

FROM AI USE TO RESPONSIBLE AI PREPAREDNESS: PROFESSIONAL LEARNING NEEDS IN UKRAINIAN HIGHER EDUCATION

ARTEM ARTYUKHOV*, DMYTRO CHUMACHENKO, DENYS BABAIEV, ARTEM KOLDOVSKYI,
VICTOR CHENTSOV

*Corresponding author: artem.artiukhov@euba.sk

Abstract. The rapid integration of artificial intelligence into higher education has increased the need to distinguish routine AI use from preparedness to use this technology responsibly and ethically. The study examines responsible AI preparedness as a dimension of continuous digital professional learning in Ukrainian higher education by analysing differences in perceived ethical AI learning needs across career stages and levels of AI use and their association with institutional AI-policy environments. Cross-sectional survey data from 2,004 respondents representing Ukrainian higher education institutions were analysed using descriptive statistics, chi-squared tests, Cramér's V, cumulative-link ordinal logistic regression, interaction models, adjusted predicted probabilities, and binary logistic regression. AI use was widespread: 74.0% used AI at least periodically, while 33.1% reported high ethical AI learning needs and 42.2% substantial gaps in institutional rules or guidance. Among active AI users, 472 respondents were classified as active but underprepared, representing 31.8% of active users and 23.6% of the HEI sample. In the binary logistic model restricted to active users, reporting no institutional AI policy was associated with 47.3% higher odds of high ethical learning need (OR = 1.47, 95% CI [1.11, 1.95]), while policy uncertainty was associated with 64.2% higher odds (OR = 1.64, 95% CI [1.26, 2.14]). In the cumulative-link ordinal model for the full HEI sample, ethical learning needs were higher among respondents aged 50–59 (OR = 1.64) and 60–69 (OR = 1.86) than among those aged 18–29. Research experience significantly moderated the association between AI-use intensity and perceived learning need (LR $\chi^2(3) = 8.82$, $p = 0.032$). The findings support targeted professional learning.

Keywords: artificial intelligence, higher education, ethical preparedness, professional learning, AI policy, academic staff, digital competence.

1. INTRODUCTION

The rapid diffusion of generative AI has shifted the higher-education debate from whether artificial intelligence should be adopted to whether academics are prepared to use it responsibly, critically and ethically. International guidance increasingly treats AI competence as more than technical proficiency, incorporating ethical awareness, pedagogical application, critical evaluation and continuing professional learning (Miao & Holmes, 2023; Miao & Cukurova, 2024; UNESCO, 2024). This shift is reinforced by evidence that professional learning needs remain substantial even where AI use is already widespread. OECD findings show that AI-related professional development has become one of the most important emerging needs among educators, while European and World Bank initiatives similarly emphasise

ethical AI literacy, institutional readiness and continuous adaptation of skills (OECD, 2024; OECD, 2025; European Commission, 2026). AI is also increasingly embedded in teaching, assessment, academic planning and research, making responsible preparedness an institutional as well as an individual challenge (Molina & Medina, 2025; World Bank, 2025; World Bank, EdTech Hub, & AI Observatory, 2026).

Research on AI in higher education has consequently moved beyond a narrow technology-adoption perspective towards questions of organisational transformation, educational practice and institutional capacity. Earlier studies situated AI within broader processes of digitalisation, innovation and organisational change, while educational research has documented its expanding role in learning analytics, teaching, knowledge support and problem-solving (Bilan et al., 2022; Chugh et al., 2023; Koibichuk et al., 2023). AI-enabled educational methodologies have developed rapidly (Skrynnyk et al., 2022; Salas-Pilco et al., 2022; Cela et al., 2025), but their implementation remains shaped by pedagogical, organisational and human barriers rather than by technological availability alone (Sarwar et al., 2025; Vorontsova et al., 2025). Recent studies further describe AI as becoming a structural element of the university environment and show that patterns of adoption vary across institutional and social contexts (Okulich-Kazarin & Artyukhov, 2025; Sieciński & Oliński, 2026; Żulicki, 2026). This broader transformation also carries economic and organisational consequences, yet evidence suggests that greater AI intensity does not automatically translate into proportional gains in productivity or performance, reinforcing the need to distinguish technology use from the conditions required for its effective and responsible integration (Kuzior et al., 2025; Škare et al., 2025).

