“Institutional AI policies in Ukrainian higher education: A thematic analysis and assessment using the taxonomy of institutional AI policy maturity”

AUTHORS Yana Suchikova
Serhii Omelchuk

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Yana Suchikova (Ukraine), **Serhii Omelchuk** (Ukraine)

INSTITUTIONAL AI POLICIES IN UKRAINIAN HIGHER EDUCATION: A THEMATIC ANALYSIS AND ASSESSMENT USING THE TAXONOMY OF INSTITUTIONAL AI POLICY MATURITY

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Yana Suchikova, Doctor of Technical Sciences, Vice-Rector for Research, Berdyansk State Pedagogical University, Zaporizhzhia, Ukraine. (Corresponding author)

Serhii Omelchuk, Doctor of Sciences, Vice-Rector for Research, Kherson State University, Ivano-Frankivsk, Ukraine.

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Abstract

The study aims to analyze institutional policies governing the use of generative artificial intelligence (GenAI) in Ukrainian universities and assess their regulatory maturity. Drawing on the authors' Taxonomy of Institutional AI Policy Maturity (AI-PMT), which comprises twelve analytical dimensions, the study examines a sample of 23 publicly available institutional policy documents adopted between 2023 and 2025. The analysis combines qualitative and quantitative approaches. A directed content analysis was used to assign ordinal scores (0-2) across twelve dimensions, enabling the construction of a cumulative maturity index (0-24) for each institution. The results reveal an uneven distribution of regulatory development, with more elaborated provisions related to teaching and learning, and comparatively less developed components addressing research practices, data governance, and infrastructural support. To synthesize these patterns, an analytical typology of institutions was developed based on cumulative maturity scores, identifying three broad groups that differ in the degree of regulatory completeness and procedural specification. In parallel, thematic analysis of policy content identified recurring patterns, including the normalization of AI use in education, the emphasis on transparency and disclosure, the prevalence of precautionary approaches to data and confidentiality, and several contested provisions. Comparison with international policy frameworks suggests that Ukrainian universities broadly align with global normative trends in principles, but exhibit limited operationalization of governance mechanisms and research-related provisions. The findings highlight structural imbalances in institutional AI governance and underscore the need to further develop research-oriented regulation, institutional support mechanisms, and coordinated policy approaches.

Keywords institutional AI policies, higher education, AI governance, policy maturity, generative AI (GenAI), academic integrity, Ukraine

JEL Classification I23, O33, D83, L38, M14, O38

INTRODUCTION

Generative artificial intelligence (GenAI) systems have rapidly become routine tools in academic work – ranging from the preparation of teaching materials and assessment design to experimental planning, data analysis, and scholarly writing. On the one hand, this development creates opportunities for increased efficiency, personalized learning, and the strengthening of open science. On the other hand, it intensifies concerns related to academic integrity, intellectual property, data governance, and responsibility for outputs generated or transformed by AI systems.

Universities worldwide are responding to these challenges by developing institutional AI policies that define permissible uses, establish requirements for transparent disclosure of AI-assisted work (Suchikova & Tsybuliak, 2024; Resnik & Hosseini, 2025), and introduce mechanisms for monitoring and periodic policy revision.

The Ukrainian context introduces additional, highly specific circumstances. These include the ongoing war and the relocation of a number of universities (Finikov et al., 2025; Lopatina et al., 2023; Spivakovsky, Omelchuk, Kobets, et al., 2023), the expansion of hybrid and distance learning formats (Popova et al., 2023), unequal access to digital infrastructure (Tsybuliak et al., 2024), and elevated risks associated with confidential and sensitive data (Suchikova & Nazarovets, 2025).

At the same time, the Ukrainian higher education system is integrating into the European academic space – from open science initiatives to reforms in research evaluation (Omelchuk, 2024). This integration necessitates alignment between institutional AI policies and contemporary international frameworks.

Despite the rapid proliferation of local regulations and institutional guidelines, a systematic cross-university analysis of AI policies in Ukraine remains largely absent. This study contributes to addressing this gap by providing a comparative analysis of a sample of institutional documents, focusing on how universities define the scope of AI use, formulate disclosure requirements, regulate data use and intellectual property, establish prohibitions and exceptions, ensure inclusion and academic freedom, and organize policy governance and revision mechanisms.

1. LITERATURE REVIEW

The rapid institutionalization of generative artificial intelligence (GenAI) in higher education has given rise to a growing body of research examining university-level policies and national regulatory frameworks. Three principal strands can be identified in this literature: comparative document analysis of institutional AI policies, critical reviews of policy content and effectiveness, and analyses linking institutional policies to broader normative and regulatory environments.

In recent years, large-scale mappings of AI policies across countries and institutional clusters have emerged. McDonald et al. (2024) analyzed 116 U.S. universities and found that more than 60% of policy documents encourage the use of GenAI, while approximately 40% provide detailed guidance for classroom practice. Typical provisions include attribution requirements, warnings regarding confidential data, and cautionary notes about the unreliability of AI-generated content. A related study identified four dominant themes in U.S. university policies: integration of GenAI into teaching and assessment, use of GenAI in visual and multimodal media, safety and ethical considerations, and the role of GenAI in academic integrity (An et al., 2025).

Humble (2025) proposed the DAMHEAP model (Dynamic Alignment of Multi-Level Higher Education AI Policies), which conceptualizes policy coordination across strategic, pedagogical, ethical-legal, operational, and adaptive levels. The study revealed the predominance of the educational dimension over research and data governance components, pointing to an "uneven maturity" of AI policies within individual institutions.

Global comparative analyses further broaden the perspective. A study of 343 universities across Australia, Canada, China, the United Kingdom, and the United States (Parker et al., 2025) demonstrated significant fragmentation in regulatory approaches – from innovation-oriented permissive frameworks emphasizing learning enhancement to restrictive regimes focusing on data risks and equity of access. Common gaps include the absence of proceduralized disclosure requirements and unclear accountability mechanisms for violations. Additionally, a cross-regional study of GenAI adoption in 40 universities across six macro-regions described strategies of

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"early adopters" and confirmed that implementation practices are shaped by organizational culture and available resources no less than by formal policies (Jin et al., 2025).

