



A sociotechnical typology of AI use in educational information practices under conditions of war

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Abstract

Introduction. In the era of generative AI, information literacy increasingly depends on how educators integrate AI into educational information practices. In high-risk contexts, such as war, where informational uncertainty and manipulation intensify, distinguishing between critically reflective modes of AI use and instrumental-operational or control-oriented modes becomes particularly important.

Method. This study draws on a survey of 208 educators from frontline regions of Ukraine. Educational information practices were operationalised through two composite indices: one capturing critically reflective AI use and the other capturing instrumental-operational and control-oriented uses of AI. A 2×2 typology was constructed using median splits and validated through k-means clustering ($k = 5$), with silhouette scores indicating moderate but meaningful cluster separation.

Analysis. AI use practices were operationalised through two composite indices: critically reflective use (CR_index; $\alpha = 0.868$; $\omega = 0.869$) and instrumental-operational and control-automation use (Control_index; $\alpha = 0.769$; $\omega = 0.789$). A 2×2 typology of models (CR × Control) was constructed using median splits and its robustness was tested via k-means clustering ($k = 5$). Associations between models and respondent characteristics were assessed using χ^2 tests with Cramér's V .

Results. Four models of AI use were identified: critically reflective (14.4%), hybrid (36.1%), instrumental–control (17.3%), and low integration (32.2%). Results showed that critically reflective and operational uses frequently coexist, particularly in the dominant hybrid model. Robustness checks (clustering and rank correlations) confirmed the stability of the identified configurations.

Conclusion. The findings demonstrated that AI integration in education is shaped by a sociotechnical tension between critical engagement and operational efficiency and control. In wartime conditions, critically reflective practices function as mechanisms of epistemic security. The study contributes an empirically grounded typology that can inform institutional policy and professional development in high-risk information environments.

Introduction

Generative artificial intelligence increasingly functions not merely as a tool but as an algorithmic information mediator: it selects, reformulates, ranks, and produces content that subsequently enters learning tasks, assessment practices, communication, and everyday educational decision-making. From a sociotechnical perspective, such practices are not neutral. AI becomes “embedded” in institutional rules, ethical norms, organisational procedures, and cultural expectations, shaping how information literacy is formed, as the capacity to engage critically with information, sources, uncertainty, and trust.

In conditions of war, educational information environments are subject to additional pressures: informational uncertainty intensifies, the risks of disinformation and manipulative narratives increase, and the cost of errors, such as the uncritical reproduction or dissemination of unverified information, becomes substantially higher. In this context, it is essential to understand not only whether AI is used but also how it is integrated into educational practices.

Existing research and professional debates suggest that educational uses of AI often cluster around two broad orientations (Long & Magerko, 2020; Ng et al., 2021; OECD, 2023; UNESCO, 2023; Veldhuis et al., 2025). On the one hand, AI is employed as a resource for supporting critical thinking, ethical discussion, explicating the limitations of algorithmic systems, co-creative learning tasks, and reflection on information credibility. On the other hand, AI is used within a logic of operational efficiency: the automation of material preparation, testing and assessment, assignment checking, learning analytics, and, in some cases, the intensification of control over discipline and evaluation. For example, educators may use AI to generate lesson materials, automate assessment tasks, support grading and feedback, and engage students in discussions about misinformation, bias, and the limitations of algorithmic outputs.

These modes can coexist within the same institution and even within the practices of a single educator, forming different *human–algorithm–institution* configurations and producing divergent implications for information literacy.

Despite growing attention to AI in education, there remains a lack of studies that empirically identify typologies of AI use as coherent configurations of practices and link them to the sociotechnical conditions under which education operates in situations of heightened information risk. Much of the existing Ukrainian and international literature focuses on specific tools, user attitudes, risks, or policy recommendations, while fewer studies offer an empirically grounded typology of AI use models as coherent configurations of practices.

The contribution of this article lies in the development of a measurement framework (indices) and a typology of AI use models based on data from frontline regions of Ukraine. This approach enables a shift from the general claim that AI is *being used* to a more precise question: which sociotechnical configuration of practices predominates, and what this implies for information literacy.

This study aimed to develop an empirical typology of AI use models in the educational information practices of educators in frontline regions of Ukraine, based on indices of critically reflective and instrumental-operational (control-automation) use, and to provide a sociotechnical interpretation of these models in the context of war.

Based on our review of the literature, the research questions are:

RQ1. What models of AI use can be identified in the educational information practices of educators?

RQ2. How do these models combine (or separate) practices of critical thinking, ethical reflection, and explicating the limitations of algorithmic systems with practices of automation and control?

RQ3. What sociotechnical implications do the identified models have for understanding information literacy and the role of the educator as an information intermediary under conditions of war?

Based on the theoretical framework, the following hypotheses were formulated:

H1 (Multiplicity of models). Multiple models of AI use coexist in educational information practices, including critically reflective and instrumental-operational or control-oriented configurations.

H2 (Sociotechnical tension). Models oriented toward automation and control are less strongly associated with practices of ethical reflection and explicating AI limitations than models with a critically reflective orientation.

H3 (Contextual salience). Under conditions of war, the critically reflective mode of AI use gains heightened importance as a mechanism for supporting information literacy in environments characterised by high information risk.

