

## INSTITUTIONALIZATION OF ARTIFICIAL INTELLIGENCE IN UKRAINE'S PUBLISHING INDUSTRY

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**Introduction.** The spread of artificial intelligence in the publishing industry is transforming not only individual production operations but also professional roles, editorial procedures, management models, content quality criteria, and approaches to organizational governance. Under these conditions, AI should be considered not only as a technological tool but also as a factor of institutional change in the professional environment.

**Relevance and purpose.** The relevance of the study stems from the insufficient conceptualization of the organizational dimension of AI implementation in Ukraine's publishing industry. The article aims to identify the specific features of AI institutionalization by analyzing the relationship between individual professional use of the technology and the level of its organizational implementation.

**Methodology.** The empirical basis is a quantitative survey conducted from December 2025 to February 2026 with 374 respondents. Valid-response subsamples were used for particular analytical blocks, while a matched subsample of  $n = 240$  was used to compare individual AI use with respondent-reported organizational AI implementation. The analysis employed descriptive statistics, the chi-square test, and the two-sided McNemar test.

**Results.** AI institutionalization was found to be uneven and predominantly transitional. Some form of official AI implementation in their organization was reported by 61.3% of respondents, with localized use being the most common format. Within the matched subsample, active professional AI use at the individual level was recorded among 77.1% of respondents. The study revealed a low level of formalization of AI practices, weak internal policies and contractual regulation, the predominance of self-education, and insufficient professional training as the most frequently reported barrier to implementation.

**Conclusions.** The findings indicate that AI is already widely used at the individual level within the analyzed publishing environment, while respondent-reported organizational AI implementation remains uneven and incompletely formalized. The novelty of the study lies in identifying the asymmetry between individual use and respondent-reported organizational implementation of AI. The findings may inform the development of internal policies, training programs, mechanisms for responsible AI use, and managerial coordination.

**Keywords:** artificial intelligence, publishing industry, institutionalization, organizational implementation, media convergence, digital transformation, innovations



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**Introduction.** The rapid spread of artificial intelligence (AI) technologies over the past few years has substantially changed the nature of professional work in the publishing industry. While at the initial stage, AI was perceived primarily as a tool for automating specific operations, including text generation, translation, editing, audience analysis, and content personalization, it is now increasingly evident that its impact extends beyond purely functional application. The issue is no longer limited to accelerating particular production processes. It also concerns the transformation of professional roles, editorial procedures, management models, quality criteria, and understandings of authorship, responsibility, transparency, and the acceptable limits of technological intervention in content creation. Under these conditions, the interaction between the publishing industry and AI should be considered not only a technological issue but also an institutional one, as it directly relates to the formation of new rules, coordination mechanisms, institutional legitimation, and the organizational governance of a new technological practice.

In this study, AI is understood as machine-based systems that, based on input data, can generate predictions, recommendations, decisions, or content in accordance with human-defined objectives. For the publishing industry, this transformation means a shift from the fragmented use of individual digital services to a gradual reconsideration of the logic of creating, editing, distributing, and quality-controlling publishing products. In the broader professional context related to the media sphere, this transformation concerns not only tools but also ways of organizing work, systems of responsibility, approaches to staff training, and norms of professional interaction between humans and algorithms. Therefore, the focus of this article is not merely the use of AI, but the process of its institutionalization in the professional environment.

For the purposes of this study, the publishing industry is understood in a broad functional rather than narrowly institutional or sectoral sense. This definition reflects the functional convergence of publishing and media production driven by media convergence, cross-media production, and digitalization: content creation, editorial processing, technological production, adaptation, distribution, and audience-oriented modification increasingly operate across formerly separate professional sectors. Accordingly, the analytical field includes professional environments directly involved in these publishing-related processes, including digital and interactive content production, even when their formal affiliation extends beyond traditional book publishing. This functional perspective is consistent with transformations of publishing markets and convergent media roles [23; 27; 28].