Critical and comparative reviews highlight recurring quality deficits in institutional AI policies: ambiguous definitions of GenAI, conflation of norms for teaching and research, weak operationalization of disclosure requirements, and insufficient alignment with intellectual property and confidentiality frameworks. Luo (2024) proposes criteria for "high-quality policy," including terminological clarity, procedural specificity, proportionality of sanctions, support mechanisms for faculty and students, and structured review cycles.

Empirical research on policy effectiveness, based on surveys and interviews in two U.S. universities, revealed a persistent gap between formal policy declarations and user perceptions. Policies are frequently perceived as unclear or ineffective in the absence of accompanying support services such as training programs, disclosure templates, and secure data environments (Jiang et al., 2025).

Comparative analyses of national approaches (China, Japan, Mongolia, and the United States) suggest that higher education systems may be broadly interpreted as oscillating between two regulatory orientations: human-centered frameworks with direct pedagogical support and security-oriented approaches prioritizing societal-level risk mitigation over institutional needs (Xie et al., 2024). While these patterns should be treated with caution, given the scope of the underlying analyses, they point to structural differences that can influence the design of university policies and approaches to disclosure. Other reviews similarly indicate substantial variation even within Anglo-Saxon jurisdictions – from requirements for submitting detailed interaction records with AI systems to more general declarative statements lacking implementation tools (Saito, 2024).

Synthesizing existing reviews and comparative studies allows several conclusions. First, while there is broad consensus in favor of transparency in AI use, standardized disclosure formats remain underdeveloped, and contribution taxonomies and procedural guidelines are fragmented. Second, assessment-related regulations are generally more developed than provisions concerning research and data governance. Third, intellectual property and confidentiality are often addressed through general cautions about sensitive data, without clearly defined secure channels or environments; copyright risks are typically described in broad terms. Fourth, although policies frequently declare training initiatives, templates, and cyclical reviews, they rarely include operational performance indicators or monitoring mechanisms. Finally, significant international disparities persist: even leading universities exhibit heterogeneous and context-dependent policies, reinforcing the need for formalized comparative content analysis with a clear codebook and dedicated mapping of gaps in research-related provisions and disclosure standards.

In the Ukrainian context, no systematic review or comparative analysis of institutional AI policies has yet been conducted. Existing studies focus primarily on individual institutional cases (Spivakovsky, Omelchuk, Malchykova, et al., 2023; Spivakovsky et al., 2025) or on broader aspects of AI interaction within academic environments, rather than on the structure and content of institutional policy documents across universities. Research has concentrated, first, on academic integrity and legal regulation – examining, for example, legislative mechanisms for safeguarding integrity amid the proliferation of AI in Ukraine, as well as models for using AI-based tools to detect violations in schools and universities (Teremetskyi et al., 2024; Hryn et al., 2025).

A substantial body of empirical research examines the attitudes and practices of students and doctoral candidates regarding ChatGPT and other generative systems. These studies document both the widespread adoption of such tools and persistent concerns related to academic misconduct, as well as the need to develop competencies for ethical AI use (Fiialka et al., 2023; Chugai & Havrylenko, 2024; Kramar et al., 2024; Tsybuliak et al., 2024; Mytsyk & Suchikova, 2025).

A number of publications adopt a conceptual and methodological orientation, outlining the risks (Suchikova, 2025; Suchikova & Tsybuliak, 2025) and opportunities of AI for academic writing (Suchikova et al., 2025a) and academic integrity, while emphasizing the necessity of introducing clear and comprehensible regulatory rules within educational institutions (Tsybuliak & Suchikova, 2024). However, these works do not engage in a systematic analysis of already adopted institutional AI policies (Palamar & Naumenko, 2024; Vovk & Kryvoshyia, 2024).

Thus, the existing corpus of Ukrainian scholarship predominantly describes AI usage practices and the legal-regulatory frameworks of academic integrity, rather than examining the substantive content and typology of institutional AI policies across universities.

This article aims to fill this gap by providing a comprehensive comparative analysis of institutional AI policies in Ukrainian universities and assessing their maturity using the Taxonomy of Institutional AI Policy Maturity (AI-PMT).

2. METHODOLOGY

2.1. Construction of the document corpus

At the initial stage, authors independently conducted a systematic search for institutional documents regulating the use of AI in universities. The search strategy included:

- reviewing official university websites (sections such as “Regulatory Documents,” “Policies,” “Academic Integrity,” “Digital Technologies,” and “Artificial Intelligence”);
- conducting internal site searches using keywords (“artificial intelligence,” “generative AI,” “AI,” “ChatGPT,” etc.);
- performing additional searches through general search engines.

After completing the independent searches, the researchers consolidated their findings into a unified list, removed duplicates, and agreed upon the following inclusion criteria:

1) the document explicitly addresses the use of AI;
2) the document is formally adopted or publicly available on an official institutional resource (website, repository, or library) of a higher education institution;
3) the most recent update date falls within 2023–2025;
4) the document covers at least one of the following domains: education, research, or administrative processes.

For each document, metadata were recorded (university, date, language, and hyperlink).

Given the interpretive nature of policy documents and the use of a three-level ordinal scale, the study prioritized consensus-based coding through iterative discussion rather than relying on statistical inter-rater reliability coefficients.

2.2. Thematic analysis

At the second stage, authors independently read the entire corpus of documents and conducted an open thematic analysis. This process involved:

- generating preliminary thematic codes without predefined categories;
- identifying text fragments related to permitted or prohibited uses of AI, assessment practices, disclosure requirements, data governance, inclusion, responsibility, and policy governance mechanisms;
- grouping initial codes into broader thematic categories.

Following individual coding, several rounds of discussion were conducted to:

- agree on a consolidated list of themes;
- merge overlapping codes and refine overly general categories;
- construct a preliminary structure of dimensions reflecting the core components of institutional AI policies.

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At this stage, the thematic analysis was reflexive in nature. The authors not only identified recurring patterns but also cross-referenced them with international scholarship on institutional GenAI policies, thereby reducing the risk of overlooking relevant dimensions and enhancing analytical coherence.