A central implication of this transition is that AI preparedness should be conceptualised in terms of competence and literacy rather than frequency of use alone. Contemporary frameworks describe AI literacy as multidimensional, encompassing cognitive, behavioural, affective and ethical capacities as well as the ability to understand and critically evaluate AI outputs (Ng et al., 2023; Ng et al., 2024; Wang et al., 2023). Related work highlights critical thinking, prompt-related competence and transversal skills as important components of meaningful engagement with AI (Stolpe & Hallström, 2024; Walter, 2024; Popova, 2024). New applications, including digital twin technologies and AI-supported language learning, further demonstrate that educators' competence must evolve alongside technological possibilities (Domina et al., 2025; Pilny & Postrzednik-Lotko, 2025). These developments strengthen the role of professional learning, digital self-efficacy and leadership-supported adaptation in enabling effective engagement with AI (Lamichhane et al., 2026; Mamdouh et al., 2025). From a broader educational perspective, lifelong learning and digitalisation are also linked to institutional resilience, human capital renewal, and progress towards SDG 4 (Yeremenko, 2026; Rahmanov et al., 2025; Zimosz & Ober, 2025).

Preparedness must also be responsible preparedness. Higher-education research increasingly integrates AI literacy with pedagogical integrity, governance, and institutional policy, reflecting concerns about acceptable use, authorship, transparency, verification, and academic integrity (Adamakis & Rachiotis, 2025; Chan, 2023; Francis et al., 2025). Comparative governance research shows that universities operate within an increasingly complex environment of policies, standards and legal expectations, while knowledge-based governance can strengthen ethical literacy and legal awareness (Chumachenko et al., 2025; Oncioiu & Bularca, 2025). Evidence from university staff likewise shows that perceptions of generative AI combine cognitive evaluation, trust, teaching implications, and academic integrity concerns (Lyeonov et al., 2026). The broader ethics literature reaches a similar conclusion: meaningful AI adoption requires accountability, human oversight and attention to dignity, fairness and the boundaries of automation (Frimpong, 2025; Hayes & Burrell, 2026; Mura & Stehlíková, 2025). Comparable concerns have been observed in law enforcement, healthcare, and business leadership, where AI implementation raises questions about ethical boundaries, dual use, and accountable decision-making (Haley & Burrell, 2025; Springs, 2025; Szeberényi, 2026). These adjacent-sector studies are relevant not as direct evidence about universities, but as confirmation that responsible AI adoption is

consistently shaped by governance and human judgment across knowledge-intensive organisations.

The literature further suggests that professional learning needs are unlikely to be uniform across staff groups or career stages. Institutional implementation affects faculty experience, performance systems and organisational conditions, while studies from other knowledge-intensive environments show that workforce adaptation depends on leadership, development opportunities and employees' capacity to respond to AI-mediated change (Alakoum et al., 2025; Hart, 2025; Kot et al., 2026). AI adoption is also shaped by professional expectations, perceived opportunities and barriers, and attitudes towards AI range from optimism to concern and indifference (Kritikos et al., 2025; Schinello, 2025; Yarovenko et al., 2024). In Ukraine, these questions are especially important because higher education and scientific capacity continue to operate under the pressures of the full-scale invasion, making professional adaptation and the preservation of intellectual capital particularly salient (Iurchenko & Ponomarenko, 2025). At the same time, recent evidence shows considerable variation in the maturity of institutional AI policies across Ukrainian higher education, suggesting that the presence, visibility and clarity of policy may be closely connected with staff preparedness (Suchikova & Omelchuk, 2026).

