AI Divide as a New Axis of Social Stratification: Risks of Algorithmization of Educational Policies for Human Capital*

Myroslava Kukhta[1,*,†] and Andrii Khomiak[1,†]

[1] National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", 37 Beresteyskyi Ave., Kyiv, 03056, Ukraine

Abstract

This paper examines the AI divide as an emerging form of social stratification driven by the algorithmization of educational processes and its impact on human capital in Ukraine. Drawing on the three-level model of digital inequality (access, usage, outcome divides), we extend this framework to analyze AI-specific risks in education policy, particularly for socially vulnerable populations, including veterans, internally displaced persons, and adult learners. The study reviews international regulatory frameworks (EU AI Act, UNESCO and OECD guidelines) alongside Ukraine's fragmented domestic regulations. Empirical data on digital literacy reveal significant disparities: only 38% of the Ukrainian adult population demonstrates high digital literacy, and merely 15.7% of educators report proficient ICT mastery. These gaps form a fertile ground for the AI divide, where unequal access to AI tools, unequal ability to use them effectively, and unequal distribution of benefits deepen existing social inequalities. We argue that without targeted policy interventions grounded in human rights by design principles, the algorithmization of educational governance risks undermining human capital preservation and sustainable development, especially in the context of Ukraine's wartime recovery.

Keywords

AI divide, digital inequality, artificial intelligence, educational policy, human capital, algorithmization, social stratification, vulnerable groups, sustainable development

1. Introduction

The digital transformation of education has become one of the defining processes of the contemporary era, extending far beyond purely technological change. It is reshaping the structure of educational relations, mechanisms of access to knowledge, and models of governance over learning. As of 2024, hundreds of millions of people use ChatGPT daily, and generative artificial intelligence is increasingly assuming cognitive functions traditionally belonging to humans [1]. AI is now employed for personalizing learning, assessing outcomes, allocating resources, and supporting administrative decisions, effectively becoming a core governance infrastructure in both business and education [2].

In Ukraine, these global trends intersect with a unique context: large-scale digitization of the educational sector is occurring simultaneously with the legal regime of martial law, significant demographic losses, and a growing number of socially vulnerable groups requiring reskilling and access to adult education. Veterans, internally displaced persons (IDPs), and residents of de-occupied territories face a dual barrier: on one hand, the need for new competencies for reintegration, and on the other, limited access to digital infrastructure and low levels of digital literacy [3].

* *The Third International Conference of Young Scientists on Artificial Intelligence for Sustainable Development: Intelligent Systems and Artificial Intelligence (YAISD-WS 2026:ISAI) May 7-8, 2026, Ternopil, Ukraine*

[1,*] Corresponding author.

[†] These authors contributed equally.

miroslavakukhta@gmail.com (M. Kukhta); a.khomiak@kpi.ua (A. Khomiak);

0000-0003-4663-9670 (M. Kukhta); 0000-0002-6661-4510 (A. Khomiak)

© 2026 Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).

CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

published 2026-11-11

CEUR-WS.org/Vol-4326/paper11.pdf

At the same time, the strengthening role of algorithmic systems in shaping educational policy, absent adequate legal and ethical regulation, carries specific risks: the deepening of educational inequality, the loss of transparency in decision-making, limitations on human oversight, and the spread of discriminatory practices [4, 5]. These processes unfold against a backdrop of insufficient comprehensive, interdisciplinary research that accounts for the social, legal, and psychological consequences of digital transformation in Ukrainian education.

The aim of this paper is to analyze inequality in access to artificial intelligence, its use, and the benefits derived from it as a new form of social stratification in the context of the algorithmization of educational policies and its impact on human capital preservation in Ukraine. The main contributions of this work are: (1) the operationalization of the AI divide concept within Ukrainian educational policy under wartime conditions; (2) an original analytical framework integrating the three-level AI divide model with human capital theory and digital social mobility (Fig. 1, Fig. 2); (3) a comparative regulatory analysis culminating in a structured EU AI Act harmonization roadmap (Table 1); and (4) evidence-based policy recommendations grounded in the human rights by design approach. The study thus addresses a gap in the Ukrainian sociological literature, where comprehensive interdisciplinary analysis of AI-driven educational inequality remains absent.

Scientific novelty and contribution. The principal scientific novelty of this work lies in the introduction and operationalization of the AI divide concept within the sociological analysis of Ukrainian educational policy under conditions of armed conflict. Unlike prior Ukrainian studies that address AI primarily from legal or pedagogical angles, the present paper: (1) extends the three-level digital inequality model (van Deursen & Helsper) to the AI-specific context of algorithmized educational governance; (2) proposes an original analytical framework — the «Mechanisms of AI Inequality Reproduction in War Conditions» scheme — which integrates structural, institutional, and wartime factors into a coherent sociological model (Fig. 1); (3) applies this framework to empirical data on digital literacy in Ukraine, identifying clear stratification contours among vulnerable groups (veterans, IDPs, adult learners); and (4) provides actionable policy recommendations grounded in EU AI Act harmonization and the human rights by design approach.

This work is conducted within the framework of the research project «The Role of Artificial Intelligence in Shaping Educational Policies for the Development and Preservation of Human Capital» (State Registration No. 0126U001611), funded by the Ministry of Education and Science of Ukraine (2026–2028), as well as the Pan-European Network of Multisectoral Master's Programme in Responsible Artificial Intelligence (PANORAIMA) (Grant No. 101189994).

2. Related Work and Conceptual Background

AI's impact on education and human capital has drawn significant scholarly attention. Globally, UNESCO [6, 7] and the OECD [8] have issued recommendations for ethical AI use in education, stressing transparent regulatory mechanisms. Porayska-Pomsta, Holmes, and Nemorin [4] created an ethical framework for AI in education. Colonna [5] underscored the need for stronger regulation of AI in education.