2.3. Development of the policy maturity taxonomy

The themes identified through thematic analysis were transformed into a structured Taxonomy of Institutional AI Policy Maturity (AI-PMT), which conceptualizes institutional AI policy across twelve dimensions (Table 1).

Each dimension was operationalized using a three-level maturity scale (0-2):

- 0 – absence of provisions or purely nominal mention;
- 1 – basic regulation without procedural specification;
- 2 – elaborated and procedurally defined regulation (explicit requirements, examples, instruments, designated responsibilities, review cycles).

This scale was deliberately aligned with the logic of international maturity models in research data management, open science, and information security, where levels represent a progression from fragmented practices to systemically integrated policies (Reis et al., 2016; Wendler, 2012; Kim, 2021; Al-Matari et al., 2021; Almuhammadi & Alsaleh, 2017; Guirlet & Schneider, 2024).

The taxonomy was developed iteratively through no fewer than three rounds of joint discussion and pilot application to a subset of documents, followed by refinement of definitions and criteria for assigning levels 0-2.

Table 1. Taxonomy of institutional AI policy maturity (AI-PMT)

Dimension	0 – Absence / Minimal	1 – Basic Level	2 – Elaborated Specification
1. Scope	Covers only one domain (education / research / administration)	Covers two domains	Clearly defines all three domains with separate rules
2. Terms and Definitions of GenAI	No definitions	Basic definitions without examples	Clarified definitions, examples, exceptions, boundaries of application
3. Permissibility in Education	Prohibition by default	Permission with general caveats	Differentiated permission: task types, educational levels, examples
4. Assessment	No provisions	General principles	Concrete procedures
5. Disclosure of AI Use	Not mentioned	General requirement	Defined procedure: who / where / when / how; templates; instructions
6. Research Policy	Not mentioned	General principles	Validation requirements, methodological standards, laboratory restrictions, and data-related provisions
7. Data, Intellectual Property, and Confidentiality	General cautions	Prohibition of sensitive data use; risk statements	Secure environments, copyright provisions, RDM requirements
8. Inclusion and Accessibility	Not mentioned	Principled acknowledgment	Exceptions, reasonable accommodation, equity criteria
9. Jurisdictional Restrictions / Sanctions Risks	Not mentioned	General warnings	Explicit lists, update mechanisms, geopolitical risk considerations
10. Governance and Support	Not defined	Responsible units identified	Training programs, consultation mechanisms, and review cycles
11. Control and Remediation Mechanisms	Absent	General references to academic integrity	Review procedures, appeals mechanisms, and educational measures
12. Openness and Reproducibility	Not mentioned	Declarative statements	Alignment with open science, contribution transparency, and metadata requirements

2.4. Directed content analysis and scoring

At the next stage, the taxonomy was applied to the entire document corpus using a directed content analysis approach.

1. The authors independently assigned each document a score of 0, 1, or 2 for each of the twelve dimensions, based on a clearly specified codebook outlining the criteria for each level.

2. Discrepancies in scoring were discussed in joint sessions. In cases of substantive disagreement, relevant text fragments were re-examined until consensus was reached.

3. For each university, a cumulative AI policy maturity index was calculated (sum of the twelve indicators; range 0-24), along with thematic sub-indices (education; research and data; governance; risks and inclusion).

This approach enabled the integration of qualitative interpretation with the possibility of quantitative cross-university comparison.

2.5. Study limitations

Despite the systematic methodological design, several limitations must be considered when interpreting the findings.

First, the study includes only documents publicly available on official university resources. Some institutions may possess internal guidelines, working instructions, or draft policies that are not publicly accessible. This may result in an incomplete corpus and potentially under- or overestimate the maturity of certain institutions.

Second, cross-university comparisons are based on policy texts rather than on their actual implementation. The presence of procedural provisions does not guarantee their enforcement, just as the absence of explicit clauses does not imply that corresponding practices are not implemented de facto. The study did not include empirical data collection on policy implementation, compliance, or effectiveness.

Third, the heterogeneity of documents posed methodological challenges. Policy formats varied substantially across universities, necessitating content normalization through a unified taxonomy. This may have resulted in the loss of institution-specific nuances.

Fourth, institutional AI policies are dynamic documents that evolve rapidly in response to technological and regulatory developments. The analysis reflects the state of policies at the time of corpus collection and does not account for updates adopted thereafter.

Fifth, potential researcher bias must be acknowledged. The authors are affiliated with Ukrainian universities and hold leadership positions related to research and educational policy. This positionality may influence textual interpretation or the evaluation of certain provisions, particularly if their institutions are included in the corpus. To mitigate bias, several measures were implemented, including independent coding of the entire sample and three rounds of reconciliation and discussion of discrepancies.

Sixth, the three-level scale (0-2) simplifies the actual complexity of institutional approaches. Some policy provisions may not fit neatly into discrete categories, and individual documents may combine elements of multiple maturity levels simultaneously. The AI-PMT taxonomy should therefore be understood as an analytical comparison tool rather than an absolute measure of policy quality.

It is also essential to consider the temporal dimension: policies adopted in the early stages of generative AI diffusion (particularly in 2023) naturally exhibit lower levels of procedural specificity, reflecting contemporary understandings of risks and opportunities at the time of adoption. Given the rapid evolution of technologies and regulatory environments, policy "maturity" is a dynamic characteristic. Early documents should not be interpreted as inherently lower in quality, but rather as representing earlier stages in the evolution of institutional approaches.

Seventh, the study does not incorporate stakeholder perspectives (faculty, students, researchers, administrators). Consequently, perceptions of

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policies and actual implementation practices were not examined.

Overall, these limitations do not invalidate the findings but indicate the need for further mixed-method research combining document analysis with interviews and assessments of policy implementation in university practice.

3. RESULTS

3.1. Distribution of policy maturity levels and temporal trends

A quantitative analysis was conducted for 23 university AI policies across the twelve dimensions of the AI-PMT maturity taxonomy. This approach enabled the identification of both the degree of formalization of specific policy components and the broader structural asymmetry between different regulatory domains.