Previous research points to a conceptual progression from AI adoption through AI literacy and competence towards responsible AI preparedness, supported by professional learning and institutional governance. However, these dimensions are still frequently studied separately. In particular, limited empirical attention has been paid to whether academics who already use AI regularly also perceive substantial ethical learning needs, whether these needs differ across career stages, and whether institutional AI policy environments are associated with preparedness. The present study addresses this gap by examining responsible AI preparedness as a dimension of continuous professional learning and by linking AI-use intensity, research experience and institutional policy status within a single empirical framework.

This study aims to examine responsible AI preparedness as a dimension of continuous digital professional learning in Ukrainian higher education by identifying differences in perceived ethical AI learning needs across academic career stages and levels of AI use, and by assessing how institutional AI policies are associated with both individual learning needs and perceived gaps in institutional guidance. To address this aim, the study is guided by the following research questions:

RQ1. How does the frequency of AI use vary across age groups, research-experience levels and gender among members of Ukrainian higher education institutions?

RQ2. How are age, gender, research experience, frequency of AI use and institutional AI-policy status associated with perceived ethical AI learning needs and perceived gaps in institutional guidance?

RQ3. Does the association between AI-use intensity and perceived ethical AI learning needs vary across levels of research experience?

RQ4. Does the status of institutional AI policy moderate the association between AI use intensity and perceived ethical AI learning needs?

RQ5. Which demographic, professional and institutional characteristics are associated with being an active but underprepared AI user, defined as an individual who uses AI regularly while simultaneously reporting high perceived ethical AI learning needs?

2. RESEARCH METHODS

2.1. Research design and analytical sample

The study employed a quantitative cross-sectional survey design to examine responsible AI preparedness and professional learning needs among respondents representing higher education institutions in Ukraine. The analytical focus was not simply on whether respondents used AI, but on whether the intensity of use was accompanied by perceived preparedness for responsible use and adequate institutional guidance. This distinction is important for a pedagogical interpretation of AI

adoption: frequent use may indicate practical familiarity, yet it does not necessarily imply sufficient ethical knowledge or confidence in the rules governing AI-assisted research. The empirical strategy, therefore, separated individual learning preparedness from institutional preparedness and then examined how both dimensions varied by age, research experience, gender, AI-use frequency and institutional policy status.

The original dataset contained 2,376 completed questionnaires. For the present analysis, the sample was restricted to respondents who selected 'higher education institution' as the type of institution they represented. This yielded an HEI analytical sample of 2,004 respondents, representing 84.3% of the full survey sample. The focal demographic and professional variables contained no missing observations in this subsample, so the principal descriptive and ordinal regression analyses were conducted on the full HEI sample. No survey weight variable was included in the supplied analytical dataset; consequently, the reported estimates are unweighted sample estimates and are not presented as nationally representative population parameters.

2.2 Measures and operationalisation

The main outcome for individual preparedness was the statement 'I feel that I lack the knowledge required for the ethical use of artificial intelligence tools in research', measured on a five-point ordered response scale from 1 to 5. Higher values, therefore, indicated a greater perceived ethical-knowledge gap. The second outcome captured institutional preparedness through the statement 'I lack clear rules and/or official policies concerning the use of artificial intelligence in research at my institution', again measured on the same five-point ordered scale. The ordering of both outcomes was retained in the main models rather than dichotomising the data, because moving from a lower to a higher category represents a substantively greater level of perceived need.

For descriptive and training-priority analyses, a high ethical AI learning need was defined as a response of 4 or 5 on the ethical-knowledge-gap item. This threshold was used only to construct interpretable probabilities and training-priority groups; the primary regression models continued to use all five ordered categories. AI-use frequency comprised five survey categories: never, isolated cases/rare use, periodically, frequently and daily. In the principal ordinal models, these categories were entered as a factor, with isolated-case use as the reference category because the 'never' group was comparatively small. For parsimonious interaction tests, AI-use intensity was additionally coded from 0 (never) to 4 (daily), preserving the natural ordering of frequency.