H4 (Interpretive proposition). The identified models can be interpreted through the strengthening of the educator's role as an algorithmic information mediator who defines the rules and boundaries of interaction between learners and AI-generated information (this proposition requires further operationalisation through a dedicated risk-sensitivity scale, qualitative data, or both).

Literature review and theoretical framework

Sociotechnical framework: AI as an algorithmic information mediator

Within the sociotechnical perspective of information science, AI is conceptualised not as a neutral tool but as a mechanism of algorithmic mediation that shapes which information becomes visible, relevant, and legitimate, as well as how it circulates within educational environments. In terms of research on algorithmic governance and algorithmic relevance, algorithmic systems do not merely *recommend* content but actively structure conditions of participation in public life and practices of knowledge interpretation (Beer, 2017; Gillespie, 2014).

For information literacy, this implies a shift away from an understanding focused on a discrete set of skills toward information literacy as a social practice that is formed within specific contexts through interactions among people, norms, institutional rules, and material-technological infrastructures (Lloyd, 2017). Consequently, analysing AI use in education requires an examination of configurations of practices: who uses AI and for what purposes, which rules of *appropriate* use are established, what mechanisms of verification and explicating limitations are employed, and how these practices affect assessment, trust, and the distribution of responsibility.

The sociotechnical approach also foregrounds the relationship between algorithms and power asymmetries. Actors who define the rules of AI use, such as administrators, educators, or platform providers, effectively determine frameworks of access to knowledge, criteria of evidential validity, and acceptable modes of producing answers. In this context, the notion of epistemic responsibility becomes salient: responsibility for the quality, provenance, and consequences of information circulation, including AI-generated content, within educational processes. As shown in related sociotechnical studies of algorithmic management, *algorithmic* decisions emerge through the interaction of technological systems and organisational practices,

rather than existing independently of them (Orlikowski, 2007; Orlikowski & Scott, 2008; Pasquale, 2015).

AI in education and educational information practices: International approaches and empirical findings

AI literacy is most commonly understood as a set of competencies that enable individuals not only to use AI systems, but also to evaluate their outputs, limitations, and impacts critically. A particularly influential framework is proposed by Long and Magerko (2020), who conceptualise AI literacy as a set of design-oriented competencies that do not require programming skills, but include an understanding of AI principles, constraints, and societal implications. Subsequent review studies broaden this perspective by framing AI literacy as an integration of technical understanding, ethical considerations, critical awareness, and responsible use practices in educational contexts (Ng et al., 2021).

At the same time, a growing body of work advances the concept of critical AI literacy, emphasising that it is insufficient merely to *know how to use* AI. Instead, learners and educators must be able to recognise algorithmic bias, risks, power effects, and contextual consequences of AI deployment (Veldhuis, 2025). At the policy level, international organisations stress the need for ethical frameworks, transparency, data protection, and targeted professional development for educators working with generative AI (UNESCO, 2023, 2025). The OECD further highlights that, in many jurisdictions, regulation of generative AI in education remains largely advisory, with significant decision-making delegated to institutions and individual teachers, thereby amplifying the importance of local practices and institutional cultures (OECD, 2023).

Crucially for the present study, international research points to the existence of distinct modes or regimes of AI use in education. These include critically reflective regimes oriented toward ethical discussion, explicating algorithmic limitations, and fostering critical thinking, as well as instrumental-operational or control-oriented regimes focused on automation of assessment, learning analytics, and managerial or disciplinary applications (Long & Magerko, 2020; Ng et al., 2021; Veldhuis, 2025). This regime-based logic provides a conceptual foundation for moving beyond descriptions of individual tools toward the empirical typologisation of educational AI practices based on measurable indicators.

The Ukrainian context of AI integration in education

The Ukrainian discourse on AI in education is developing rapidly but remains heterogeneous in terms of thematic focus and empirical depth. At the level of academic publications, a visible strand of research examines the integration of AI in higher education, with particular attention to academic integrity, changes in assessment practices, and institutional conditions of use (Androschuk & Malyuga, 2024). Closely related to this line of inquiry are emerging studies and policy-oriented discussions addressing institutional AI use policies in educational institutions, which draw upon both Ukrainian and international experience, and highlighting the need to formalise rules and requirements for declaring AI use (AISE, 2024).

In the school sector, an important empirical reference point is a nationwide study conducted by the Junior Academy of Sciences of Ukraine in cooperation with Projector Institute, with analytical support from Factum Group Ukraine and informational support from the Ministry of Education and Science of Ukraine. This research documents the scale and patterns of AI use in general secondary education institutions and identifies barriers to schools' readiness for systematic AI integration (JASU, 2023; Melnyk, 2024).

In parallel, surveys disseminated in the media and professional field indicate very high levels of teacher engagement with AI tools. In particular, results published by Osvitioriia Media suggest that AI tools have become a routine component of teachers' everyday professional practices

(Osvitioriia Media, 2024). Another group of Ukrainian sources focus on normative and ethical dimensions, including academic integrity, open science, responsibility for AI use, and ethical dilemmas, often presented through professional development programmes and conference proceedings (AISE, 2024).

From an applied and analytical perspective, recent reports on digital transformation and institutional readiness in Ukrainian education emphasise managerial and cultural barriers, as well as asymmetries between the rapid pace of technological adoption and institutions' capacities to embed AI within coherent pedagogical and ethical frameworks (BDO Ukraine, 2025).