The concept of digital inequality has undergone significant evolution: from the three-level digital divide model [9] to the concept of the AI divide, proposed by Carter, Liu, and Cantrell [10] and further developed by Lutz [11]. A 2025 study in Frontiers in Education introduced a socio-techno-ethico-pedagogical (STEP) framework for analyzing AI in education, combining Actor-Network Theory with critical digital sociology [12].

In Ukraine, research has focused predominantly on individual aspects of the problem. The legal dimension is covered by Bernaziuk [13] (AI and human rights under the ECHR), Dubniak [14] (the EU AI Act and its implications for Ukraine), and Zhornokui [15] (ethical aspects of human rights protection). Questions of academic integrity under AI conditions are examined by Vasylenko [16] and Hryshko [17]. The role of AI in the educational process has been studied by Zhyla [18], Iliichuk [19], Kuklina et al. [20], and Yatsyshyn and Burov [21]. Human capital in the context of digitization is addressed by Zachosova [22], and public administration aspects by Ardelian [23].

The existing Ukrainian literature on AI in education, while growing, remains largely confined to technological or legal dimensions, leaving the sociological mechanisms through which algorithmization reproduces inequality substantially underexplored. The present study takes up this question directly, situating it within a wartime context that adds urgency to questions of equitable access and institutional resilience.

3. Theoretical and Methodological Framework

3.1. From Digital Divide to AI Divide

The concept of the digital divide has acquired a well-established structure in the works of van Deursen and Helsper [9], who identified three levels: inequality of access to technologies (first level), inequality in skills and modes of use (second level), and inequality in outcomes and benefits from digital participation (third level). This model has proven productive for analyzing digitization processes across various spheres of social life, particularly in education.

However, the rapid development of AI technologies, especially generative AI, has created a qualitatively new situation that cannot be reduced to traditional digital inequality. Carter, Liu, and Cantrell [10] proposed the concept of the AI divide, describing inequality across three dimensions: access to AI (access divide), the ability to use AI effectively (usage divide), and the ability to derive sustained benefits from AI interaction (outcome divide). Lutz [11] further developed this model, demonstrating that the AI divide is not a simple continuation of digital inequality but forms a separate axis of stratification that intersects with existing social inequalities—age-based, gender-based, educational, and regional.

The AI divide is distinguished from earlier forms of digital inequality by several interconnected characteristics that together constitute a qualitatively new stratification dynamic. Algorithmic opacity is perhaps the most fundamental: unlike conventional digital tools, AI systems operate as «black boxes» whose decision-making logic remains hidden even from trained users [1]. Compounding this is the expanding scope of automated decision-making, through which AI systems increasingly shape consequential outcomes in education — from student selection to resource allocation — without transparent rationale [15]. Underlying both is the problem of algorithmic bias, whereby systems trained on historically unequal data tend to reproduce and amplify those inequalities rather than neutralize them [13]. Finally, automation bias — the documented tendency to over-trust algorithmic outputs — further erodes the practical role of human oversight precisely where it is most needed [13].

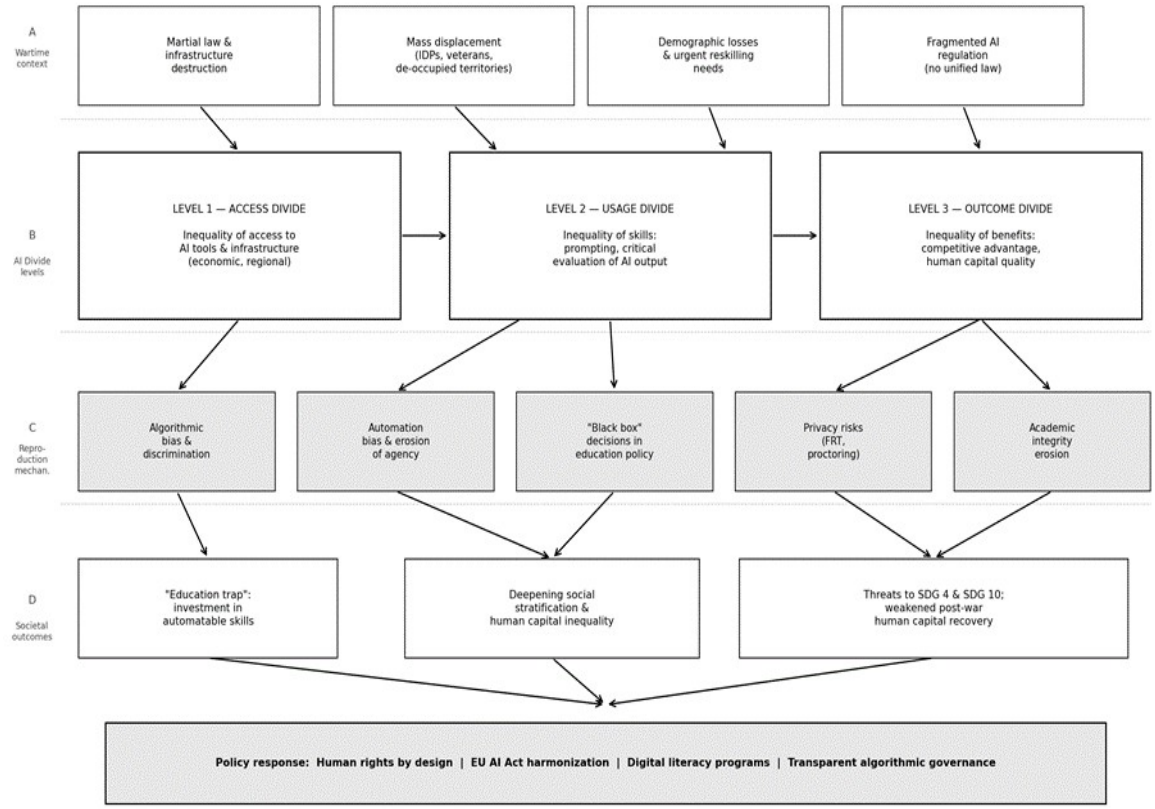


Figure 1: Mechanisms of AI Inequality Reproduction in War Conditions (authors' own model).