In this context, despite the rapid growth in the number of studies devoted to AI, a considerable part of the existing research focuses either on the technical capabilities of tools or on individual practices of their application. In particular, contemporary studies in journalism and news production actively examine journalists' perceptions of the opportunities and risks of generative AI, the role of professional identities in its adoption, and specific newsroom cases of integrating algorithmic systems into production processes [5; 16]. At the same time, even studies that approach the organizational level of analysis mostly consider individual examples of interaction between journalists, media professionals, and AI systems or role-based differences in the adoption of the technology, rather than systematically conceptualizing internal policies, contractual formalization, training mechanisms, and institutional conditions for AI implementation [11]. In studies directly focused on the publishing sector, the emphasis also tends to shift towards the reengineering of business processes, the transformation of the publishing value chain, intellectual property, and professional challenges, while the organizational institutionalization of AI remains less developed [19; 21].

In Ukrainian scholarly discourse, the issue of AI in the publishing and media spheres is already being addressed through the lens of reengineering the publishing industry, transforming editorial processes, and changing professional roles. In particular, previous studies have substantiated that AI implementation affects the production logic of publishing activity, changes the structure of editorial and publishing processes, and actualizes the need to reconsider professional competencies [28]. Some studies identify instrumental and creative

ways to integrate generative AI into Ukrainian book publishing, emphasizing the importance of human oversight and editorial responsibility in these processes [29]. At the same time, Ukrainian research also raises the issue of the institutionalization of new professional roles in the digital media industry, which provides an important context for understanding organizational changes caused by technological transformation [27].

Existing studies primarily address the technological, process-related, and professional-role consequences of AI implementation, whereas its organizational institutionalization in Ukraine's publishing industry remains underexplored. Here, institutionalization concerns the transition from individually initiated practices to formalized arrangements involving internal policies, contractual provisions, training, support, and managerial coordination. The research gap therefore concerns how professional practices, organizational readiness, structural barriers, and legitimation mechanisms interact within a functionally convergent publishing environment.

The purpose of this article is to identify the specific features of AI institutionalization in Ukraine's publishing industry through an analysis of the relationship between the individual professional use of this technology and the level of its organizational implementation. Achieving this purpose involves outlining theoretical approaches to the analysis of AI institutionalization in the professional environment, clarifying the nature of its organizational implementation in the publishing industry, determining the level of AI use formalization through the presence of internal policies, contractual provisions, training practices, and support mechanisms, identifying key barriers to institutional implementation, and comparing active individual AI use with the level of its organizational formalization. This set of research tasks enables combining descriptive, analytical, and interpretive approaches and considers AI institutionalization not as a one-time act of technology adoption but as a process of gradually forming new professional and organizational norms.

**Research methods.** The organizational dimension of AI implementation in the publishing industry should be analyzed as a process of institutionalizing a new technological practice, rather than merely as the fact of using individual tools in employees' work. This approach requires attention to the extent to which individual practices are supported, or conversely not supported, by organizational rules, procedures, forms of training, managerial coordination, and mechanisms of responsibility. Therefore, the theoretical basis of the study is the integration of several complementary approaches that enable the examination of AI implementation at different analytical levels. These include the technology acceptance model [7], diffusion of innovations theory [18], organizational learning theory [1], the concept of technological maturity models [2], and the classical sociological tradition of institutional analysis [8; 15].

Neo-institutional organizational theory is particularly important for conceptualizing the phenomenon under study. In their concept of institutional isomorphism, DiMaggio and Powell showed that organizations within the same organizational field gradually become similar to one another under the influence of normative, mimetic, and coercive pressures [8]. In the context of AI implementation, this theory helps explain why the degree of formalization of organizational practices for technology use may differ substantially from the actual level of its application.

A key theoretical foundation for the analysis is the concept of organizational AI readiness developed by Jöhnk et al. [13]. The authors consider organizational AI readiness as a prerequisite for successful technology implementation and associate it with five dimensions: strategic alignment, resources, employees' knowledge and competencies, organizational culture, and data quality. For the present study, this approach is methodologically significant because it shifts the focus from the mere fact of AI use to the conditions of its organizational formalization. In the publishing environment, this approach means that AI implementation requires not only technical access to tools but also internal policies, training mechanisms, accountability frameworks, quality control procedures, and managerial coordination.