Institutional AI-policy status was derived from the question asking whether the respondent's institution had an official policy on the use or implementation of AI in research. The two affirmative response variants were combined into a single 'AI policy in place' category. The remaining categories were 'no AI policy' and 'uncertain/do not know', with 'AI policy in place' serving as the reference category in regression models. Age was entered in six ordered groups (18–29, 30–39, 40–49, 50–59, 60–69, and 70 years and over), and research experience in four groups (less than 1 year, 1–5 years, 5–10 years, and more than 10 years). Gender and field of research were included as covariates. Discipline was treated as a control rather than as the central explanatory factor because the article's objective is to identify learning and institutional support needs, not disciplinary heterogeneity.

The exact wording and response options of the two outcome items, the AI-use-frequency item and the institutional-policy-status item, are provided in Appendix A to support transparency and reproducibility.

2.3. Training-priority classification

For educational interpretation, AI activity and ethical learning needs were combined into four training-priority groups. Active users (periodic, frequent, or daily use) who scored 1–3 on the ethical-gap item were classified as prepared active users, and those who scored 4–5 were classified as active but

underprepared. Low-use respondents (never or isolated cases) with scores of 4–5 were potential learners; the remainder formed the low-engagement/low-need group. This is an analyst-derived classification, not a validated psychometric scale.

2.4. Statistical analysis

The analysis began with frequencies and percentages, followed by Pearson chi-squared tests of AI-use frequency by age, research experience and gender. Monte Carlo p-values based on 10,000 simulated tables were used when expected counts were small, and Cramér's V quantified association strength.

Cumulative-link ordinal logistic models were estimated separately for the ethical-knowledge and institutional-rules gaps. For five ordered categories, $\log[P(Y \leq j)/P(Y > j)] = \theta_j - X\beta$, $j = 1, \dots, 4$. Exponentiated slopes are reported as odds ratios (ORs) with 95% confidence intervals; $OR > 1$ denotes higher odds of a higher response category. Age, gender, research experience, AI use frequency, policy status, and discipline were entered simultaneously. Nominal-effect diagnostics assessed the proportional-odds assumption, and threshold parameters were omitted from substantive tables.

Moderation was tested using likelihood ratio tests with an ordered AI-intensity score ranging from 0 (never) to 4 (daily), separately interacted with research experience and institutional policy status. Adjusted high-need probabilities were calculated by g-computation: focal variables were set to each scenario, other covariates were retained at observed values, $P(Y = 4)$ and $P(Y = 5)$ were predicted for each respondent, and the resulting values were then averaged. The age figure used an additive model because empty cells in the oldest age group rendered the full age-by-frequency interaction rank-deficient.

Among active AI users, a binary logistic model estimated a high ethical learning need (4–5) based on age, gender, research experience, policy status, and discipline. A supplementary multinomial logistic regression compared the four training-priority groups, with prepared active users as the reference outcome category. Education, the largest disciplinary group, was used as the reference field. Because the field of research was included as an adjustment variable rather than a focal predictor, four comparatively small disciplinary categories (Health and Welfare, Agriculture, Transport and Services, and Security and Defence) were combined into an 'Other fields' category to reduce sparse-cell instability. Full model-fit statistics, proportional-odds diagnostics and coefficients for the field-of-research controls are reported in Supplementary Tables S1–S4.

2.5. Data collection and ethical considerations

The survey was conducted in Ukraine between 29 November and 8 December 2025. Participation was voluntary and anonymous. The questionnaire was administered online, and no financial or other material incentives were offered. Before completing the questionnaire, respondents were informed about the purpose of the study, the general scope of the questions and the intended use of the collected data for scientific research. Participation proceeded only with informed consent. Respondents were free to decline participation or discontinue the questionnaire at any stage without adverse consequences. No directly identifying personal information was collected, and the analytical dataset did not contain information that could identify individual respondents. Data were analysed and reported only in aggregate form to preserve confidentiality. The study protocol was reviewed and approved by the Commission of Ethics at the Ukrainian Research Integrity Office.