Overall, the Ukrainian context of AI integration in education is characterised by three persistent patterns: (1) uneven infrastructure and practices across regions and institutions; (2) the predominance of instrumental uses of AI, such as material preparation and automation, alongside growing concerns regarding academic integrity; and (3) a lack of comprehensive institutional policies and methodological frameworks capable of transforming AI use from individual *life hacks* into responsible educational practice (Androschuk & Malyuga, 2024; Melnyk, 2024).

Research gap and transition to the present study

Despite the rapid expansion of research on AI in education, the existing Ukrainian and international literature tends to follow several dominant trajectories. Most studies (a) focus on specific tools or user attitudes, (b) analyse individual risks or ethical concerns, or (c) formulate policy recommendations. Far less frequently do they offer an empirically grounded typology of AI use models understood as coherent configurations of practices that can be reproduced, compared, and applied for diagnosing institutions or groups of educators, particularly in high-risk informational contexts (Ng et al., 2021; Melnyk, 2024).

To address these gaps, this article proposes a sociotechnical research design that combines a conceptualisation of AI as an algorithmic information mediator with a quantitative operationalisation of educational information practices through indices of critically reflective AI use and instrumental-operational (control-automation) AI use. Based on a survey of educators from frontline regions of Ukraine, the study constructed a 2×2 typology of AI use models that enabled an empirical distinction between critically reflective and instrumental-operational configurations of practice and supported their interpretation in the context of heightened information risks associated with war.

Method

The study adopted a cross-sectional design and was based on a one-time survey of educators working in educational institutions located in frontline regions of Ukraine. The total sample size was $N = 208$ respondents. Inclusion criteria were: (1) current teaching or instructional practice in an educational institution; (2) employment in regions classified as frontline or characterised by elevated security risks; and (3) voluntary participation with informed consent to complete the questionnaire. For reasons of participant safety and anonymity, as well as in light of the wartime context, the article does not provide detailed geographic identifiers at the level of specific communities or institutions. Regional information is, therefore, reported in aggregated form. A description of the sample's socio-professional characteristics (type of institution, position, ownership form, years of professional experience, and regional affiliation in aggregated form) is presented in Appendix A, Table A1.

Empirical data were collected using an author-developed AI Usage Profile questionnaire, which captures AI use practices in educational information environments. Items cover critically-reflective practices (e.g., ethical discussion, explicating limitations, verification, critical thinking, and co-creative tasks), as well as instrumental-operational uses (e.g., automated assessment, learning analytics, and administrative or control-oriented applications). All items were measured

on a five-point Likert scale (1–5), with higher scores indicating greater frequency or intensity. The online survey was voluntary and anonymous.

To operationalise educational information practices quantitatively, two composite indices were constructed. These indices capture two analytically-distinct dimensions of AI use: critically-reflective practices and instrumental-operational or control-oriented practices. Each index was calculated as the arithmetic mean of the corresponding items (mean score), preserving interpretability on the original 1–5 scale and ensuring comparability between indices. Missing values were handled by computing the mean across available responses within each index, provided that a sufficient number of valid items were present; this approach reduced data loss without artificially imputing values. The composition of the indices and their internal consistency indicators are reported in Table 1.

Index	k (items)	Cronbach's α	McDonald's ω (total)
CR_Index	6	0.868	0.869
Control_Index	5	0.769	0.789
Control_assess_Index	3	0.710	0.744
Control_efficiency_Index	2	0.763	0.763

Table 1. Composition of composite indices and internal consistency

Internal consistency of the indices was assessed using Cronbach's α and McDonald's ω , allowing for an evaluation of the extent to which items coherently measure a shared latent construct. In addition, the distributional properties of the composite indices were examined using histograms and skewness–kurtosis statistics. The distributions approximated normality, supporting the use of Pearson correlations in subsequent analyses. The correlation structure further supported the conceptual distinction between the indices, providing preliminary evidence of construct validity. These patterns indicated that the indices captured related but analytically distinguishable dimensions of educational information practices, although the exploratory factor analysis reported below also indicated partial empirical overlap between critically reflective and broader developmental uses. The α/ω values for each index are reported in Table 1. Taken together, these reliability and distributional results indicated that the indices were suitable for subsequent inferential and clustering analyses. In addition, Appendix A (Table A2) presents correlations between the indices and, where applicable, subscales, supporting the interpretation of relationships among the measured practice dimensions.

As an additional step of construct validation, an exploratory factor analysis (EFA) was conducted on the 14 AI-use items. The data were suitable for factor analysis (KMO = 0.933; Bartlett's test of sphericity: χ^2 (91) = 1657.40, $p < .001$) and the eigenvalue structure supported a two-factor solution. The EFA also suggested partial empirical overlap between critically reflective and broader developmental uses of AI, indicating that the CR dimension may capture a broader reflective-developmental orientation, rather than a narrowly bounded critical-use construct. The first factor represented this broader reflective-developmental orientation, whereas the second represented a more distinct control-administrative orientation. These results broadly supported the general two-dimensional logic of the instrument. Full factor loadings are presented in Appendix A (Table A3).