Within the technology acceptance model, the central assumption is that the use of a new technology is determined not only by its objective characteristics but primarily by how users perceive its usefulness and ease of use [7]. However, for the analysis of AI in the publishing industry, this explanation is insufficient, as decisions to use the technology are also linked to risks of error, issues of authorship, ethical dilemmas, data confidentiality, and reputational consequences. It is therefore appropriate to take into account its extended interpretations, in particular the TAM3 model [25], in which social influence, facilitating conditions, and expected risks play an important role, as well as the concept of responsible AI use, which is becoming increasingly significant in academic and industry discussions [10; 12]. This logic directly implies the need to analyze not only the individual adoption of AI but also the organizational environment and the normative context of its application.

The diffusion of innovations theory allows considering AI implementation as a process of uneven dissemination of a new technology across different segments of the professional environment, organizations, and employment types [18]. For this approach, it is crucial not to reduce the analysis to a binary distinction between users and non-users. Instead, it is important to capture intermediate states, including pilot attempts, localized use, unofficial application, and strategic integration. Therefore, the question of the stage of organizational AI implementation has not only a descriptive but also a conceptual status in this study, as it enables identification of the degree of an organization's institutional engagement with the new technology.

Organizational learning theory shifts the analytical focus from the individual employee to the organization as an environment that is either capable or incapable of transforming individual experience into shared knowledge, established routines, and new norms of activity [1]. From this perspective, AI implementation appears not simply as a matter of mastering tools but as a question of an organization's capacity to learn, reconsider its processes, and integrate new knowledge into managerial and professional practice. The concept of communities of practice complements this approach by emphasizing the role of informal professional interactions in disseminating knowledge and developing working solutions. For this reason, the analysis includes indicators related to forms of training, sources of competence acquisition, and support mechanisms.

The concept of technological maturity models provides the most direct basis for analyzing institutionalization. Its value lies in the fact that it allows the implementation of a new technology to be interpreted as the gradual development of organizational capacity rather than as a one-time decision-making act [13; 20]. In this logic, what matters is not only whether AI is present in an organization's work but also the level of formalization, coordination, strategic embeddedness, resource provision, and managerial support for its use. This framework made it methodologically appropriate to include indicators related to the stage of implementation, internal policies, contractual practices, training approaches, and barriers to the transition toward more mature models of AI use.

The empirical basis of the study consists of the results of a quantitative survey conducted from December 2025 to February 2026. A total of 374 respondents participated in the survey. Since participation was voluntary and the questionnaire did not contain mandatory questions, the number of responses to particular questions varied. Therefore, valid-response subsamples were used for individual analytical blocks. This approach allowed the analyses to be based on the available valid responses for each indicator rather than combining observations obtained from non-equivalent response sets. To compare individual professional AI use with respondent-reported organizational AI implementation, a matched subsample was used, consisting of respondents who answered both questions. In this case, the number of observations was  $n = 240$ , which enabled a paired comparison of the individual and organizational dimensions within the same respondents. The unit of observation throughout the survey analysis was the individual respondent. Accordingly, organizational implementation indicators reflect respondents' reports concerning AI practices and formalization in their pri-

mary workplace rather than independently verified organization-level characteristics.

The sample includes respondents from professional segments involved in contemporary publishing and convergent content production: book publishing, educational and scholarly publishing, specialized publications, press and online media, television and radio, PR and communications, freelance activity, publishing and media education, and digital publishing and publishing technologies. Classification followed functional involvement in content creation, editorial processing, technological production, or distribution rather than the employer's formal sector alone. The category "digital publishing and publishing technologies" covered electronic and interactive publications, e-books, digital applications, and related production technologies; it does not represent the IT sector in general.

The age structure of the sample is characterized by a clear predominance of the younger cohort: 48% of survey participants belong to the 18–25 age group. This distribution reflects the recruitment strategy, which included student communities enrolled in relevant specialized programs. At the same time, the age groups of 26–30, 31–40, and 41–50 together account for 44.1% of the sample, providing substantial representation of respondents beyond the youngest cohort. Participants over 50 constitute the least represented age group (7.9%). Women account for 82.7% of participants and men for 17.0%. These socio-demographic characteristics should be taken into account when interpreting the findings, particularly given the voluntary and self-selected nature of the online sample and the consequent limitations on population-level generalization.