2.6. Recruitment and survey dissemination.

Respondents were recruited through institutional and professional communication channels involving higher education institutions, professional pre-higher education institutions, and research organisations across Ukraine. The survey invitation was distributed electronically through the participating institutions and professional academic networks. The completed questionnaires

represented approximately 100 higher education and professional pre-higher education institutions, as well as research organisations. The invitation was distributed to approximately 3,000 potentially eligible respondents, of whom 2,376 completed the questionnaire, corresponding to an approximate completion rate of 79.2%. Because the invitation denominator was approximate and the survey link could be disseminated through multiple institutional and professional channels, this figure should not be interpreted as a conventional probability-sample response rate. Participation was voluntary and based on self-selection. Accordingly, the realised sample should be regarded as a large non-probability sample rather than as statistically representative of all academic and research staff in Ukraine.

2.7. Statistical software

All statistical analyses were performed in R version 4.4.0 (2024-04-24 ucrt), ‘Puppy Cup’ (R Foundation for Statistical Computing), running on the x86_64-w64-mingw32/x64 platform. Data management and restructuring were carried out using the readxl, dplyr and tidyr packages; contingency-table analysis and Cramér’s V were performed with DescTools; cumulative-link models were estimated using ordinal, binary and multinomial logistic models using base R; model summaries were generated with broom; and publication figures were produced with ggplot2. Reproducible scripts were used throughout to ensure a consistent analytical workflow from data preparation and model estimation to predicted probabilities and reported tables. Appendix A complements this workflow by documenting the questionnaire items and analytical coding underlying the principal variables. Given the cross-sectional and self-reported nature of the data, all estimated relationships are interpreted as associations rather than causal effects.

Data Availability Statement. The anonymised dataset used in this study is available from the corresponding author upon reasonable request, subject to applicable ethical and institutional data-sharing requirements. The R scripts used for data preparation, statistical analysis and figure generation are openly available via Zenodo (Artyukhov et al., 2026).

3. RESULTS AND DISCUSSION

3.1. Hei sample profile, ai use and perceived preparedness

The HEI subsample comprised 2,004 respondents. Women represented 76.3% of the sample and men 23.7%. The largest age group was 40–49 years (38.5%), followed by 50–59 years (24.2%) and 30–39 years (19.1%). Respondents were generally experienced researchers: 69.3% reported more than 10 years of research experience, while 12.7% had 5–10 years, 12.4% had 1–5 years, and 5.6% had less than one year. These distributions are relevant to the later models because the sample contains a substantial concentration of mid- and late-career respondents rather than an even distribution across career stages.

AI use was already widespread. Nearly half of respondents (48.5%) reported using AI periodically, 18.4% frequently and 7.1% daily. A further 22.9% used AI only in isolated cases, while just 3.1% reported never using it. On the operational definition adopted for the training-priority analysis, 1,483 respondents (74.0%) were active AI users. Institutional preparedness was less uniform: 41.6% reported that an AI policy was in place, 24.3% reported no policy, and 34.1% were uncertain or did not know whether such a policy existed. Thus, more than half of the HEI sample either reported no formal policy or lacked clarity about its existence.