3.2. Analytical Framework of the Study

The present paper proposes an integrated analytical framework that combines three-level AI divide theory with human capital theory and digital social mobility, contextualized within Ukraine's wartime conditions. Figure 2 presents this framework as a block diagram illustrating the research logic: from the input (algorithmization of educational processes) through the three stratification levels and wartime multipliers to societal outcomes and evidence-based policy recommendations.

Gary Becker's traditional human capital theory considers investments in education and skills as the primary means to enhance individual productivity and welfare [22]. However, the emergence of artificial intelligence as a general-purpose technology complicates this linear relationship by simultaneously transforming human capital production in educational institutions and labor market demand [23]. Peterson observes that these forces are often analyzed separately, causing systemic distortion: educational planners, responding to AI's effectiveness in teaching structured, codified disciplines, tend to invest in skills most vulnerable to automation [24]. This results in an «education trap,» where technology improves short-term learning efficiency but undermines the long-term value of acquired competencies. Empirical evidence supports this asymmetry. Unlike industrial robots, which mainly replace low-skilled labor, contemporary AI substitutes tasks traditionally performed by high-skilled workers, such as diagnostics, report writing, legal analysis, and programming [24, 25]. Consequently, the skill premium and wage gap between high- and low-skilled workers decline, assuming AI access is not limited by wealth inequality.

A comprehensive understanding of how algorithmization in education reshapes social structure requires integrating the AI divide concept with human capital theory and digital social mobility. In this framework, human capital theory views education as an investment in worker productivity within the digital economy. Zachosova defines «human capital for recovery» as «knowledge, skills,

and health that people have acquired throughout their lives, along with the internal desire and motivation to help restore and rebuild Ukraine» [3]. The concept of digital social mobility, encompassing professional, educational, and economic dimensions, facilitates analysis of how digital technologies influence access to resources and development opportunities across social groups.

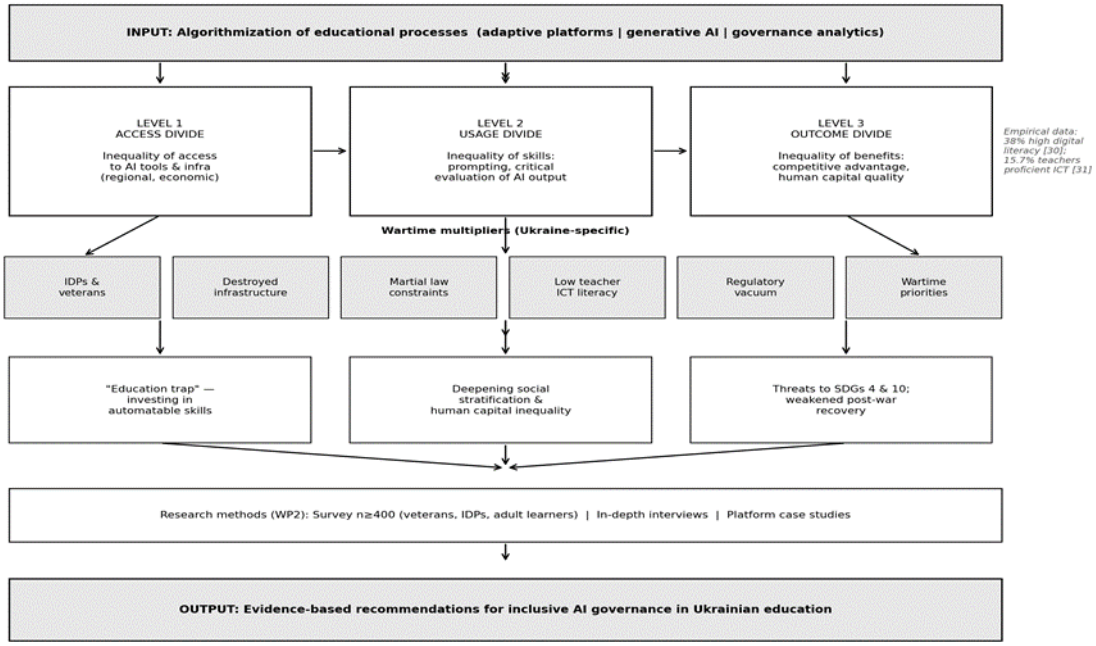


Figure 2: Analytical framework: Three-level AI divide in Ukrainian education (block diagram of the research approach).

The integrated framework exposes a structural tension at the heart of AI-driven education: the same technological infrastructure that enables personalized learning, broader knowledge access, and inclusivity support also concentrates advantages among those already best positioned to exploit it, through unequal access to quality tools, algorithmic discrimination, and dependence on commercial platforms whose design priorities do not always align with public educational goals. Zhyla emphasizes that without clear AI usage regulations in education, risks escalate from formal «learning» deficiencies to actual declines in human capital quality [18].

Advancing human capital theory in the AI context requires considering social network mechanisms, cognitive constraints, and digitally mediated social mobility pathways. Broekel and Klarl's endogenous growth model demonstrates that learning within knowledge networks is vital for human capital formation; however, cognitively constrained agents cannot optimally utilize these networks, exacerbating inequality, especially amid accelerated knowledge obsolescence [22]. Cross-national data from 238 regions in twenty-one European countries reveal that increased AI patenting correlates with a decline in labor's income share, particularly among medium- and high-skilled workers [26]. Korinek and Stiglitz argue that, even under technological singularity, policy interventions such as non-distortionary taxation and redistribution can mitigate these effects; however, institutional capacity to ensure equitable benefit distribution remains crucial [27].