Organizational AI implementation was operationalized through respondents' reports about their primary workplace: adoption stage, internal AI-related policies and contractual provisions, and organizational training and support. These indicators therefore capture respondent-reported organizational conditions rather than independently audited organization-level characteristics. The questionnaire also covered barriers to integration and the relationship between individual AI use and organizational formalization.

Data were analyzed using descriptive statistics, cross-segment comparisons, the chi-square test, and the exact two-sided McNemar test. The chi-square test assessed differences in reported implementation stages across professional segments, while the McNemar test compared paired binary indicators of individual AI use and respondent-reported organizational implementation within the matched subsample [9; 14].

**Results and Discussion.** The analysis of respondent-reported stages of organizational AI implementation showed an uneven and predominantly transitional pattern (Table 1). Among respondents who answered this question, 61.3% reported some form of official AI implementation in their primary workplace, with localized use as the most common form. These percentages characterize reported organizational practices within the analytical sample and should not be interpreted as prevalence estimates for Ukrainian organizations.

**Table 1. Stages of Organizational AI Implementation**

| Stage of implementation                                                    | %    |
|----------------------------------------------------------------------------|------|
| Not implemented (either in principle or due to the absence of initiatives) | 14.7 |
| Pilot attempts / experimental implementation                               | 17.7 |
| Localized use (in specific processes or teams)                             | 33.5 |
| Strategically integrated / regular use                                     | 10.2 |
| Unofficial use (at employees' discretion)                                  | 24.1 |

*Note: n = 266 respondents answered this question.*

Reported implementation stages differed across professional segments (Table 2). Localized AI use was the most common form in several segments, including book publishing, educational and scholarly publishing, press and online media, television and radio, and PR and communications.

**Table 2.** *Distribution of Respondent-Reported Organizational AI Implementation Stages by Professional Segment, %*

| Stage of AI implementation | Book publishing | Educational / scholarly literature | Specialized publications | Press / online media | Television / radio | PR / communications | Freelance | Publishing / media education | Digital publishing | Other |
|----------------------------|-----------------|------------------------------------|--------------------------|----------------------|--------------------|---------------------|-----------|------------------------------|--------------------|-------|
| Not implemented            | 26.7%           | 12.5%                              | 0.0%                     | 6.1%                 | 8.3%               | 8.3%                | 4.2%      | 17.9%                        | 0.0%               | 9.1%  |
| Pilot attempts             | 16.7%           | 21.9%                              | 0.0%                     | 28.6%                | 8.3%               | 8.3%                | 12.5%     | 12.6%                        | 10.0%              | 4.5%  |
| Localized use              | 30.0%           | 34.4%                              | 100.0%                   | 34.7%                | 41.7%              | 36.1%               | 16.7%     | 20.0%                        | 30.0%              | 27.3% |
| Strategically integrated   | 0.0%            | 3.1%                               | 0.0%                     | 8.2%                 | 0.0%               | 22.2%               | 12.5%     | 5.3%                         | 50.0%              | 4.5%  |
| Unofficial use             | 23.3%           | 21.9%                              | 0.0%                     | 18.4%                | 16.7%              | 11.1%               | 33.3%     | 22.1%                        | 0.0%               | 27.3% |

The highest reported share of strategic integration occurred in digital publishing and publishing technologies, followed by PR and communications. Freelancers reported unofficial AI use relatively more often, whereas book publishing and educational and scholarly publishing showed higher shares of “not implemented” and “pilot attempts”.

An important indicator of organizational maturity is the presence of internal policies and contractual provisions related to AI use. The analysis of responses from participants who answered both questions in this block (Table 3) showed that formalized normative regulation of AI use has not yet become a typical characteristic of the organizational environment.

