tool for ensuring educational equality, allowing for the early identification of risk-group learners and the provision of targeted support. The experience of using AI graders and personalised chatbots in countries across various income levels demonstrates the technology's potential to bridge the "opportunity chasm" caused by socio-economic status or geographical isolation, turning AI into an inclusive amplifier of society's intellectual potential.

For Ukraine, the integration of AI into national monitoring systems, such as ZNO and NMT, is a strategic priority that necessitates the development of localised language models adapted to the domestic cultural and educational context. Initial steps within projects like ZNOVision highlight the need to transition from fragmented initiatives to a comprehensive state policy regulating ethical aspects, data security, and algorithmic transparency. The use of AI for grading open-ended tasks and analysing applicant trajectories is capable of increasing the efficiency of administrative processes by 40%, which is critical amidst limited resources and wartime challenges. In conclusion, the future of educational quality depends on the ability to harmoniously combine the power of algorithmic systems with human pedagogical mastery, where AI serves not as a replacement for the educator but as a high-performance analytical partner in ensuring the global competitiveness of national education.