4. Mechanisms of Algorithmization in Education

The algorithmization of educational processes occurs simultaneously at several levels. At the level of the learning process, AI enables personalization through adaptive platforms (DreamBox, Knewton, Coursera) that adjust content and pace based on analysis of learner interaction data [19, 29]. Natural language processing tools (Grammarly, Duolingo) create unique language learning

experiences. Generative AI (ChatGPT, Gemini, Copilot) is used for information retrieval, text generation, translation, and preparation of teaching materials [16, 20].

At the level of educational governance, AI allows the automation of routine administrative tasks, the optimization of management processes, and the improvement of decision-making quality [21, 32]. AI analytics enable administrators to effectively track student performance, forecast educational needs, and make strategically informed decisions, contributing to more adaptive and personalized educational systems [2].

At the level of educational policy, AI becomes a tool for modeling the consequences of governance decisions, forecasting labor market needs, and optimizing resource allocation. Kuklina et al. [20] note that modeling the trajectory of AI integration into the educational environment enables «developing education policy aimed at supporting innovation, ensuring the quality of educational services, and overcoming the skills gap». Importantly, the potential of AI also extends to inclusivity—speech recognition systems, text-to-audio conversion, and sign language identification facilitate educational accessibility for persons with disabilities [19].

5. Risks of Algorithmization for Social Groups and Sustainable Development

Despite its significant potential, the algorithmization of educational processes harbors systemic risks with a pronounced sociological dimension that directly threaten the goals of sustainable human capital development.

Algorithmic bias and reproduction of inequality. Bernaziuk [13] analyzes in detail how the selection of training data, target variables, and model criteria leads to systemic inequality—specifically in access to services, justice, and social support. Zhornokui [15] describes how facial recognition algorithms, selection systems, and machine learning models can entrench inequality and violate the right to equality and non-discrimination. In the educational context, these risks manifest in algorithmic student selection, automated assessment of achievements, and the distribution of scholarships and grants, where biased algorithms may systematically discriminate against vulnerable groups.

Automation bias and the erosion of agency. Voloshyn [1] demonstrates that humans interacting with AI gradually transition to the role of users who formulate queries and work with responses but do not control the model's internal processes. Bernaziuk [13] identifies the problems of automation bias and the anchoring effect—the reduction of the real role of humans (human-in-the-loop) under conditions of trust in algorithms. Yatsyshyn and Burov [21] warn of the risk of "excessive reliance on technology, where decisions are made automatically without sufficient human oversight, potentially reducing ethical responsibility."

Threats to confidentiality and privacy. The use of facial recognition technologies (FRT), learning analytics, and proctoring in education creates risks for privacy and personal autonomy. Bernaziuk [13] analyzes these risks through the lens of ECHR case law (S. and Marper v. UK, Big Brother Watch v. UK), demonstrating that mass collection and processing of personal data without adequate safeguards contradicts Convention standards.

Erosion of academic integrity and human capital quality. Vasylenko [16] and Hryshko [17] document the mass use of generative AI by students for writing papers, translation, and paraphrasing. The problem lies not only in formal plagiarism but in the loss of independent analytical thinking skills, directly affecting human capital quality. As Zachosova [3] observes, instead of using digital technologies to expand their educational opportunities, young people employ them to violate academic integrity norms.

Deepening educational inequality and threats to sustainable development. Zhyla [18] specifically highlights the risk of deepening educational inequality when access to quality AI tools is available only to certain social groups. This aligns with the AI divide model: inequality in access to AI generates inequality in its use, which in turn deepens inequality of outcomes—and ultimately inequality of human capital. In the context of Ukraine's Sustainable Development Goals (SDGs),

particularly SDG 4 (Quality Education) and SDG 10 (Reduced Inequalities), the unchecked algorithmization of educational governance threatens to undermine the very foundations of inclusive, sustainable human capital development needed for post-war recovery.

6. Regulatory Frameworks: International and Ukrainian Context

6.1. International Regulatory Landscape

The European AI Act (AIA, 2024), analyzed in detail by Dubniak [14], classifies AI systems into four risk levels: unacceptable (prohibited applications), high, limited, and minimal. Critically, education is explicitly designated as a high-risk area, requiring mandatory data quality, documentation, transparency, and human oversight. For high-risk systems, the AIA prescribes: a risk management system; training data quality; technical documentation; logging; user transparency; human control; and system accuracy and robustness. Additionally, the AIA requires an assessment of the impact on fundamental rights under the EU Charter.

In addition to its risk classification framework, the AIA establishes specific provisions for General-Purpose AI (GPAI) models under Title VIII, which are directly relevant to educational practice. Providers of GPAI models with systemic risk, including ChatGPT, Gemini, and Copilot, which are already widely implemented in Ukrainian higher education [16, 20], must comply with transparency and copyright requirements, conduct adversarial testing, and report serious incidents to competent national authorities [14]. The lack of comparable provisions in Ukrainian regulation results in domestic educational institutions operating these tools within a normative vacuum, without established accountability mechanisms for model developers or deployers.

Another significant international development is the Framework Convention on Artificial Intelligence and Human Rights, Democracy and the Rule of Law (CETS No. 225), adopted by the Council of Europe in 2024 [35]. This convention constitutes the first legally binding international treaty on AI governance, establishing obligations regarding transparency, accountability, and the protection of human rights throughout the AI lifecycle. In contrast to the AIA, which is a regional EU instrument, CETS 225 is open to signature by non-EU states, including Ukraine as a Council of Europe member. Clarification is needed in domestic policy discourse regarding whether Ukraine has signed or ratified this convention, as accession would create binding international obligations and provide a complementary normative foundation to the EU harmonization process discussed in Section 6.3.