Tab. 1

Characteristics of the HEI analytical sample (N = 2,004)

Characteristic	n (%)
Gender: women	1,530 (76.3%)
Gender: men	474 (23.7%)
Age: 18–29 years	170 (8.5%)
Age: 30–39 years	382 (19.1%)

Characteristic	n (%)
Age: 40–49 years	771 (38.5%)
Age: 50–59 years	485 (24.2%)
Age: 60–69 years	164 (8.2%)
Age: 70 years and over	32 (1.6%)
Research experience: <1 year	112 (5.6%)
Research experience: 1–5 years	248 (12.4%)
Research experience: 5–10 years	255 (12.7%)
Research experience: >10 years	1,389 (69.3%)
AI use: never	63 (3.1%)
AI use: rarely	458 (22.9%)
AI use: periodically	971 (48.5%)
AI use: frequently	369 (18.4%)
AI use: daily	143 (7.1%)
Institutional AI policy: in place	834 (41.6%)
Institutional AI policy: no policy	486 (24.3%)
Institutional AI policy: uncertain / do not know	684 (34.1%)
High ethical AI learning need (4–5)	664 (33.1%)
High institutional-rules gap (4–5)	846 (42.2%)
Active AI users	1,483 (74.0%)

Notes: Percentages are calculated within the HEI sample. ‘Active AI users’ are respondents reporting periodic, frequent or daily AI use. High need/gap denotes scores of 4 or 5 on the corresponding five-point item

The two preparedness indicators were not equivalent in prevalence. One-third of respondents (33.1%; $n = 664$) reported a high need for ethical AI learning, whereas 42.2% ($n = 846$) reported a high institutional-rules gap. The latter difference suggests that the shortage of clear institutional guidance is more widespread than the perceived shortage of personal ethical knowledge. Raw policy-group comparisons reinforce this distinction: 28.5% of respondents in institutions with an AI policy reported a high rules gap, compared with 57.4% in institutions with no policy and 48.1% among respondents uncertain about policy status. For ethical learning needs, the corresponding raw proportions were 26.5%, 36.8% and 38.6%.

3.2. Differences in AI-use frequency across age, experience and gender

The bivariate analysis identified age as the only demographic characteristic with a statistically detectable association with AI-use frequency, although the magnitude was very small. The age-by-AI-use table produced Pearson $\chi^2(20) = 34.04$, $p = 0.026$, with a Monte Carlo p-value of approximately 0.031 and Cramér’s $V = 0.065$. The small effect size is important: the finding indicates modest distributional differences across age groups rather than a strong digital divide. The lowest expected count was close to one, reflecting the small number of respondents aged 70 years and over in some AI-use categories, which is why the simulated p-value was also examined.

The descriptive pattern was not a simple monotonic decline in use with age. Periodic use remained the modal category across all age groups, ranging from 46.3% among those aged 30–39 to 51.3% among those aged 50–59. More visible differences occurred at the extremes of intensity. Frequent use was highest among respondents aged 30–39 (24.1%) and lower among those aged 60–69 (12.2%) and 70 years and over (12.5%). Isolated-case use increased to 31.7% among those aged 60–69 and 40.6% among those aged 70 years and over. The oldest category contained no respondents reporting either ‘never’ or ‘daily’ use, which also explains why a fully interacted age-by-frequency ordinal model was not used for the adjusted-probability figure.

Tab. 2

Associations between respondent characteristics and AI-use frequency

Characteristic	χ^2	df	p	Monte Carlo p	Cramér's V	Min. expected
Age group	34.04	20	0.026	0.031	0.065	1.01
Research experience	15.96	12	0.193	0.183	0.052	3.52
Gender	3.10	4	0.542	0.536	0.039	14.90

Notes: Monte Carlo *p*-values are based on simulated contingency tables and are reported as a robustness check for sparse expected counts. Cramér's *V* values below approximately 0.10 indicate small associations in this context

Research experience was not significantly associated with AI-use frequency, $\chi^2(12) = 15.96$, $p = 0.193$, Monte Carlo $p \approx 0.183$, Cramér's $V = 0.052$. Although the least experienced group appeared less intensive in descriptive terms (10.7% reported frequent use and 3.6% daily use compared with 18.1% and 7.5%, respectively, among respondents with more than 10 years of experience), the overall contingency pattern did not differ beyond sampling variation. This is useful for the later interaction analysis because it suggests that any experience-related difference in perceived learning need cannot be reduced simply to large differences in the marginal frequency of AI use.