The results of the dimension-level analysis are presented in Figure 1. The findings indicate that the most developed components are those directly related to the educational process and to the general architecture of institutional policies. In particular, within the dimensions "Scope" and "Permissibility in Education," the majority of universities demonstrated high levels of maturity. This suggests clearly defined domains of AI application and the normalization of AI use in teaching and learning activities.

In contrast, the dimensions "Governance and Support" and "Disclosure of AI Use" exhibit a mixed distribution between basic and elaborated maturity levels. This indicates that while a number of universities have introduced formal requirements and designated responsible units, in many cases these provisions remain procedurally incomplete or largely declarative.

Across several other dimensions, the basic maturity level predominates. In the categories "Assessment," "Research Policy," "Data, Intellectual Property, and Confidentiality," "Inclusion and Accessibility," and "Control and Remediation Mechanisms," most universities received a score of 1. This signifies that relevant provisions are present but typically formulated in general terms, without detailed procedural guidance, clearly assigned responsibilities, or operational implementation mechanisms.

Two dimensions reveal a persistent institutional gap. The category "Jurisdictional Restrictions and Sanctions Risks" received a score of 0 in the majority of cases, indicating the absence of systematic consideration of risks associated with AI tools potentially subject to international sanctions or linked to high-risk jurisdictions. Similarly, the dimension "Openness and Reproducibility" shows the lowest overall level of development: most policies lack provisions addressing documentation of AI use, transparency of contributions, or reproducibility of research outputs.

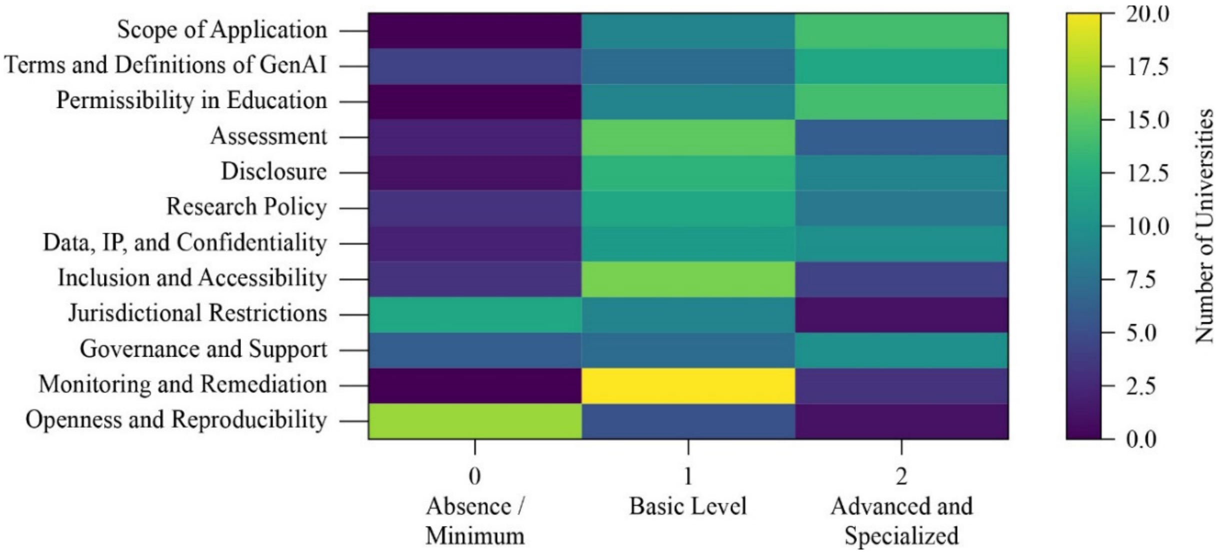

Figure 1. Heatmap of AI-PMT dimensions across institutions

Figure 2. Distribution of cumulative AI policy maturity scores by year of adoption (2023–2025)

In addition, the temporal distribution of cumulative maturity scores was analyzed according to the year of policy adoption. Figure 2 presents the distribution of cumulative scores for 2023–2025, while Table 2 summarizes the corresponding descriptive statistics. Policies adopted in 2023 (N = 3) are clustered within a relatively narrow range of values, with lower mean and median scores, reflecting predominantly basic levels of procedural specification.

Documents adopted in 2024 (N = 4) demonstrate a modest increase in mean values without a substantial expansion of the score range. This pattern may indicate a transitional phase in the formalization of institutional approaches to regulating AI use.

Policies adopted in 2025 (N = 16), by contrast, are characterized by noticeably higher mean and median scores, as well as a considerably wider score range. This suggests not only an overall increase in regulatory maturity but also a growing heterogeneity of institutional approaches within the most recent cohort.

Table 2. Descriptive statistics of cumulative AI policy maturity scores by year of adoption

Year	N	Mean	Median	Min	Max
2023	3	13.33	11.00	11	18
2024	4	11.75	11.50	11	13
2025	16	15.00	15.50	7	20

A comparison of indicators across adoption years reveals a stable temporal association between the date of policy adoption and its level of regulatory maturity. On average, more recently adopted policies exhibit higher cumulative scores. However, they are also accompanied by greater internal variability in maturity structures, whereas earlier documents tend to be confined to more basic levels of procedural specification.

3.2. Typology of universities by cumulative AI policy maturity index

To synthesize the quantitative findings, an analytical typology of universities was developed based on the cumulative AI policy maturity index (0–24), calculated as the sum of scores across the twelve AI-PMT dimensions. Based on the natural clustering of index values, three relatively homogeneous policy types were identified, differing in their level of regulatory completeness and degree of procedural specification (Table 3).

Universities classified within the high-maturity cluster demonstrate the most systematic approach to regulating AI use. Their policies are characterized by structured design, clearly defined roles and procedures, and integration of provisions addressing teaching, research activities, and institutional governance, including selected aspects of data governance and user support.