For the empirical typologisation of AI use models, a 2×2 design was employed based on two dimensions: CR_index and Control_index. Each index was dichotomised using a median split (above/below the median), yielding four distinct models:

Critically reflective model (CR_↑ / Control_↓) – characterised by the predominance of ethical reflection, verification practices, and the development of critical thinking, combined with a low orientation toward control and automation;

Hybrid model (CR_↑ / Control_↑) – marked by the coexistence of critically-reflective practices and a high intensity of instrumental-operational applications;

Instrumental-control model (CR_↓ / Control_↑) – defined by a prioritisation of automation, efficiency, and/or control, accompanied by a weak, critically reflective component;

Low-integration model (CR_↓ / Control_↓) – characterised by low levels of AI engagement in both critically-reflective and operational control practices.

The median split was employed as a communicative heuristic to construct an interpretable typology, while acknowledging the potential loss of information associated with dichotomisation, which was mitigated through clustering-based robustness checks. To address this limitation, all substantive conclusions were supported by robustness checks using threshold-free clustering.

To test the robustness of the 2×2 typology and reduce reliance on median-based dichotomisation, a threshold-free clustering approach was additionally applied. K-means clustering (k = 5) was performed on standardised (z-score) values of CR_index and Control_index, ensuring equal weighting of both dimensions and allowing the identification of natural groupings of respondents. The resulting clusters were interpreted as empirical practice profiles, ranging from low integration to hybrid configurations, thereby refining the typology and revealing transitional regimes. To support the choice of k, clustering solutions for k = 3–6 were evaluated using the silhouette score. The silhouette coefficients ranged between approximately 0.34 and 0.41 across the evaluated solutions, indicating moderate cluster separation typical for behavioural survey data. The k = 5 solution provided the most interpretable balance between parsimony and differentiation of practice profiles, and Ward's hierarchical clustering was conducted as a sensitivity check. Silhouette plots and the dendrogram are reported in Figure A1 (Appendix). Cluster characteristics (size, mean index values, and variability) are presented in Table A4. To relate the cluster-based solution to the threshold-based 2×2 typology, a cross-mapping of cluster membership across the four quadrants was performed. This mapping is reported in Table A5 (Appendix) and used to distinguish *pure* models from mixed or transitional configurations.

The study adhered to the principles of voluntariness and informed consent. Participation was voluntary and anonymous, with no personal or institutional identifiers collected. In light of the wartime context and heightened security risks, regional data were reported in aggregated form. All data were stored securely with access limited to the research team and used exclusively for academic purposes. acknowledge

Results

Descriptive overview (indices and overall structure)

In the sample (N = 208), the mean value of CR_index (critically reflective practices) was M = 3.64, SD = 0.86, while Control_index (instrumental-operational and control-automation practices) averages were M = 2.95, SD = 0.86 (scale 1–5). Median thresholds used for the typology were 3.83 for CR_index and 3.00 for Control_index. A positive association between CR_index and Control_index was observed (r ≈ 0.61; see Table A2), indicating that educators who used AI more intensively in a critically reflective manner also tended to employ it for operational tasks. As a robustness check, Spearman rank correlations were additionally calculated; the results were substantively consistent with the Pearson correlations reported in the manuscript. At the same

time, the distribution revealed distinct poles—high CR with low Control and low CR with relatively high Control—supporting the analytical relevance of typologisation. Correlation analysis further indicated heterogeneity within the operational dimension: CR_index was more strongly related to Efficiency/Analytics ($r \approx 0.77$) than to Assess Control ($r \approx 0.36$), suggesting that efficiency-oriented uses more often coexisted with critically reflective practices than assessment- and control-oriented logics. Overall, the observed structure suggested that AI use practices were not dichotomous, but formed overlapping configurations, supporting the analytical relevance of typological modelling.

Distribution of the 2×2 models (CR × Control)

The distribution of respondents across the four models is presented in Table 2. The hybrid model (CR↑/Control↑) was dominant, accounting for 36.1% of the sample ($n = 75$). This indicated that the most prevalent configuration combined critically reflective practices with intensive instrumental-operational uses of AI. The second most common pattern was the low-integration model (CR↓/Control↓), representing 32.2% of respondents ($n = 67$), pointing to a substantial segment of educators with limited AI engagement across both dimensions. The instrumental-control model (CR↓/Control↑) comprised 17.3% of the sample ($n = 36$), while the critically-reflective model (CR↑/Control↓) was the least prevalent, accounting for 14.4% ($n = 30$).

Model (CR × Control)	n	%
Critically reflective (CR↑ / Control↓)	30	14.4
Hybrid (CR↑ / Control↑)	75	36.1
Instrumental-control (CR↓ / Control↑)	36	17.3
Low integration (CR↓ / Control↓)	67	32.2

Note. Models are based on median splits of CR_index (3.83) and Control_index (3.00).

Table 2. Distribution of the 2×2 AI use models (CR × Control)

Model profiles (indices and key subcomponents)

Comparative profiles of the four models are reported in Table 3. The critically-reflective model (CR↑/Control↓) combined a high CR_index (4.27) with a relatively low Control_index (2.41), with efficiency-oriented uses prevailing over assessment-control (Assess Control = 1.70). The hybrid model (CR↑/Control↑) showed the highest levels on both dimensions (CR_index = 4.34; Control_index = 3.72), with the highest values for both Assess Control (3.33) and Efficiency/Analytics (4.30), representing a maximally integrated regime. The instrumental-control model (CR↓/Control↑) was characterised by a lower CR_index (3.26) and a relatively high Control_index (3.31), with elevated Assess Control (3.19) and moderately high Efficiency/Analytics (3.49). The low-integration model (CR↓/Control↓) exhibited the lowest values across both dimensions (CR_index = 2.76; Control_index = 2.15), indicating minimal AI engagement in educational information practices.