Gender differences were smaller still. AI-use frequency was statistically similar for women and men, $\chi^2(4) = 3.10$, $p = 0.542$, Monte Carlo $p \approx 0.536$, Cramér's $V = 0.039$. Periodic use was reported by 48.8% of women and 47.5% of men; daily use by 7.1% and 7.2%, respectively. The absence of a meaningful gender gap in use does not rule out differences in other dimensions of AI preparedness. Still, it indicates that the frequency of use itself was not strongly gendered in this HEI sample. Taken together, Table 2 supports a cautious interpretation: age has a statistically detectable but weak association with AI-use patterns. At the same time, research experience and gender do not show clear bivariate relationships with frequency.

3.3. Ordinal models of ethical learning need and institutional-rules gap

Table 3 presents the two cumulative-link ordinal models for the full HEI sample ($N = 2,004$). In the cumulative-link ordinal model of ethical AI learning need, reporting no institutional AI policy was associated with higher ethical-learning-need categories (OR = 1.48, 95% CI [1.20, 1.81], $p < 0.001$), as was uncertainty about policy status (OR = 1.61, 95% CI [1.34, 1.95], $p < 0.001$).

Age was associated with ethical learning needs but not with the rules gap. Relative to respondents aged 18–29, the 50–59 group had OR = 1.64 ($p = 0.014$) and the 60–69 group OR = 1.86 ($p = 0.009$); the remaining age contrasts were not significant. Thus, age differences appear to concern perceived personal preparedness rather than institutional guidance.

Tab. 3

Ordinal logistic regression models for ethical learning needs and the institutional-rules gap

Predictor	Ethical need OR [95% CI]	p	Rules gap OR [95% CI]	p
Age 30–39 vs 18–29	1.14 [0.79, 1.64]	0.497	0.83 [0.57, 1.20]	0.313
Age 40–49 vs 18–29	1.43 [0.99, 2.08]	0.059	1.03 [0.71, 1.50]	0.868
Age 50–59 vs 18–29	1.64 [1.11, 2.43]	0.014	1.10 [0.74, 1.63]	0.626
Age 60–69 vs 18–29	1.86 [1.17, 2.96]	0.009	1.07 [0.67, 1.69]	0.781
Age ≥ 70 vs 18–29	2.10 [0.99, 4.44]	0.052	0.76 [0.36, 1.60]	0.475
Women vs men	0.99 [0.81, 1.20]	0.897	1.00 [0.83, 1.22]	0.962
Experience 1–5 vs <1 year	1.00 [0.66, 1.51]	0.997	0.97 [0.64, 1.46]	0.887
Experience 5–10 vs <1 year	1.02 [0.66, 1.57]	0.946	0.99 [0.64, 1.53]	0.976
Experience >10 vs <1 year	0.72 [0.48, 1.08]	0.113	0.84 [0.56, 1.26]	0.396
AI use: never vs rarely	0.71 [0.43, 1.18]	0.191	0.93 [0.56, 1.52]	0.763
AI use: periodically vs rarely	0.87 [0.72, 1.07]	0.192	1.09 [0.89, 1.34]	0.389

Predictor	Ethical need OR [95% CI]	p	Rules gap OR [95% CI]	p
AI use: frequently vs rarely	0.77 [0.60, 1.00]	0.046	1.07 [0.83, 1.37]	0.626
AI use: daily vs rarely	0.74 [0.52, 1.05]	0.092	1.06 [0.74, 1.52]	0.765
No AI policy vs policy in place	1.48 [1.20, 1.81]	<0.001	3.64 [2.94, 4.49]	<0.001
Uncertain/do not know vs policy in place	1.61 [1.34, 1.95]	<0.001	2.41 [2.00, 2.91]	<0.001