The medium-maturity cluster, which is numerically dominant in the sample, includes universities

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Table 3. Clusters of institutional AI policies by maturity level (AI-PMT)

Cluster	Score Range	Number of Universities	Dominant Characteristics
High Maturity	20-23	2	Comprehensive coverage of education, research, and governance; presence of procedural provisions; regulation of data practices and specific research activities
Medium Maturity	12-19	13	Well-developed educational component; basic transparency requirements; partial regulation of research and data-related aspects
Low Maturity	< 12	8	Fragmentary provisions; absence of operational procedures; limited coverage of AI-PMT dimensions

with relatively coherent and internally consistent regulatory frameworks. These policies typically provide substantive regulation of AI use in education and establish basic transparency requirements. However, elements related to the research lifecycle, reproducibility, or procedural data governance are addressed selectively or at a general level.

The low-maturity cluster comprises universities where AI regulation is fragmentary or embedded within broader normative documents without systematic integration. In these cases, most AI-PMT dimensions are insufficiently developed, and clear implementation and support mechanisms are largely absent.

3.3. Thematic patterns and illustrative institutional cases

To complement the quantitative findings, a thematic analysis of university policies governing the use of generative artificial intelligence was conducted. The analysis was based on inductive coding of normative documents, followed by the aggregation of recurring motifs and regulatory approaches. As a result, a set of stable thematic patterns was identified. These patterns recur across institutions regardless of overall maturity level, although they differ in terms of detail, procedural specification, and degree of operationalization (Table 4).

Content analysis reveals several recurring thematic patterns across institutional contexts, implemented with varying degrees of procedural clarity and strategic depth.

The leading pattern in the sample is the normalization of generative AI use in the educational process. Most policies provide relatively detailed descriptions of permissible scenarios for AI use in teaching, including preparation of instructional

Table 4. Thematic patterns in institutional AI policies

Thematic Pattern	Brief Description	Typical Codes / Indicators	Prevalence*
Normalization of AI Use in Education	Recognition of AI as a permissible educational tool under defined conditions	permissible use; learning support; preparation of materials; ideation; editing	High
Academic Integrity and Disclosure	Requirement for transparent reporting of AI use	disclosure of use; specification of tool; author responsibility	High
Control and Sanctions	Regulation of violations and consequences of non-compliance	prohibition; violation; annulment of results; disciplinary responsibility	Medium (largely declarative)
Data, Confidentiality, and Security	Warnings against entering personal, institutional, or unpublished data	personal data; confidential information; prohibition of processing	Medium (restrictive focus)
AI Use in Research	Regulation of AI applications in research activities	authorship; publication preparation; data analysis; research practices	Low
Institutional Governance and Support	Definition of roles, responsibilities, and policy review procedures	responsible units; policy updates; training initiatives	Medium (fragmentary)
Inclusion and Accessibility	AI use to support individuals with diverse educational needs	inclusion; accessibility; assistive technologies	Low
Jurisdictional and Sanctions Risks	Restrictions on tools associated with high-risk jurisdictions	sanctions; jurisdictional limitations; prohibited services	Very low

Note: * Prevalence indicates relative frequency across the analyzed corpus.

materials, text editing, translation, idea generation, and task structuring. In some universities, this approach is complemented by procedural specification of disclosure requirements.

For example, in the policies of Berdyansk State Pedagogical University and Metinvest Polytechnic Technical University, disclosure of AI use extends beyond a general obligation to acknowledge its application. Instead, institutions recommend the use of a structured declaration tool – specifically the GAIDeT AI contribution declaration generator (Suchikova et al., 2025b). In these cases, disclosure is operationalized as a systematic description of the AI system used, the type of delegated tasks, the role of AI in the workflow, and the boundaries of user responsibility. This approach reflects a shift from declarative transparency toward operationalized disclosure practices that can be integrated into both educational and research processes.

A second significant pattern concerns the expansion of policy scope beyond teaching and research. In several cases, AI is conceptualized not only as a tool for academic activities but also as an instrument for institutional governance, administrative processes, and decision-support systems.

A notable example is Kherson State University, where the regulatory framework encompasses AI use for managerial and analytical tasks, and the policy architecture consists of a structured set of interrelated documents (concept, procedural order, regulation). This multi-layered design indicates an institutional understanding of AI as part of managerial infrastructure rather than merely a pedagogical or ethical challenge. A similar logic is observed at Sumy State University, where the policy explicitly envisions AI integration into institutional IT systems and identifies potential implementation domains ranging from educational analytics to administrative workflows and cybersecurity.

In these cases, AI is framed as a component of digital transformation, extending beyond text-centric use scenarios and embedding generative technologies within broader institutional governance ecosystems.

A distinct thematic pattern relates to risk-oriented approaches to regulating AI use. While most policies contain general warnings regarding confidentiality and personal data, only a limited number of universities formalize risks associated with jurisdictional restrictions and the use of AI tools subject to heightened regulatory scrutiny.

In particular, the policies of Yuriy Fedkovych Chernivtsi National University and Sumy State University explicitly prohibit the use of tools linked to sanctioned countries or the aggressor state. The Chernivtsi National University policy further includes formalized criteria for preliminary evaluation of AI systems, covering the jurisdiction of the provider, intellectual property rights, protection of confidential data, and allocation of responsibility. In contrast, Sumy State University places greater emphasis on the technical and organizational aspects of secure AI integration within the institutional IT environment.

Unlike the majority of policies that focus primarily on AI use for text generation, certain documents demonstrate a broader understanding of the AI ecosystem. The policies of Sumy State University and Chernivtsi National University extend regulatory coverage to tools for code generation, image, video, and audio production, as well as data analytics. This broader scope is particularly relevant for technical and interdisciplinary programs. Such a non-text-centric approach is combined with elements of infrastructural thinking, including attention to cybersecurity, integration of AI tools into internal university systems, data backup mechanisms, and monitoring of service usage. Although these approaches remain relatively rare within the analyzed sample, they outline potential directions for the further evolution of institutional AI policies.

Taken together, the identified thematic patterns and illustrative cases demonstrate that even institutions with comparable cumulative maturity indices may differ substantially in internal logic, scope, and degree of operationalization. Some universities prioritize educational normalization and baseline transparency, while others focus on governance, infrastructure, or risk-oriented dimensions. This diversity provides an empirical basis for further discussion of the drivers of these differences and for developing recommendations aimed at fostering coherent and functional models of AI governance in higher education.