UNESCO has issued specific recommendations for policymakers concerning artificial intelligence in education [6, 7]. In 2021, UNESCO adopted the Recommendation on the Ethics of Artificial Intelligence, a normative instrument endorsed by all 193 UNESCO member states, including Ukraine [36]. This recommendation articulates principles such as proportionality, safety, fairness, sustainability, the right to privacy, human oversight, transparency, and accountability as foundational standards for AI governance across all policy domains, including education. Although not legally binding, Ukraine's formal endorsement constitutes a political commitment that should guide domestic regulatory frameworks. The OECD published a 2025 report highlighting opportunities for innovative technologies to transform vocational education in Ukraine [8]. At the Council of Europe level, Bernaziuk [13] examines European Court of Human Rights (ECHR) case law as a mechanism for adapting human rights standards to digital risks. A notable conflict exists between the Artificial Intelligence Act (AIA) and the General Data Protection Regulation (GDPR): the GDPR requires minimization of personal data, whereas AI model training often necessitates large data volumes. Federated learning, which involves training models on distributed data without central collection, has been proposed as a potential solution [14].

6.2. Ukraine's Fragmentary Regulation

Ukraine's AI regulation is fragmented. Dubniak [14] identifies key documents: CMU Decree No. 1556-2020 on the Concept of AI Development in Ukraine (defining three directions: technology development, research, and workforce training); the Concept of a state program for AI until 2026

(CMU No. 320-r, 13.04.2024); and laws on information and electronic communications. However, Decree 1556-2020 is a framework document without specific implementation mechanisms, and Ukraine has neither a unified AI law nor a risk classification system modeled on the AIA.
In education, Vasylenko [16] analyzes MES recommendations for higher education institutions regarding AI use. Hryshko and Kyrychuk [17] note that «conscientious AI use does not yet have clearly prescribed rules, creating a 'gray zone' for students and faculty». Concurrently, digital infrastructure initiatives such as «Diia» system are being developed [28], yet the gap between digital transformation ambitions and the actual state of regulation remains significant: there are no special norms for AI in education, no risk classification for educational AI systems, and no transparency or accountability requirements.

6.3. Pathways to Harmonization with the EU AI Act
A comparative analysis of Ukraine's regulatory framework in relation to the EU AI Act identifies a structural gap with significant consequences for educational governance. Table 1 presents the key requirements of the EU AI Act for high-risk AI systems in education, the current status of Ukrainian regulation, proposed harmonization measures, and the corresponding responsible institutional actors.

Table 1.
Harmonization of Ukrainian AI regulation in education with EU AI Act requirements (authors' analysis)

EU AI Act Requirement (Education as High-Risk)	Current Status in Ukraine	Recommended Harmonization Steps
Risk classification for AI systems in education	Absent; no unified AI law; no sector-specific classification	Adopt risk-tiered framework in the draft Law on AI; include education explicitly as high-risk
Mandatory human oversight for high-risk decisions	Mentioned declaratively in CMU Concept 1556-2020; no enforcement mechanism	Introduce binding human-in-the-loop requirements in MES regulations for AI-assisted grading and selection
Transparency & documentation requirements	No requirements for algorithmic transparency in educational platforms	Mandate disclosure of AI use and algorithmic logic in public educational platforms; establish algorithmic impact assessment procedures
Prohibition of biometric real-time surveillance in education	No explicit prohibition; FRT used in some proctoring systems	Explicitly restrict real-time biometric surveillance in educational settings; align with EU prohibition under AIA Art. 5
Fundamental rights impact assessment	Not required under current Ukrainian law	Integrate rights impact assessment into procurement procedures for AI tools in state educational institutions
Data governance & GDPR-AIA conflict resolution	Data minimization principle exists in Ukrainian law, but no federated learning provisions	Develop technical standards for federated learning in education analytics; amend personal data law to accommodate privacy-preserving AI training

EU AI Act Requirement (Education as High-Risk)	Current Status in Ukraine	Recommended Harmonization Steps
GPAI model transparency (AIA Title VIII)	No specific provisions; generative AI tools (ChatGPT, Gemini, Copilot) used in education without dedicated regulatory framework [16, 20]	Develop sector-specific guidelines for GPAI use in educational settings; require disclosure of AI-generated content in accredited programs. Responsible actors: Ministry of Education and Science.
Harmonization with CETS 225 (Council of Europe Framework Convention on AI, 2024) [35]	Ratification status unconfirmed; CETS 225 obligations not integrated into domestic AI governance framework	Initiate accession process; incorporate CETS 225 obligations into the draft Law on AI and related sector legislation. Responsible actors: Ministry of Foreign Affairs; Ministry of Justice.

Implementation of these steps requires a phased approach: in the short term (2026–2027), priority should be given to legislative definition of risk categories and mandatory transparency requirements for public educational AI systems; in the medium term (2027–2028), to enforcement mechanisms, algorithmic audit capacity, and educator training in AI literacy. This aligns with the OECD's 2025 recommendations for Ukraine [8] and provides the legal foundation for the empirical research planned in the subsequent phases of the MES-funded project.

7. AI Divide in Ukrainian Education: Empirical Evidence and Case Analysis of the Diia.Osvita Platform

Empirical evidence indicates pronounced digital inequality in Ukraine, which underpins the development of an AI divide. The Diia.Osvita 2025 study reports that 58% of adults possess basic digital literacy, 93% have mastered basic digital skills, yet only 38% exhibit advanced digital literacy [30, 33]. This demonstrates a considerable disparity between basic digital engagement and the capacity to utilize sophisticated digital tools, such as AI.