Model (CR × Control)	n	CR_index M (SD)	Control_index M (SD)	Assess Control M (SD)	Efficiency/Analytics M (SD)
Critically-reflective (CR↑ / Control↓)	30	4.27 (0.33)	2.41 (0.44)	1.70 (0.58)	3.48 (0.78)
Hybrid (CR↑ / Control↑)	75	4.34 (0.38)	3.72 (0.58)	3.33 (0.81)	4.30 (0.60)
Instrumental-control (CR↓ / Control↑)	36	3.26 (0.33)	3.31 (0.38)	3.19 (0.55)	3.49 (0.60)
Low integration (CR↓ / Control↓)	67	2.76 (0.65)	2.15 (0.49)	1.90 (0.54)	2.51 (0.81)

Note. Values are means with standard deviations in parentheses. Models are based on median splits of CR_index and Control_index.

Table 3. Profiles of AI use models based on CR × Control typology

Item-level results (Table B1, Appendix B) indicated that differences between models were primarily associated with ethical discussion, verification practices, and the use of control-oriented applications.

Clustering as a robustness check

K-means clustering ($k = 5$) on standardised CR_index and Control_index values indicated that the data contained not only four broad quadrants, but also more fine-grained practice profiles (Table A4). Two hybrid clusters emerged: one with moderately high Control, and another with very high Control, alongside clusters characterised by very low integration and by moderate CR combined with low Control. Mapping these clusters onto the 2×2 typology (Table A5) showed that one cluster aligned entirely with the CR↓/Control↓ quadrant (low integration, 100%), while the high-control hybrid cluster fell almost exclusively within CR↑/Control↑ (≈87%). The remaining clusters spanned adjacent quadrants, indicating transitional configurations. Overall, the results confirmed the 2×2 typology as a parsimonious representation, while demonstrating that AI use regimes formed a continuum with intermediate modes.

Associations between models and demographic/contextual characteristics

χ^2 -tests examining associations between the 2×2 models and respondent characteristics (type of institution, ownership form, position, and years of experience) revealed no statistically significant relationships (all $p > 0.05$; see Table B2). Cramer's V values predominantly fall within the range of weak effects (≈0.11–0.27). For variables with a large number of categories, particularly institution type and position, some cells exhibited very low expected frequencies. Accordingly, χ^2 results for these tables are interpreted with caution, relying primarily on effect size estimates (Cramer's V) and diagnostics of expected cell counts (Table B2). To ensure robustness, Fisher's exact test was additionally applied in cases with small, expected cell frequencies, yielding results consistent with the χ^2 tests reported.

Discussion

Sociotechnical interpretation: typology as an expression of tension between criticality, operationality, and control

The empirical findings allow us to address the research questions formulated in the introduction.

RQ1 was addressed through the identification of four empirically distinguishable models of AI use in educational information practices: critically reflective, hybrid, instrumental-control, and low-integration.

RQ2 was addressed by demonstrating that critically reflective practices and instrumental-operational uses of AI frequently coexist, particularly in the hybrid model, which represented the dominant configuration in the sample. At the same time, control-oriented uses showed weaker alignment with critically reflective practices than efficiency-oriented applications.

RQ3 was addressed through the sociotechnical interpretation of these models in the context of wartime informational risk, where critically reflective practices functioned as mechanisms of epistemic security and responsible engagement with AI-generated information.

The 2×2 typology (CR × Control) demonstrated that AI integration in educational information practices cannot be reduced to a simple for or against position. Instead, the hybrid model (CR↑/Control↑) predominated, indicating that critically reflective practices frequently coexisted with logics of operational efficiency, automation, and, to some extent, control. From a sociotechnical perspective, this outcome suggested that the same technology became embedded in different regimes of organising information work, functioning simultaneously as a learning support tool and as an instrument of administrative ordering.

The data further showed that operationality is not monolithic. Efficiency- and analytics-oriented uses of AI more often aligned with critically reflective practices, whereas assessment- and control-oriented sub-logics exhibited weaker alignment with the CR dimension. Thus, sociotechnical tension arose not between criticality and operationality per se, but primarily between critically reflective practices and AI applications oriented toward control, standardisation, and performance-based governance. The typology, therefore, captured a competition between two institutional logics: a) a pedagogical logic, centred on meaning-making and critical engagement, and b) a technocratic logic, oriented toward productivity, manageability, and control.

This interpretation aligned with STS accounts of algorithmic mediation and sociomateriality, which emphasise that algorithms actively reconfigure regimes of visibility, authority, and accountability, rather than merely supporting existing practices (Gillespie, 2014; Orlikowski & Scott, 2008). From this perspective, the expansion of control-oriented AI applications exemplifies the diffusion of responsibility within algorithmic systems, where governance increasingly operates through metrics and opaque decision infrastructures (Pasquale, 2015).