**Table 3.** *Presence of Organizational Policies on AI*

| Indicator                                                  | %    |
|------------------------------------------------------------|------|
| Presence of an official AI use policy                      |      |
| Yes, there is an official policy                           | 26.6 |
| No, there is no policy                                     | 41.9 |
| I do not know / I am not sure                              | 27.5 |
| Inclusion of AI-related clauses in the employment contract |      |
| Yes, the contract contains AI-related clauses              | 7.7  |
| No, the contract does not contain such clauses             | 49.5 |
| I do not know / I am not sure                              | 41.0 |

**Note:** The table presents the distribution of responses among respondents who answered both questions concerning internal AI-related policies and contractual provisions ( $n = 222$ ). Percentages are calculated using  $n = 222$  as the denominator. The displayed categories do not sum to 100% because 9 respondents (4.1%) provided an open-ended response to the policy question and 4 respondents (1.8%) provided an open-ended response to the contractual-provisions question; these responses are not shown as a separate analytical category. The question about contractual provisions is primarily relevant to respondents working within formalized contractual relationships and may be less applicable to self-employed respondents and freelancers.

The level of contractual formalization reported by respondents is even lower. The gap between reported internal policies and contractual provisions is 18.9 percentage points,

suggesting that softer forms of internal governance are reported more frequently than formal contractual regulation. Overall, approximately 69.4% of respondents either reported the absence of an official AI policy in their organization or indicated that they did not know whether such a policy existed. These two response categories should not be interpreted as equivalent: a negative response indicates the reported absence of a policy, whereas uncertainty reflects limited respondent awareness or visibility of organizational rules. The relatively large share of “I do not know / I am not sure” responses therefore constitutes an additional indicator of the limited visibility of AI governance arrangements within the surveyed organizational environments.

The analysis of training practices showed that, for a considerable share of respondents, the development of competencies related to AI use occurs outside systematically organized training programs (Table 4). When special training and self-education are combined, approximately three-quarters of respondents develop their competencies without structured organizational programs.

**Table 4. Sources and Formats of Training on AI Use**

| Source/format of training                                                                     | %    |
|-----------------------------------------------------------------------------------------------|------|
| No special training, meaning no AI-related courses or training sessions completed             | 42.5 |
| Independently, through self-education such as books, articles, online materials, videos, etc. | 33.6 |
| External courses or seminars initiated by the organization, such as courses or webinars       | 17.4 |
| Internal organizational training, meaning in-house corporate training                         | 4.6  |
| Other, including mixed or non-standard training formats, mentioned in open-ended responses    | 1.9  |

**Note:** The table presents the distribution of responses among respondents who provided valid answers to the question about AI training ( $n = 259$ ). The total survey sample was  $N = 374$  respondents; some did not reach this question or skipped it and were therefore not included in the table. Percentages were calculated based on the number of valid responses ( $n = 259$ ) and therefore exclude 115 respondents with missing values. The “other” category includes rare or mixed training formats described by respondents in open-ended comments.

The results concerning barriers to organizational AI implementation (Table 5) showed that insufficient professional training was the most frequently reported barrier, rather than direct managerial opposition. This pattern points to the potential importance of training, skills development, and internal support in the transition toward more mature forms of AI implementation, but does not in itself establish a causal relationship between competence development and organizational institutionalization.

**Table 5. Barriers to AI Implementation**

| Barrier                                                                             | %    |
|-------------------------------------------------------------------------------------|------|
| Insufficient professional training of employees                                     | 50.8 |
| Limited or absent funding                                                           | 28.1 |
| A principled position of the administration or management against AI implementation | 17.2 |
| Other barriers                                                                      | 21.1 |

**Note:** Respondents could select any number of barriers; therefore, the sum of percentages exceeds 100%. The analysis includes only those who provided a valid answer to the barrier question ( $n = 256$ ). The total number of questionnaires in the study was  $N = 374$ , but some respondents skipped this question and were therefore excluded from the table. Percentages were calculated based on the number of valid responses ( $n = 256$ ).

One of the central findings of the study was the identification of an asymmetry between active individual AI use and the level of its organizational implementation. To compare these two levels correctly, a matched subsample was used, consisting of respondents who provided valid responses to both questions about their own professional AI use and about the stage of its implementation in their organization. In this subsample, active professional AI use at the individual level was recorded among 77.1% of respondents.