The situation among educators is similarly concerning. Bandura et al. [31] found that only 15.7% of teachers possess proficient ICT skills, while 38.7% report that ICT challenges complicate their professional and personal activities. Furthermore, only 21.5% of educators use search engines professionally, 47.1% can assess information reliability, and 15% are able to secure their digital devices and personal data. These findings indicate that a substantial portion of educators are unprepared for AI integration in education and lack the capacity for critical evaluation of algorithmic decisions.

Zachosova [3] identifies several barriers faced by learners at different educational levels: lack of direct instructor contact, stringent digital literacy and foreign language requirements, uneven workload distribution, limited use of interactive teaching methods, and information overload. Notably, the demands for digital skills and foreign language proficiency disproportionately disadvantage older learners.

Veterans, internally displaced persons (IDPs), and residents of de-occupied territories encounter further obstacles, including restricted access to reliable digital infrastructure, psychological effects of combat and displacement, and the necessity for reskilling amid limited time and resources [34]. Martial law exacerbates inequality by generating new vulnerable groups and intensifying existing disparities in access to digital educational resources.

7.1. Diia.Osvita as an Algorithmic Educational Platform: Background and Analytical Rationale

This section situates the AI divide analysis within the institutional framework of Diia.Osvita (osvita.diia.gov.ua), the national digital education platform operated by the Ministry of Digital

Transformation of Ukraine. The platform is selected for three reasons: it serves as the primary governmental tool for digital literacy policy, with 2.8 million registered users by 2025 [38]; it is directly referenced in the empirical data supporting this study [30]; and it has recently transitioned from a digital literacy portal to an AI-powered educational ecosystem, making it a pertinent case for examining AI-driven educational governance in Ukraine.

Diia.Osvita was launched in 2020 as part of the broader Diia digital transformation initiative, initially delivering digital literacy content through online courses, webinars, and skills assessments. Its infrastructure now encompasses approximately 5,000 Digital Education Hubs in libraries, administrative centers, and educational institutions across Ukraine [39]. By 2025, with support from Google.org, the platform introduced a new AI-driven architecture, featuring an AI navigator for personalized course selection, an AI assistant for terminology explanation, note creation, and content recommendations, and a planned Digital Skills Passport documenting verified user competencies linked to learning data [38]. The assessment methodology, including the national Digigram digital literacy test, is based on the EU DigComp 2.2 Digital Competence Framework, adapted by Ukrainian experts [40].

7.2. Indicators for Analysis

The analysis utilizes indicators derived from the three-level AI divide model (Section 3.1) and risk dimensions outlined in Section 5. Access divide indicators include: cost of access (free or freemium model), device and connectivity requirements, and geographic coverage of offline hub infrastructure. Usage divide indicators encompass entry-level digital literacy requirements for effective AI tool use, language accessibility, and transparency of algorithmic recommendations. Outcome divide indicators address institutional recognition of the Digigram certificate, alignment of AI-generated recommendations with labor market demand, and distribution of AI-enhanced outcomes across social groups. Risk indicators, based on Section 5, comprise the scope and transparency of personal data collection by AI features, presence of human oversight in AI-mediated recommendations, and documentation of bias risk in the AI navigator and career orientation test.

7.3. Analysis Along the Three Levels of the AI Divide

Access divide. Diia.Osvita offers free access, mitigating first-level cost-based exclusion [20]. Its network of approximately 5,000 Digital Education Hubs provides physical access in communities lacking home digital infrastructure [39]. Nevertheless, connectivity inequalities remain: residents of de-occupied and conflict-affected regions often lack stable internet, excluding them from algorithmic learning tools despite the platform's zero-cost model [34]. Additionally, the Digital Skills Passport, which may hold labor market value, is available only to users who complete structured digital assessments, creating a secondary barrier for those with equivalent skills acquired through informal means.

Usage divide. The AI navigator personalizes course selection based on user-stated goals [38]. Its effectiveness depends on users' ability to articulate goals in a system-compatible format, which is influenced by prior digital experience and education [1, 20]. Empirical data from 2025 show that only 38% of Ukrainians possess high digital literacy [30], indicating that most users lack the skills to interact effectively with AI-enhanced features. The Digigram assessment assumes familiarity with digital environments, disadvantaging older individuals, rural populations, and those displaced by conflict. Notably, the platform's public documentation omits details about the algorithmic logic and data attributes used for personalized recommendations. This constitutes algorithmic opacity [13], as users receive recommendations without transparent rationale or the ability to challenge the system's logic.

Outcome divide. Users who effectively engage with the platform's AI tools may achieve substantial benefits: the Digigram certificate is recognized by employers as evidence of digital competency [40], and AI-assisted job-search preparation has been shown to improve hiring rates [20]. However, these advantages are not evenly distributed. The 61.3% of educators reporting ICT difficulties [31] are structurally disadvantaged in accessing algorithmic learning benefits, as limited digital

confidence impairs both AI navigator interactions and learning outcomes. Veterans and IDPs, facing infrastructure barriers and psychosocial stressors, are particularly at risk of exclusion from the outcome level of Diia.Osvita's AI ecosystem [34].

Risk indicators. Diia.Osvita's transition to an AI-powered architecture in 2025 heightens the need for comprehensive risk assessment, as outlined in Section 5. Regarding data governance, the AI assistant and navigator collect user interaction data, goal declarations, and learning history to generate personalized recommendations [38]. However, there is no public documentation of privacy impact assessments, data retention policies, or federated learning architectures for these features, which constitutes a gap relative to standards in Table 1 (Section 6.3). In terms of human oversight, the AI-driven career orientation test produces professional trajectory recommendations without documented mechanisms for expert review or user appeal, exemplifying automated decision-making without sufficient human involvement [13, 21]. The lack of published bias documentation is especially concerning, as the training data for the AI navigator and career test likely reflect pre-war labor market structures, which have been disrupted by conflict. Consequently, recommendations may be misaligned with the reintegration needs of veterans and IDPs.