Finally, clustering results ($k = 5$) indicated that real-world practices are often transitional. Profiles of moderate and high-control hybridity suggested that sociotechnical regimes are not binary, but assembled from multiple practice elements, with institutional rules and professional expectations, shifting the balance toward either critical engagement or operational-control-oriented reduction.

The empirical results provided partial support for the hypotheses formulated in the study. Hypothesis H1 (Multiplicity of models) was supported by the identification of four distinct AI use configurations in the data. Hypothesis H2 (Sociotechnical tension) was supported insofar as control-oriented uses are less strongly associated with critically reflective practices than efficiency-oriented uses. Hypothesis H3 was supported conceptually, rather than directly tested empirically, highlighting the importance of critically reflective practices in high-risk informational contexts. Hypothesis H4 remained interpretive in nature and indicated a direction for future research, focusing on the role of educators as algorithmic information mediators. Thus, the proposed typology not only described empirical patterns, but also provided an analytical lens for understanding how algorithmic mediation restructures educational information practices under conditions of uncertainty.

Wartime information risks and the role of the educator as an information mediator

The context of war foregrounded not only the efficiency of AI use but also epistemic security—the capacity of educational environments to distinguish reliable information from manipulative content, withstand information attacks, work with uncertainty, and sustain critical practices. Under such conditions, critically-reflective practices — ethical discussion, explicating limitations, verification of outputs, and the cultivation of critical thinking — acquired not merely a pedagogical but also a protective societal function, reducing the risk of uncritical reproduction of AI-generated errors, hallucinations, or manipulative narratives.

Accordingly, the role of the educator in AI-mediated environments can be conceptualised as that of an algorithmic information mediator: an actor who establishes rules for interacting with AI-generated information, defines verification criteria, moderates boundaries of acceptable use, and fosters a culture of explainability within existing constraints. From this perspective, the hybrid model (the most prevalent in the data) appeared inherently ambivalent. The hybrid model may represent a productive configuration in which operational efficiency does not displace critical engagement, but it may also constitute a potential risk point when increasing operational dependence on AI reinforces tendencies toward standardisation and control, thereby narrowing

the space for critical information work. The wartime context intensified this ambivalence since the cost of *fast but unchecked* responses was substantially higher than in stable information environments.

From the perspective of critical information literacy, this mediating role extended beyond technical competence to include responsibility for shaping how authority, credibility, and trust are negotiated in AI-mediated learning environments (Drabinski, 2019; Elmborg, 2006). In wartime contexts, such mediation becomes a core dimension of information literacy itself, reframing it as a practice of epistemic risk management, rather than merely efficient information use.

Practical implications: Policy, professional development, and avoiding control-oriented reduction

The practical value of the proposed typology lies in its potential use as a diagnostic tool for educational institutions and governance bodies, enabling them to identify dominant AI use regimes and to assess which competencies require reinforcement. At the level of institutional policy (for schools and universities, the Ministry of Education, and professional development programmes), the findings supported three main directions for action.

Strengthening critically reflective competencies as a standard.

This involves a *minimum core* of practices, including explicating the limitations of AI systems, verifying outputs, working with sources, recognising manipulation, addressing ethical dilemmas, and upholding principles of academic integrity under conditions of generative AI. These competencies should not be treated as optional add-ons, but embedded as a core component of digital and information literacy.

Differentiating efficiency from control as distinct policy trajectories.

The results showed that automation and analytics can coexist with high levels of critical reflection, whereas control-oriented logics pose greater risks for information literacy. Policies should, therefore, explicitly constrain high-risk applications (e.g., automated assessment without transparent criteria and human verification), while supporting lower-risk scenarios, such as AI-assisted material preparation with verification, task personalisation, and the use of learning analytics, as tools for reflection rather than sanction.

Establishing rules of transparency and accountability in AI use.

In practical terms, this may include requirements to disclose AI use in certain types of work, protocols for fact checking and source verification, the principle of *human-in-the-loop* final decision-making, and clearly defined limits on AI use in disciplinary or control procedures. In wartime contexts, additional guidance is required regarding the handling of sensitive information and the mitigation of risks related to unsafe data dissemination.

Limitations and directions for future research

This study had several limitations. While the indices demonstrated satisfactory internal consistency and their empirical structure was additionally examined using exploratory factor analysis, the current study did not employ confirmatory factor analysis or latent-variable modelling. The design, therefore, prioritised reliability, interpretability, and typological usefulness over full psychometric validation. Future research should test the stability of the factor structure in larger samples and across different educational contexts. In addition, while the theoretical framework emphasised wartime and disinformation risks, the current design lacked a dedicated risk-sensitivity index that would allow direct testing of links between disinformation sensitivity and AI use models. Future research should develop and validate such a scale, incorporating behavioural indicators (e.g., fact-checking practices, detection of

manipulation, source-evaluation rules, and responses to suspicious content), or complement the survey with qualitative methods, such as interviews or practice diaries.

The self-reported nature of the data may have introduced social desirability bias, particularly regarding ethical and critically reflective practices. Furthermore, the cross-sectional design precluded causal inference, capturing the coexistence of practice regimes without explaining transitions between them. Finally, the sample was drawn from frontline regions, which enhanced relevance for high-risk contexts but warrants caution in generalising to other settings.