**Table 6. Gap Between Active Professional AI Use and Organizational Implementation in the Matched Subsample**

| Analytical perspective | Individual AI use | Organizational AI implementation | Gap, pp |
|------------------------|-------------------|----------------------------------|---------|
| Narrow                 | 77.1%             | 11.3%                            | 65.8    |
| Moderate               | 77.1%             | 46.3%                            | 30.8    |
| Broad                  | 77.1%             | 62.9%                            | 14.2    |

**Note:** Only matched valid responses were used for the comparison,  $n = 240$ . Active professional AI use was defined as the two highest categories on the corresponding scale of professional application intensity. pp = percentage points, the unit used to measure the difference between two percentage indicators.

Table 6 shows that the scale of organizational implementation changes substantially depending on the criterion selected. Under the narrow approach, which considers only strategic integration, organizational implementation is 11.3%, and the gap between the individual and organizational levels reaches 65.8 percentage points. Under the moderate approach, in which localized use also counts as organizational implementation, this gap decreases to 30.8 percentage points. The gap decreases to 14.2 percentage points under the broad approach, which encompasses any form of official implementation, ranging from pilot attempts to strategic integration. However, in all three cases, the individual level remains higher than the organizational level.

Statistical testing confirmed that this asymmetry is not random. In all three analytical perspectives, the comparison between individual AI use and its organizational status produced statistically significant results (Table 7).

**Table 7. Paired Contingency Tables for Testing the Gap Using the McNemar Test**

| Analytical perspective | Individual yes, organizational yes | Individual yes, organizational no | Individual no, organizational yes | Individual no, organizational no | Exact p                |
|------------------------|------------------------------------|-----------------------------------|-----------------------------------|----------------------------------|------------------------|
| Narrow                 | 22                                 | 163                               | 5                                 | 50                               | $5.79 \times 10^{-42}$ |
| Moderate               | 93                                 | 92                                | 18                                | 37                               | $3.80 \times 10^{-13}$ |
| Broad                  | 121                                | 64                                | 30                                | 25                               | 0.000588               |

**Note:** The table presents the results of the exact two-sided McNemar test. The two central discordant cells are key to interpretation: cases in which AI is actively used individually without a corresponding organizational status and cases of the opposite type.

The findings indicate an active but uneven stage of AI institutionalization in the analyzed publishing environment. Respondents most often reported localized rather than strategic integration, while unofficial use points to employee-initiated practices not consistently accompanied by formal rules, resources, or support. This configuration is consistent with gradual

institutionalization in which regulative, normative, and cultural-cognitive dimensions develop unevenly rather than as a completed organizational transformation.

At the level of individual professional practice, AI was widely used among respondents, while a substantial share of reported practices operated unofficially and without consistent formal organizational support. These findings are consistent with the AI readiness framework of Jöhnk et al. [13], in which technology use does not necessarily coincide with organizational readiness. Differences in respondent-reported implementation across professional segments may reflect variation in production logic, resources, and managerial readiness [16]. Thus, the observed forms of implementation vary across the functionally defined publishing environment rather than following a uniform trajectory.

The observed asymmetry between individual AI use and respondent-reported organizational implementation is consistent with an uneven diffusion process and may be interpreted through DiMaggio and Powell's concept of mimetic isomorphism [8]. Under conditions of uncertainty, organizations may adopt emerging practices without developing equivalent normative or regulatory standards. This interpretation resonates with research on generative AI in journalism [5] while extending attention from individual adoption to respondent-reported organizational formalization and institutional support.

The low reported level of formal normative consolidation provides another indication of limited institutionalization. Respondents reported active everyday AI use alongside still-emerging internal policies, training practices, control mechanisms, and responsibility frameworks. This configuration can be interpreted through the broader logic of organizational decoupling, which describes divergence between formal structures and operational practice [3; 15]. Here, the relevant divergence is between technological application and its organizational and normative formalization. Such arrangements may preserve flexibility but may also create governance risks related to content quality, transparency, responsibility, and organizational reputation [4; 10].