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A separate subgroup within the sample comprises policies with low cumulative maturity indices, which nevertheless share certain structural characteristics. These documents often exhibit a high degree of formalization regarding disclosure requirements, including detailed descriptions of tools and interaction processes, as well as provisions permitting the use of generative AI only with prior instructor approval.

Moreover, within a single normative framework, multiple mechanisms of academic integrity control are frequently combined – such as plagiarism detection, assessment of textual originality, and AI-use detection – without clearly distinguishing their functional purposes. Comprehensive prohibitions on AI use in specific genres of academic and research work are also common. Overall, these policies demonstrate fragmentary coverage of AI-PMT dimensions, with an emphasis on formal requirements and control mechanisms rather than systemic integration and procedural coherence.

3.4. Types of institutional documents and coverage models

Analysis of institutional document types reveals several established models for formalizing AI use policies in universities.

The first and most prevalent type consists of generalized policies or regulations that, within a single document, govern the permissibility of AI use in the educational process and outline basic principles of academic integrity.

The second type comprises thematically specialized documents focused on specific aspects of AI application, such as ethics, assessment, faculty support, or organizational procedures.

The third, less common type includes institutional regulations and operational guidelines of a more applied nature. These documents provide detailed procedural mechanisms for the use of AI services, including aspects related to implementation, funding, reporting, and disclosure of AI tool usage.

Quantitative and structural analysis indicates that universities employing a combined model – characterized by multiple interrelated documents of different types – tend to demonstrate broader regulatory coverage and higher cumulative maturity scores. An example of such a modular model with extensive coverage is Berdyansk State Pedagogical University, where separate policies for education and research operate alongside applied guidelines and recommendations. This configuration enables coordinated coverage of educational, research, infrastructural, and procedural dimensions.

A notable case is Kherson State University, which demonstrates an iterative approach to developing institutional AI policies. In this instance, a foundational document is progressively supplemented by specialized regulations and procedural guidelines that clarify particular aspects of AI implementation, including organizational, financial, and infrastructural components. This practice of sequential updating allows for the expansion of regulatory coverage without fully replacing earlier policies and reflects a dynamic adaptation of institutional governance to evolving technological and normative contexts.

4. DISCUSSION

4.1. Discussion of findings in the international context

The patterns identified in this study are broadly consistent with previous empirical analyses of institutional policies regulating the use of generative artificial intelligence in higher education. International document-based studies likewise report the predominance of the educational domain over the research dimension, strong emphasis on academic integrity and disclosure requirements, and a tendency toward formalized or restrictive approaches in the early stages of regulation.

Similar to findings from European, American, and Asian samples (Jin et al., 2025; Luo, 2024; Parker et al., 2025; Jiang et al., 2025), the analyzed corpus reveals the coexistence of multiple control regimes (plagiarism detection, textual originality checks, AI-use detection) and the use of broad prohibitions without clear contextual differentiation. At the same time, as observed in other jurisdictions, more recently adopted documents demonstrate a gradual expansion of thematic coverage and at-

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tempts to operationalize selected aspects of AI use. This suggests an evolutionary logic in the development of institutional AI policies in response to the rapid advancement of generative technologies.

Overall, the findings align with leading international frameworks for AI governance, while simultaneously revealing a gap between declarative principles and institutional implementation. At the level of foundational values, university policies resonate with the *UNESCO Recommendation on the Ethics of Artificial Intelligence* (UNESCO, 2022) and the *OECD AI Principles* (OECD, 2025). The analyzed documents reflect a human-centered approach, emphasize user responsibility, prohibit delegating authorship or decision-making to algorithms, and highlight privacy and confidentiality concerns. This indicates the adoption of a global normative vocabulary in which AI is framed as an object of ethical and social regulation.

However, the principled nature of the UNESCO and OECD frameworks – neither of which provides detailed implementation mechanisms – partially explains the observed gap between general declarations and operational procedures in institutional policies. In many cases, declared commitments to transparency or accountability are not accompanied by structured implementation tools, such as formalized AI contribution disclosure procedures or review mechanisms for contested decisions.

Comparison with the risk-based logic of the *EU AI Act* (EU, 2024) reveals an additional divergence. The European model differentiates AI use scenarios according to risk level, whereas many institutional policies rely on a binary logic of permission or prohibition without contextual gradation. The absence of a risk-based approach complicates the transition toward more proportional and adaptive models of institutional AI governance.

A particularly illustrative contrast emerges in relation to the *NIST AI Risk Management Framework* (NIST, 2023), which advances a process-oriented model of risk governance. In contrast, university policies predominantly emphasize normative requirements and control mechanisms, without encompassing the full cycle of risk assessment, monitoring, and revision as technologies evolve.

In the research domain, policies generally reflect the recommendations of *COPE* (COPE, 2024) and the *STM Association* (STM, 2023) regarding the inadmissibility of recognizing AI systems as authors. However, they less frequently integrate detailed requirements concerning documentation of AI contributions, allocation of author responsibility, and reproducibility standards.

Taken together, these observations indicate convergence of Ukrainian institutional AI policies with international frameworks at the level of principles and values, while revealing insufficient operationalization and infrastructural support – an essential factor for interpreting the observed maturity patterns.

4.2. Contested and problematic provisions in institutional policies

Alongside the gradual emergence of more structured approaches to regulating generative AI, the analysis revealed a number of recurring problematic provisions that complicate practical implementation and reduce overall institutional maturity. These provisions are neither isolated nor incidental: they recur across multiple institutions and reflect common constraints characteristic of the early phase of regulatory adaptation. Importantly, these patterns should be interpreted not as institutional failures but as typical features of an initial stage of normative adjustment.

One of the most problematic patterns is the dominance of a punitive regulatory logic. In several policies, transparency and disclosure of AI use are formally articulated as principles, yet function in practice as mechanisms of surveillance and sanctioning. For example, failure to comply with formal disclosure requirements may automatically constitute grounds for annulment of assessment results or disciplinary action, even in the absence of demonstrable intent to deceive.

Such an approach rests on a presumption of potential misconduct and does not provide procedural safeguards, such as the right to explanation or appeal. As a result, policies create incentives not for open disclosure of AI use, but for risk minimization and concealment – contradicting the stated objective of fostering a culture of transparency.