Despite these limitations, the index-based operationalisation and typologisation of AI use models provided a robust basis for comparative and longitudinal research. Future studies could examine how institutional policies, professional development, and contextual change shape shifts in AI use regimes toward either greater critical engagement or increased control-oriented reduction.

Although grounded in a wartime Ukrainian context, the proposed CR × Control typology is transferable to other high-uncertainty information environments. Such as post-pandemic education, data-driven school systems, or AI-mediated governance settings, where educators similarly navigate tensions between critical engagement and operational automation. Future research may also employ latent profile analysis or longitudinal designs to examine transitions between AI use regimes over time.

Conclusions

This article proposed a sociotechnical approach to analysing AI use in education that conceptualised AI as an algorithmic information mediator and operationalised educational information practices along two dimensions: critically-reflective use (CR_index) and instrumental-operational and control-automation use (Control_index). Based on a survey of 208 educators from frontline regions of Ukraine, the study constructed a 2×2 typology of AI use models and demonstrated the predominance of a hybrid regime in which critical reflection coexists with operational automation and elements of control. The robustness of the typology was supported by cluster analysis (k-means, $k = 5$), which revealed stable practice profiles, as well as transitional configurations that refined the boundaries of the *pure* models.

The contribution of this study is threefold: theoretically, it advanced a sociotechnical conceptualisation of AI as an algorithmic information mediator in educational information practices; methodologically, it introduced an index-based operationalisation and a robust typology of AI use models combining heuristic and threshold-free approaches; and contextually, it provided empirical insight into AI-mediated information practices in high-risk information environments, exemplified by wartime conditions.

These findings are significant for information science, since they show that information literacy in the age of AI is not merely an individual competence, but also a contextually situated practice, shaped at the intersection of pedagogical norms, institutional rules, and algorithmic mediation. Practically, the proposed typology can serve as a diagnostic tool for the sociotechnical design of educational policies and professional development programmes aimed at strengthening critically reflective practices and preventing control-oriented reduction in environments characterised by heightened information risks associated with war.

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Appendix A. Methodological and descriptive supplementary results

Characteristic	Category	n	%
Type of institution	Lyceum	70	33.7
	Gymnasium	59	28.4
	Primary school	22	10.6
	General secondary education institution (GSEI)	8	3.8
	Comprehensive school	6	2.9
	University	5	2.4
	Other	38	18.3
Region (aggregated)	Donetsk Oblast	169	81.2
	Other regions / communities	39	18.8
Ownership form	State	139	66.8
	Municipal	67	32.2
	Private	2	1
Respondent position	Teacher / Lecturer	174	83.7
	Teaching assistant	12	5.8
	Deputy principal	7	3.4
	Other / rare positions	15	7.2
Years of experience in education	Up to 5 years	25	11.5
	6–10 years	24	12
	11–20 years	41	19.7
	More than 20 years	118	56.7

Notes: 1. Percentages may not sum to 100 due to rounding. 2. Regional information is reported in aggregated form for security reasons.

Table A1. Socio-professional characteristics of the sample (N = 208)

	CR_index	Control_index	Assess Control	Efficiency/Analytics	Experience (years, midpoint)
CR_index	1.000	0.607	0.356	0.769	0.046
Control_index	0.607	1.000	0.909	0.799	0.042
Assess Control	0.356	0.909	1.000	0.477	0.063
Efficiency/Analytics	0.769	0.799	0.477	1.000	-0.003
Experience (years, midpoint)	0.046	0.042	0.063	-0.003	1.000

Note. Pearson's r . Experience was operationalised using midpoint values of experience categories.

Table A2. Pearson correlations between composite indices and experience

Item	Factor 1	Factor 2
Personalising learning	0.704	0.324
Creating new materials	0.758	—
Formative assessment	0.649	0.434
Ethical discussion	0.625	—
Experimenting in projects	0.674	—
Control of attendance/grades/discipline	—	0.840
Automated checking/testing	0.305	0.688
Supporting creativity/research	0.768	—
Checking AI outputs / explaining limitations	0.669	—
Reducing routine tasks	0.764	—
Collaborative human-AI tasks	0.725	0.364
Learning analytics	0.625	0.491
Administrative use of AI	—	0.503
Critical thinking about information	0.664	—

Note. The table reports factor loadings from the two-factor exploratory factor analysis with promax rotation. Factor 1 captures reflective-developmental uses of AI, whereas Factor 2 captures control-administrative uses.

Table A3. Exploratory factor analysis of AI-use items (two-factor solution, promax rotation)