An equally important finding is that structured organizational support for AI-related learning appears less developed than individual competence acquisition within the analyzed sample. Approximately three-quarters of respondents developed their AI competencies outside structured organizational training programs, relying primarily on personal experience, independent research, and informal exchange. This pattern can be interpreted within the logic of organizational learning theory, in which individual knowledge acquisition is viewed as a necessary but insufficient condition for the formation of organizational knowledge [1]. In situations where formal structures are reported as providing limited mechanisms for transmitting, coordinating, and consolidating new competencies, informal communities of practice may partially compensate through the exchange of experience, examples of use, practical techniques, and situational norms for working with AI tools [26]. Such learning can support rapid technology adoption. However, by itself, it does not guarantee the transformation of individual experience into systematized organizational knowledge, shared quality standards, or generally accepted rules for responsible AI use. This interpretation is consistent with Jöhnk et al., who treat knowledge, AI awareness, and employee upskilling as key factors in organizational readiness for AI implementation [13]. Accordingly, the low reported level of formal training may be regarded as a correlate of the observed asymmetry between individual AI use and organizational formalization and as a factor that could contribute to its persistence, rather than as an empirically established causal mechanism.

Among the reported organizational barriers, insufficient professional training was the most frequently selected factor: it was identified by 50.8% of respondents, compared with 28.1% for limited or absent funding and 17.2% for a principled reluctance on the part of administration or management. This distribution suggests that respondents perceive competence-related limitations as more salient than direct managerial opposition or resource constraints. From a neo-institutional perspective, this pattern is more consistent with limitations in internal organizational capacity than with coercive pressures alone [8], although the cross-sectional survey

design does not permit determination of the causal contribution of any individual barrier to the institutionalization process. This interpretation aligns with the study by Grimme and Zabel [11], which examines collaboration between journalists and AI systems through the lens of human–machine communication, identifying interaction intensity and knowledge creation in the newsroom as important dimensions of such collaboration. Broader studies of AI implementation in organizations support a similar conceptual interpretation. Davenport and Ronanki [6] emphasize that effective AI scaling requires not only technological solutions but also appropriate organizational capabilities, integration with existing processes, the involvement of business process owners, the development of expertise, and well-considered implementation planning. Thus, the low reported level of professional training can be regarded as one indicator associated with limited organizational readiness for systematic AI implementation rather than as an independently established determinant of such readiness.

At the same time, the results obtained do not contradict studies that consider AI a factor in the reengineering of publishing processes but rather refine them. The study by Ryzhko et al. [19] shows that generative AI transforms book publishing processes and opens new directions for reengineering publishing practices. Salani and Tapfuma [21], in their analysis of the educational book sector in Africa, also emphasize the transformative impact of AI on the production, dissemination, and distribution of educational materials. In the broader context of the digital transformation of the book industry, Thompson [23] shows that the development of e-books, self-publishing, audiobooks, and digital platforms changes the established models of the publishing market. However, as the present study shows, the technological transformation of the publishing chain does not automatically entail institutional maturity within organizations. Process reengineering requires appropriate policies, training, contractual formalization, quality control procedures, and clear frameworks of professional responsibility. This thesis is consistent with the conceptualization proposed by Raisch and Krakowski [17], who caution against a simplified division of AI into either automation or the augmentation of human labor and emphasize the interdependence of these modes in real organizational practices. Thus, the productive integration of AI involves not only the implementation of tools but also the purposeful organizational design of models of collaboration between humans and technology.

**Conclusions and Prospects.** The findings indicate that AI institutionalization in Ukraine's functionally defined publishing environment is associated not simply with technology use but with the extent of organizational formalization and governance, corresponding to Scott's regulative, normative, and cultural-cognitive dimensions of institutions [22]. AI is already widely used at the individual level, while respondent-reported organizational integration remains less mature and uneven. This pattern is consistent with a transitional phase in which practical adoption may outpace the development of policies, structured training, quality-control mechanisms, and responsibility frameworks. Further institutional development therefore requires stronger alignment between technological practice and organizational governance.