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A second recurrent issue concerns excessive formalization of disclosure requirements without regard to the actual dynamics of interaction with generative systems. In some cases, students are required to submit complete prompt histories, precise timestamps of interaction, percentages of text "generated by AI," and detailed descriptions of each stage of tool usage.

These requirements are grounded in a linear conception of generative AI use as a single-step "prompt–output" process. In reality, academic interaction with AI systems is iterative, fragmentary, and often leaves no stable artifacts that can be retrospectively documented with precision. Consequently, users may find themselves technically unable to comply with policy requirements or forced to reconstruct approximate prompts post hoc, thereby undermining the very principle of good-faith disclosure.

In several documents, the use of generative AI is permitted only with prior approval from an instructor or administrator. Non-compliance with this requirement – even in the absence of substantive misconduct – may result in invalidation of assessment outcomes. Such an approach creates significant administrative barriers, particularly in contexts where AI is widely used for auxiliary or routine tasks. In effect, responsibility for regulating AI use is shifted to the individualized "student–instructor" relationship, without providing institutional mechanisms for standardization, predefined permissible scenarios, or harmonized practices. This contributes to inequality across courses and programs and reduces predictability within the regulatory environment.

Another problematic feature is the uncritical conflation of distinct academic integrity control mechanisms. In several policies, plagiarism detection tools, textual "originality" metrics, and AI-detection systems are referenced in the same regulatory context without differentiation of their purpose, reliability, or evidentiary value. The absence of defined error thresholds, verification procedures, or clear standards for the use of detection tools creates risks of procedural unfairness. Under such conditions, automated services may become grounds for sanctions without appropriate human oversight, contrary to international recommendations and basic principles of due process.

A further category of problematic provisions consists of absolute prohibitions on AI use in essays, research papers, literature reviews, or analytical texts. These prohibitions are typically not accompanied by pedagogical justification or alternative assessment models, even though such genres are precisely those most affected by AI-driven transformation. Rather than rethinking task design or defining criteria for responsible use, policies frequently adopt blanket bans that reflect concerns about loss of control rather than a strategic regulatory approach. In the long term, this may result in formal compliance without substantive engagement with evolving educational and research practices.

Overall, the problematic provisions identified in lower-maturity policies indicate attempts to incorporate generative AI into pre-existing academic integrity frameworks without reconsidering those frameworks themselves. Excessive formalization, punitive logic, and unrealistic transparency requirements do not promote responsible AI use; instead, they may incentivize concealment and procedural compliance detached from actual practice.

These tensions suggest that the development of effective institutional AI policies requires a shift from reactive prohibition and control toward supportive, procedurally balanced governance models that acknowledge the iterative nature of generative AI interaction and the diversity of academic contexts.

4.3. Factors shaping divergence in institutional AI policies

The differences identified among university policies regulating the use of generative artificial intelligence are neither accidental nor merely the result of individual managerial choices. Rather, they emerge from a combination of structural, organizational, and contextual factors that shape institutional capacity to design, implement, and regularly update AI governance frameworks.

A key factor is the deficit of interdisciplinary expertise. The development of institutional AI policies requires integration of technical understanding of generative models, knowledge of digital law, academic integrity standards, open science principles, research data management, and pedagogical design. In most universities, such competencies are not consolidated within stable, cross-functional teams. As a result, policies are often drafted by narrowly composed working groups or adapted from pre-existing regulatory texts.

Equally significant is the level of AI literacy among faculty, administrators, and institutional leaders involved in policy development. Limited understanding of the functioning of generative models, the iterative nature of prompting, the legal status of data, or the risks associated with automated analysis contributes to the prevalence of cautious, restrictive, or excessively formalized approaches. Under such conditions, prohibition or strict control may appear institutionally safer than regulated permissibility with clearly defined responsibility boundaries.

A second systemic factor is the absence of nationally coordinated guidelines or standards governing the use of generative AI in higher education and research. In the absence of such frameworks, universities must independently interpret international principles or rely on general academic integrity norms. This leads to policy fragmentation, divergent interpretations of similar concepts, and the emergence of inconsistent provisions that are not always aligned with established international practices.

Infrastructural constraints also play a substantial role. Many universities lack access to secure institutional platforms, locally hosted models, or research data management tools capable of supporting technically grounded procedures. As a consequence, policies often remain limited to general warnings about confidentiality and data protection, without advancing toward operational mechanisms that would enable reproducibility, secure integration of AI into research workflows, or institutional oversight of AI services.

Regulatory inertia represents another influential factor. A significant portion of institutional AI policies has been developed through modification of pre-existing academic integrity or assessment regulations created prior to the advent of generative AI. New provisions are therefore embedded within older normative structures, reinforcing punitive logic, a focus on violations and sanctions, and limiting the development of supportive or educational components.

Finally, the rapid pace of technological change exerts structural pressure on institutional regulation. Generative tools, licensing terms, and usage practices evolve far more quickly than institutional cycles of policy adoption and revision. As a result, policies may quickly become outdated or reflect provisional understandings of AI-related risks and opportunities that require subsequent revision.

Collectively, these factors indicate that variation in the maturity of institutional AI policies reflects not only strategic choices but also broader constraints related to institutional capacity, human resources, infrastructure, and regulatory environments. Recognizing these determinants is essential for interpreting the findings and for formulating realistic recommendations for further development of AI governance in higher education.

4.4. Strategic implications and directions for further development

Despite the identified limitations, the findings generate several strategic implications for universities, policymakers, and the research community. First, they underscore the necessity of moving from static, declarative AI policies toward dynamic regulatory models. Institutional documents governing AI use should not be treated as one-time normative acts, but as adaptive instruments subject to regular review and revision in response to technological evolution and shifting regulatory environments.

A second strategic implication concerns the need to rebalance institutional logic from punitive and control-oriented mechanisms toward supportive and educational approaches. Mature AI governance cannot be achieved without systematic development of AI literacy among students, academic staff, and administrators. Structured training initiatives, advisory support, exemplars of responsible practice, and accessible guidance materials are essential for fostering transparency and accountability in the use of generative systems.