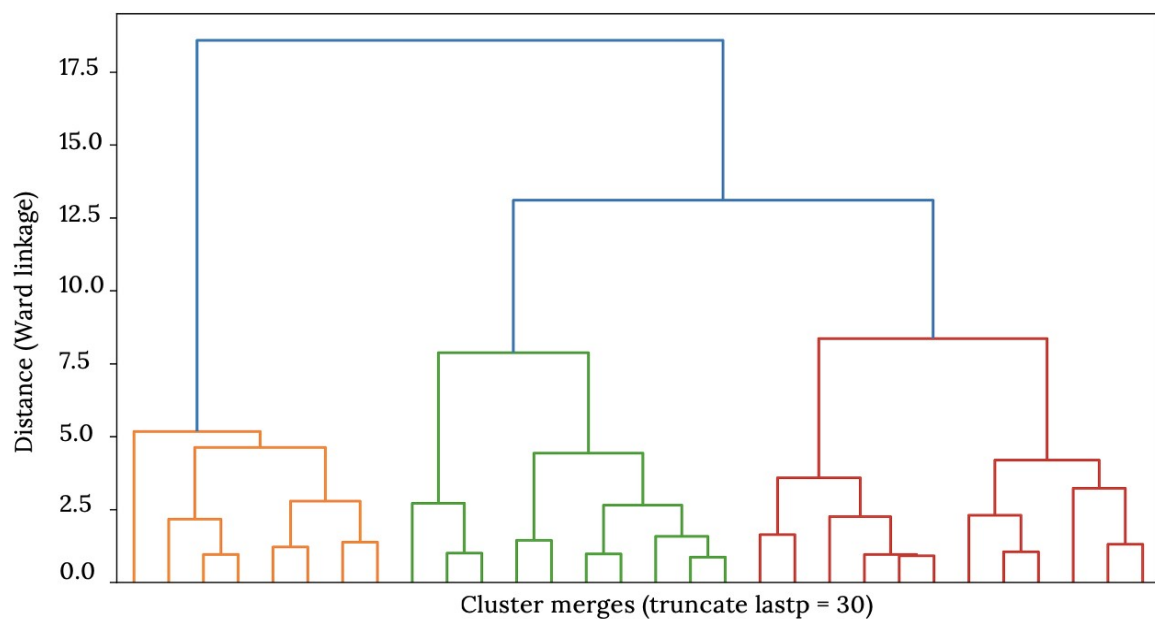


Figure A1. Ward hierarchical clustering dendrogram (Ward linkage), used as robustness check for k selection

Cluster (k = 5)	Cluster label	n	%	CR_index M (SD)	Control_index M (SD)	Dominant 2×2 quadrant	Dominant share
1	Very low integration	28	13	2.17 (0.42)	1.78 (0.42)	CR ↓ / Control ↓	1.000
4	Moderate CR, low Control	29	14	3.74 (0.43)	2.03 (0.29)	CR ↑ / Control ↓	0.759
3	Moderate Control, low CR	43	21	2.99 (0.31)	2.92 (0.34)	CR ↓ / Control ↑	0.744
0	Hybrid (moderate)	62	30	4.18 (0.39)	3.05 (0.28)	CR ↑ / Control ↑	0.726
2	Hybrid (high Control)	46	22	4.33 (0.47)	4.14 (0.40)	CR ↑ / Control ↑	0.891

Note. Clusters are ordered by dominant configuration and relative prevalence. Values are means with standard deviations in parentheses.

Table A4. Cluster profiles based on k-means clustering (k = 5)

Cluster (k = 5)	n (cluster)	Critically reflective (CR ↑ / Control ↓)	Hybrid (CR ↑ / Control ↑)	Instrumental-control (CR ↓ / Control ↑)	Low integration (CR ↓ / Control ↓)
0	62	18 (29.0%)	35 (56.5%)	6 (9.7%)	3 (4.8%)
1	28	0 (0.0%)	0 (0.0%)	0 (0.0%)	28 (100.0%)
2	46	0 (0.0%)	40 (87.0%)	6 (13.0%)	0 (0.0%)
3	43	0 (0.0%)	0 (0.0%)	24 (55.8%)	19 (44.2%)
4	29	12 (41.4%)	0 (0.0%)	0 (0.0%)	17 (58.6%)

Note. Values are counts with percentages in parentheses. The table shows how empirically derived clusters map onto the threshold-based 2×2 typology.

Table A5. Mapping of k-means clusters (k = 5) onto the 2×2 CR × Control typology.

Appendix B. Additional statistical analyses

Model (CR × Control)	n	Ethics (discussion)	Verification & limitations	Critical thinking	Co-creative tasks	Automated assessment / tests	Discipline / assessment control	Learning analytics	Routine reduction
Critically reflective (CR ↑ Control ↓) /	30	4.50	4.50	4.20	3.50	1.93	1.77	3.00	3.97
Hybrid (CR ↑ Control ↑) /	75	4.36	4.41	4.31	4.07	3.85	3.85	4.04	4.56
Instrumental-control (CR ↓ Control ↑) /	36	3.17	3.39	3.36	2.94	3.39	3.33	3.28	3.69
Low integration (CR ↓ Control ↓) /	67	2.72	2.93	2.81	2.19	2.10	1.84	2.15	2.88

Note. Item means are reported on a five-point Likert scale (1–5).

Table B1. Item-level means by CR × Control model

Variable	Categories (after grouping)	N	χ^2	df	p	Cramer's V
Type of institution	7	208	22.865	18	0.196	0.191
Ownership form	3	208	5.382	6	0.496	0.114
Position	4	208	6.271	9	0.712	0.100
Years of experience	4	208	9.977	9	0.352	0.126

Note. None of the examined demographic or institutional variables show statistically significant associations with AI use models (all $p > 0.05$). Effect sizes measured by Cramer's V fall within the weak range (≈ 0.10 – 0.19), indicating that the identified practice models are not strongly tied to institution type, position, or years of experience, but rather cut across different respondent groups.

Table B2. χ^2 tests of associations between AI use models and respondent characteristics