The findings should be interpreted in light of several limitations. The voluntary online survey entails self-selection risk and may overrepresent respondents with greater interest in AI. The age and gender structure of the sample, together with its broad functional coverage of convergent publishing and media production, limits population-level generalization to formally defined publishing organizations. Valid-response subsamples may also introduce item non-response bias. The cross-sectional design does not permit causal inference or analysis of institutionalization over time. Finally, organizational implementation was measured through respondents' reports about their primary workplace rather than independently verified organization-level data; the results therefore characterize respondent-reported practices within the analytical sample.

The identified limitations outline several priority directions for further research. The most urgent need is for longitudinal studies capable of tracing the dynamics of transition between stages

of institutionalization, as proposed by Tolbert and Zucker [24]. The combination of quantitative and qualitative designs, namely in-depth interviews and case studies, would enable the identification of the organizational mechanisms of AI governance that remain invisible in survey data. Comparative analysis across industry segments, as well as between Ukraine and other countries with similar conditions of regulatory uncertainty, also requires particular attention. Such analysis would help assess the extent to which the identified patterns are specific to the national context and the extent to which they reflect more universal patterns of uneven AI institutionalization.

**Ethical approval.** The study was approved by the Bioethics Committee for Scientific Research of Taras Shevchenko National University of Kyiv (Protocol 8, 19/12/2025). The study was conducted in accordance with the standards of academic integrity and the ethics of research involving human participants.

**Informed consent.** Electronic informed consent was obtained from all survey respondents before participation. Participants were informed about the purpose and procedures of the study, the voluntary nature of participation, and their right to skip individual questions or withdraw before proceeding with the questionnaire.

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## ІНСТИТУЦІОНАЛІЗАЦІЯ ШТУЧНОГО ІНТЕЛЕКТУ У ВИДАВНИЧІЙ ІНДУСТРІЇ УКРАЇНИ

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**Вступ.** Поширення штучного інтелекту у видавничій індустрії трансформує не лише окремі виробничі операції, а й професійні ролі, редакційні процедури, моделі управління, критерії якості контенту та підходи до організаційного врядування. За таких умов ШІ доцільно розглядати не лише як технологічний інструмент, а і як чинник інституційних змін у професійному середовищі.

**Актуальність і мета.** Актуальність дослідження зумовлена недостатньою концептуалізацією організаційного виміру впровадження ШІ у видавничій індустрії України. Метою статті є виявлення особливостей інституціоналізації ШІ через аналіз співвідношення між

індивідуальним професійним використанням технології та рівнем її організаційного впровадження.

**Методологія.** Емпіричну основу дослідження становить кількісне опитування, проведене в грудні 2025 – лютому 2026 року, у якому взяли участь 374 респонденти. Для окремих аналітичних блоків використано підвибірку валідних відповідей, а для зіставлення індивідуального використання ІІІ з організаційним упровадженням ІІІ за повідомленнями респондентів зіставлену підвибірку  $n = 240$ . Застосовано описову статистику, критерій  $\chi^2$  та двобічний критерій Мак-Немара.

**Результати.** Установлено, що інституціоналізація ІІІ має нерівномірний і переважно перехідний характер. Про певну форму офіційного впровадження ІІІ у своїй організації повідомили 61,3 % респондентів, а найпоширенішою формою є точкове використання. У зіставленій підвибірці активне професійне використання ІІІ на індивідуальному рівні зафіксовано у 77,1 % респондентів. Виявлено низький рівень формалізації практик використання ІІІ, слабку поширеність внутрішніх політик і договірного регулювання, переважання самоосвіти, а недостатню професійну підготовку визначено як найчастіше зазначуваний респондентами бар'єр упровадження.

**Висновки.** Результати свідчать, що в аналізованому видавничому середовищі ІІІ вже широко використовується на індивідуальному рівні, тоді як організаційне впровадження за повідомленнями респондентів залишається нерівномірним і недостатньо формалізованим. Наукова новизна дослідження полягає у виявленні асиметрії між індивідуальним використанням ІІІ та його організаційним упровадженням. Отримані результати можуть бути використані для розроблення внутрішніх політик, навчальних програм, механізмів відповідального використання ІІІ та управлінської координації.

**Ключові слова:** штучний інтелект, видавнича індустрія, інституціоналізація, організаційне впровадження, медійна конвергенція, цифрова трансформація, інновації.

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