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The research dimension of AI governance requires particular strengthening. The results indicate a clear need to integrate provisions addressing research data management, documentation of human–AI interaction, reproducibility of AI-assisted analyses, and explicit attribution practices in scientific publications. Without such integration, institutional AI policies risk remaining confined to the educational domain and failing to respond to the methodological transformations currently unfolding in research environments.

Institutional infrastructure constitutes an additional strategic condition for policy maturity. Access to secure platforms, institutional subscriptions, or locally hosted AI solutions enables universities not only to mitigate data protection risks but also to reduce inequalities of access among user groups. In this respect, AI policies should be conceptualized in close connection with broader digital and research infrastructure strategies. Governance frameworks that lack infrastructural grounding are unlikely to achieve operational effectiveness.

It is also important to acknowledge the boundaries of the present analysis. Certain domains of AI application were intentionally excluded to preserve comparability across institutions. The use of AI in expert review processes – such as internal evaluations, grant assessment, or peer review – raises distinct questions of confidentiality, procedural fairness, and epistemic responsibility. Similarly, artistic and creative disciplines, where AI may function as a co-creative agent, require differentiated normative approaches. Both domains warrant dedicated methodological frameworks and constitute promising directions for future research.

Finally, the proposed maturity taxonomy is not intended as a tool for external evaluation, ranking, or competitive benchmarking. Its analytical application in this study is secondary to its primary function: supporting institutional self-assessment and reflective development of AI governance practices. The taxonomy is designed to help universities identify structural gaps, imbalances, and areas for strategic improvement rather than to assign static labels of "success" or "failure."

Given the rapid development of generative technologies, evolving international guidance, and emerging institutional practices, the taxonomy itself cannot be regarded as final or exhaustive. It requires further refinement, contextual adaptation, and iterative validation through dialogue among universities, researchers, policymakers, and international partners. In this sense, the findings of the study should be interpreted not as a definitive conclusion, but as a contribution to an ongoing scholarly and institutional conversation on how to build flexible, reflexive, and procedurally grounded models of AI governance in higher education.

CONCLUSIONS

This study aimed to comprehensively analyze institutional policies governing the use of generative artificial intelligence in Ukrainian universities and to propose a maturity taxonomy as a structured instrument for institutional self-assessment and strategic development of AI governance in higher education. The findings demonstrate that university policies are situated at different stages of institutional development and exhibit an uneven distribution of regulatory attention across educational, managerial, and research domains.

The quantitative analysis of 23 institutional policies across twelve regulatory dimensions revealed a pronounced asymmetry in normative maturity. The most elaborated components are those directly related to the educational process and the overall architecture of policies – particularly scope and permissibility of AI use in teaching – which received extended specification in the majority of universities (14 cases each). By contrast, dimensions such as governance, support, and disclosure of AI use display a mixed distribution between basic and advanced levels of maturity, indicating the presence of formalized requirements without full procedural specification in a substantial proportion of documents.

More infrastructure-intensive and research-related dimensions – openness and reproducibility, jurisdictional and sanctions-related risks, and specific elements of research data management – remain largely outside systematic regulation, as reflected in the prevalence of zero or minimal scores. This imbalance suggests that institutional policies primarily respond to immediate educational challenges, while long-term infrastructural capacity and risk governance are insufficiently integrated into institutional models.

Analysis of cumulative maturity indices (0-24) indicates substantial inter-institutional variability, ranging from 7 to 20 points. Policies adopted in 2025 demonstrate higher mean and median values (Mean = 15.0; Median = 15.5) and a significantly broader score range compared to documents from 2023–2024. This pattern reflects not only an overall increase in normative formalization but also growing heterogeneity of institutional approaches, marking a transition from reactive responses toward more differentiated – though unevenly operationalized – regulatory models. The proposed typology identifies three generalized clusters of policies distinguished by the depth of regulatory coverage and the degree of procedural implementation.

Thematic analysis complements the quantitative findings by confirming the dominance of educational normalization and transparency-oriented provisions, while research practices, reproducibility, and data governance remain fragmentary. Recurrent problematic features include overly formalized disclosure requirements, binary logics of permission and prohibition, and conceptual conflation of AI detection with plagiarism control. These inconsistencies complicate policy implementation and weaken alignment with actual academic practices.

Comparison with international regulatory frameworks indicates that Ukrainian universities broadly internalize global principles of responsible AI use; however, they less frequently adopt process-oriented and infrastructural mechanisms characteristic of risk-based governance and research management standards. The central challenge, therefore, lies not in normative alignment at the level of values, but in the transition toward operationally robust models of institutional AI governance capable of supporting decision-making, organizational learning, and sustainable development.

The proposed Taxonomy of Institutional AI Policy Maturity (AI-PMT) is not intended as a ranking instrument but as a flexible analytical framework for institutional self-reflection, inter-university learning, and gradual improvement of governance practices. More broadly, the findings contribute to international scholarly debates by documenting typical challenges faced by universities during the rapid integration of generative AI and by providing an empirical basis for comparative research and the development of coordinated models of knowledge governance and institutional effectiveness in higher education.

DATA AVAILABILITY STATEMENT

The datasets generated and analyzed during this study are openly available in the Zenodo repository at https://doi.org/10.5281/zenodo.19216498

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AUTHOR CONTRIBUTIONS

Conceptualization: Yana Suchikova, Serhii Omelchuk.
Data curation: Yana Suchikova, Serhii Omelchuk.
Formal analysis: Yana Suchikova, Serhii Omelchuk.
Investigation: Yana Suchikova, Serhii Omelchuk.
Methodology: Yana Suchikova, Serhii Omelchuk.
Project administration: Yana Suchikova, Serhii Omelchuk.
Resources: Yana Suchikova, Serhii Omelchuk.
Software: Yana Suchikova.
Supervision: Yana Suchikova, Serhii Omelchuk.
Visualization: Yana Suchikova.
Validation: Yana Suchikova, Serhii Omelchuk.
Writing – original draft: Yana Suchikova, Serhii Omelchuk.
Writing – review and editing: Yana Suchikova, Serhii Omelchuk.
Funding acquisition: Yana Suchikova.

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