Applying the three-level AI divide model, the Diia.Osvita case exemplifies a broader trend in algorithmic educational governance: platforms intended for universal access often create stratified beneficiary structures. Vulnerable groups with limited digital experience, connectivity challenges, and psychosocial stressors are least able to benefit from AI-enhanced features [1, 20]. At the access level, advanced AI tools are typically available in paid versions with expanded functionality, while free versions remain limited [20].

Conclusions and Future Work

The foregoing analysis converges on several interconnected conclusions that carry implications for both scholarship and governance in the domain of AI-driven educational reform.

The AI divide emerges from this study not as a derivative of traditional digital inequality but as a qualitatively distinct axis of social stratification. Unequal access to AI tools, unequal capacity to use them effectively, and unequal ability to translate that engagement into lasting outcomes interact with pre-existing cleavages of age, region, and displacement status in ways that compound rather than merely replicate prior disadvantages. This dynamic poses a direct threat to SDG 4 (Quality Education) and SDG 10 (Reduced Inequalities) at precisely the moment when Ukraine most needs inclusive human capital development.

The algorithmization of educational processes proves to be an inherently ambivalent force. On one hand, adaptive platforms, generative AI tools, and learning analytics meaningfully expand possibilities for personalization, inclusion, and administrative efficiency. On the other hand, algorithmic opacity, automation bias, surveillance through proctoring and facial recognition, and the erosion of independent analytical thinking create systemic risks that are particularly acute for socially vulnerable learners.

Ukraine's regulatory landscape for AI in education remains fragmented and significantly lags behind European standards. The EU AI Act's explicit classification of education as a high-risk domain has no equivalent in Ukrainian law: there is no unified AI statute, no risk classification framework, and no sector-specific norms governing the use of algorithmic systems in educational settings. This legal vacuum allows consequential decisions about learners to be made without meaningful oversight or accountability. Table 1 offers a structured roadmap for closing this gap through phased harmonization with the EU AI Act.

Taken together, these structural, regulatory, and empirical realities confirm that Ukraine currently lacks the institutional conditions necessary to prevent the AI divide from deepening existing social inequalities. Vulnerable groups—veterans, internally displaced persons, adult learners in de-occupied territories—face the steepest barriers precisely when their inclusion in a digitally literate workforce is most critical for the country's post-war recovery. Without targeted policy

intervention guided by human rights by design principles, the algorithmization of educational governance risks undermining rather than advancing sustainable human capital development.
Future research within the MES-funded project will focus on empirically verifying the proposed analytical framework: structured surveys of adult education program participants, including veterans (minimum 400 respondents); in-depth interviews with educational administrators and digital service developers; and case analyses of educational platforms that employ algorithmic tools. The human rights by design approach [15], which embeds human rights protection requirements into the design of educational AI systems at the development stage, should serve as a guiding principle for the formulation of inclusive educational policies that support sustainable human capital development in Ukraine.

Acknowledgements

This work was supported by the state-funded research project No. 2916f of the National Technical University of Ukraine «Igor Sikorsky Kyiv Polytechnic Institute»: «The Role of Artificial Intelligence in Shaping Educational Policies for the Development and Preservation of Human Capital» (State Registration No. 0126U001611), as well as the Pan-European Network of Multisectoral Master's Programme in Responsible Artificial Intelligence (PANORAIMA) (Grant No. 101189994).

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

[1] V. S. Voloshyn, The role of the new generation of artificial intelligence systems in human development (the case of the ChatGPT network), Visnyk Pryazovskoho Derzhavnoho Tekhnichnoho Universytetu. Seriia: Tekhnichni Nauky 49(1) (2024) 47–56

[2] Yu. S. Hrynchuk, N. A. Liashenko, S. K. Vasylyk, Artificial intelligence and strategic management: interaction trends in the digital age, Internauka. Seriia: Ekonomichni Nauky 6(1) (2025) 94–101.

[3] N. V. Zachosova, Directions for human capital development through education for shaping the intellectual potential of post-war economic recovery, Naukovyi Visnyk Odeskoho Natsionalnoho Ekonomichnoho Universytetu 1–2(314–315) (2024) 7–16. doi:10.32680/2409-9260-2024-1-2-314-315-7-16.

[4] K. Porayska-Pomsta, W. Holmes, S. Nemorin, The ethics of AI in education, in: B. du Boulay, A. Mitrovic, K. Yacef (Eds.), Handbook of Artificial Intelligence in Education, Edward Elgar Publishing, 2023, pp. 571–604. doi:10.4337/9781800375413.00038.

[5] L. Colonna, Artificial Intelligence in Education (AIED): Towards more effective regulation, European Journal of Risk Regulation (2025) 1–21. doi:10.1017/err.2025.10039.

[6] F. Miao, W. Holmes, AI and education: guidance for policy-makers, UNESCO, 2021. URL: https://unesdoc.unesco.org/ark:/48223/pf0000376709.

[7] F. Miao, W. Holmes, Guidance for generative AI in education and research, UNESCO, 2023. URL: https://unesdoc.unesco.org/ark:/48223/pf0000386693.

[8] OECD, How can innovative technologies transform vocational education and training: Insights for Ukraine, OECD, 2025. URL: https://www.oecd.org/content/dam/oecd/uk/publications/reports/2025/05/how-can-innovative-technologies-transform-vocational-education-and-training_5b10f8ac/b9c78227-uk.pdf.

[9] A. J. A. M. Van Deursen, E. J. Helsper, The third-level digital divide: Who benefits most from being online? Communication and Information Technologies Annual 10 (2015) 29–52.

[10] L. Carter, D. Liu, C. Cantrell, Exploring the intersection of the digital divide and artificial intelligence: A hermeneutic literature review, AIS Transactions on Human-Computer Interaction 12(4) (2020) 253–275.
[11] C. Lutz, Digital inequalities in the age of artificial intelligence and big data, Human Behavior and Emerging Technologies 1 (2024) 1–18.
[12] A. Tlili, B. Shehata, M. A. Adarkwah, A. Bozkurt, D. T. Hickey, R. Huang, B. Agyemang, AI in education: a sociological exploration of technology in learning, Frontiers in Education 10 (2025) 1700876. doi:10.3389/feduc.2025.1700876.
[13] I. M. Bernaziuk, Artificial intelligence and human rights: challenges for the European Convention on Human Rights, Analitychno-Porivnialne Pravoznavstvo 3(1) (2025) 89–99.
[14] M. V. Dubniak, Legal approaches in the EU Artificial Intelligence Act: experience for Ukraine, Informatsiia i Pravo 3 (2024) 40–53.
[15] Yu. M. Zhornokui, Artificial intelligence: protection and defence of human rights (ethical aspect), Visnyk Kharkivskoho Natsionalnoho Universytetu Vnutrishnikh Sprav 1(1) (2025) 71–83.
[16] N. V. Vasylenko, Artificial intelligence and academic integrity: forming ethical norms in the digital environment, Suspilstvo ta Natsionalni Interesy 7 (2025) 306–313.
[17] V. I. Hryshko, B. S. Kyrychuk, Academic integrity and artificial intelligence: overcoming challenges in educational and scientific activities, Naukovyi Visnyk Uzhhorodskoho Natsionalnoho Universytetu. Seriia: Pravo 85(2) (2024) 305–310.
[18] H. Zhyla, Artificial intelligence and education: new challenges, Molod i Rynok 4 (2025) 180–183.
[19] L. Iliichuk, Artificial intelligence and the quality of education: opportunities, challenges and threats, Naukovo-Pedahohichni Studii 8 (2024) 232–248.
[20] O. Kuklina, I. Ivanova, T. Borovyk, Modeling the integration of artificial intelligence in the educational environment, Informatsiini Tekhnolohii i Zasoby Navchannia 5(103) (2024) 207–232.
[21] A. Yatsyshyn, O. Burov, L. Kondratova, Integration of generative artificial intelligence in the professional development of education managers, Naukovyi Visnyk Melitopolskoho Derzhavnoho Pedahohichnoho Universytetu. Seriia: Pedahohika 2(35) (2025) 241–249.
[22] T. Broekel, T. Klarl, Knowledge Obsolescence, Human Capital Inequality, and Growth: A Network Perspective in an Automated Knowledge Society, Economic Modelling 155 (2026) 107416.
[23] A. J. Peterson, Training for Obsolescence? The AI-Driven Education Trap, arXiv (2025). doi:10.48550/arXiv.2508.19625.
[24] D. Bloom, K. Prettner, J. Saadaoui, M. Veruete, Artificial Intelligence and the Skill Premium, Finance Research Letters 81 (2025) 107401.
[25] R. Grant, M. Üngör, The AI Revolution with 21st Century Skills: Implications for the Wage Inequality and Technical Change, Scottish Journal of Political Economy (2024). doi:10.1111/sjpe.12395.
[26] A. Minniti, K. Prettner, F. Venturini, AI Innovation and the Labor Share in European Regions, European Economic Review 177 (2025) 105043.
[27] A. Korinek, J. Stiglitz, Artificial Intelligence and Its Implications for Income Distribution and Unemployment, in: The Economics of Artificial Intelligence: An Agenda, University of Chicago Press, 2019, pp. 349–390.
[28] I. S. Ardelian, Artificial intelligence in public administration: examples of successful integration, Publichne Administruvannia ta Natsionalna Bezpeka 8 (2024) 14–25.
[29] O. I. Papach, O. Yu. Horozhankina, H. V. Rizak, Analyzing the role of artificial intelligence in the implementation of a differentiated approach to learning, Prydniprovska State Academy of Civil Engineering and Architecture, Dnipro, 2024.

[30] Digital and AI literacy study in Ukraine 2025, Diia.Osvita, 2025. URL: https://osvita.diia.gov.ua/uploads/3/16239-povna_doslidzenna_cifrovoi_ta_si_gramotnosti_v_ukraini_2025_pptx_pptx.pdf.

[31] Z. L. Bandura, Ya. Ya. Kril, S. V. Dudnyk, Analysis of the level of digital competence development among educational process participants: wartime challenges, Akademichni Vizii 17 (2023).

[32] M. N. Yenin, M. P. Kukhta, O. M. Holovko, Artificial intelligence and the transformation of managerial decisions: a sociological and legal analysis of the role of the manager and power structure, Visnyk NTUU “KPI”. Politolohiia. Sotsiolohiia. Pravo (2025) 30–37

[33] L. F. Panchenko, M. N. Yenin, M. P. Kukhta, Development of digital literacy of women in the context of digitalization of cities, Visnyk NTUU “KPI”. Politolohiia. Sotsiolohiia. Pravo (2025) 40–52

[34] M. Yenin, M. Kukhta, T. Prykhodko, Social needs and problems of forced migrants from Ukraine on the path to social adaptation and integration into the recipient society (the case of Germany), Sotsiolohiia: teoriia, metody, marketynh 3 (2024) 117–138. doi:10.15407/sociology2024.03.117.

[35] Council of Europe, Framework Convention on Artificial Intelligence and Human Rights, Democracy and the Rule of Law (CETS No. 225), Council of Europe, Strasbourg, 2024. URL: https://www.coe.int/en/web/conventions/full-list?module=treaty-detail&treatynum=225.