Notes: Both models include field-of-research controls. OR > 1 denotes higher odds of being in a higher response category. Reference categories: age 18–29; men; <1 year research experience; AI use in isolated cases; institutional AI policy in place. Discipline coefficients are omitted from the table for compactness because discipline is a control rather than the focal explanatory variable

AI-use frequency had a limited independent association with ethical learning need: frequent use was associated with lower odds than isolated-case use (OR = 0.77, $p = 0.046$), while daily use showed the same direction but was non-significant (OR = 0.74, $p = 0.092$). Gender and research-experience main effects were non-significant in both models. For the rules gap, institutional status dominated: no policy corresponded to OR = 3.64 and uncertainty to OR = 2.41 (both $p < 0.001$).

3.4. Does the AI-use gradient vary by research experience or institutional policy?

The interaction analysis distinguished career-stage heterogeneity from policy moderation. AI intensity $\times$ research experience significantly improved model fit, LR $\chi^2(3) = 8.82$, $p = 0.032$. In contrast, AI intensity $\times$ policy was non-significant, LR $\chi^2(2) = 0.34$, $p = 0.843$, and the categorical policy $\times$ AI-frequency interaction used for Figure 2 was also non-significant, $\chi^2(8) = 5.51$, $p = 0.702$. Thus, experience modifies the AI-use/learning-need relationship, whereas policy status mainly shifts its level.

Tab. 4

Interaction tests and experience-specific AI-intensity associations

Statistic	Comparison/subgroup	χ^2	df	p	OR per one-step AI-intensity increase
Joint interaction test	AI intensity $\times$ research experience	8.82	3	0.032	–
Joint interaction test	AI intensity $\times$ institutional policy	0.34	2	0.843	–
Figure-specific test	Policy status $\times$ categorical AI frequency	5.51	8	0.702	–
Experience-specific slope	<1 year	–	–	0.500	1.17 [0.75, 1.82]
Experience-specific slope	1–5 years	–	–	0.060	1.28 [0.99, 1.65]
Experience-specific slope	5–10 years	–	–	0.493	0.92 [0.71, 1.18]
Experience-specific slope	>10 years	–	–	0.007	0.86 [0.77, 0.96]

Notes: The AI-intensity score ranges from 0 (never) to 4 (daily). Experience-specific ORs are linear combinations from the interacted ordinal model. Values below 1 indicate lower odds of a higher ethical-learning-need category as AI-use intensity increases

Experience-specific slopes clarify the joint interaction. For respondents with more than 10 years of experience, each one-step increase in AI intensity was associated with lower odds of a higher ethical-learning-need category (OR = 0.86, 95% CI [0.77, 0.96], $p = 0.007$). The 5–10-year and <1-year slopes were non-significant, while the 1–5-year group showed a borderline positive gradient (OR = 1.28, $p = 0.060$). This pattern is compatible with greater recognition of ethical complexity at earlier career stages and greater perceived preparedness among experienced, intensive users.

The interaction is associative rather than causal, because more prepared researchers may self-select into intensive AI use. Even so, it argues against a uniform training model: learning needs vary by career

stage, despite the non-significant bivariate association between research experience and the frequency of AI use.

Policy status was strongly associated with perceived need, but it did not significantly alter the AI-intensity gradient. Institutional policy, therefore, appears to shift the general level of preparedness rather than alter how additional AI use relates to learning need; non-parallel lines in Figure 2 should not be read as evidence of a supported interaction.

3.5. Adjusted ethical ai learning needs across age groups

Figure 1 translates the ordinal model into the adjusted probability of reporting a high need for ethical AI learning (scores 4–5). Because the oldest age category contained empty cells for some AI-use levels, the figure is based on an additive model with age and AI-use frequency entered as main effects. At the same time, gender, research experience, institutional policy status and discipline are held at their observed distributions through g-computation. The figure should therefore be read as a comparison of adjusted age and AI-use profiles rather than as a formal test of an age-by-frequency interaction.

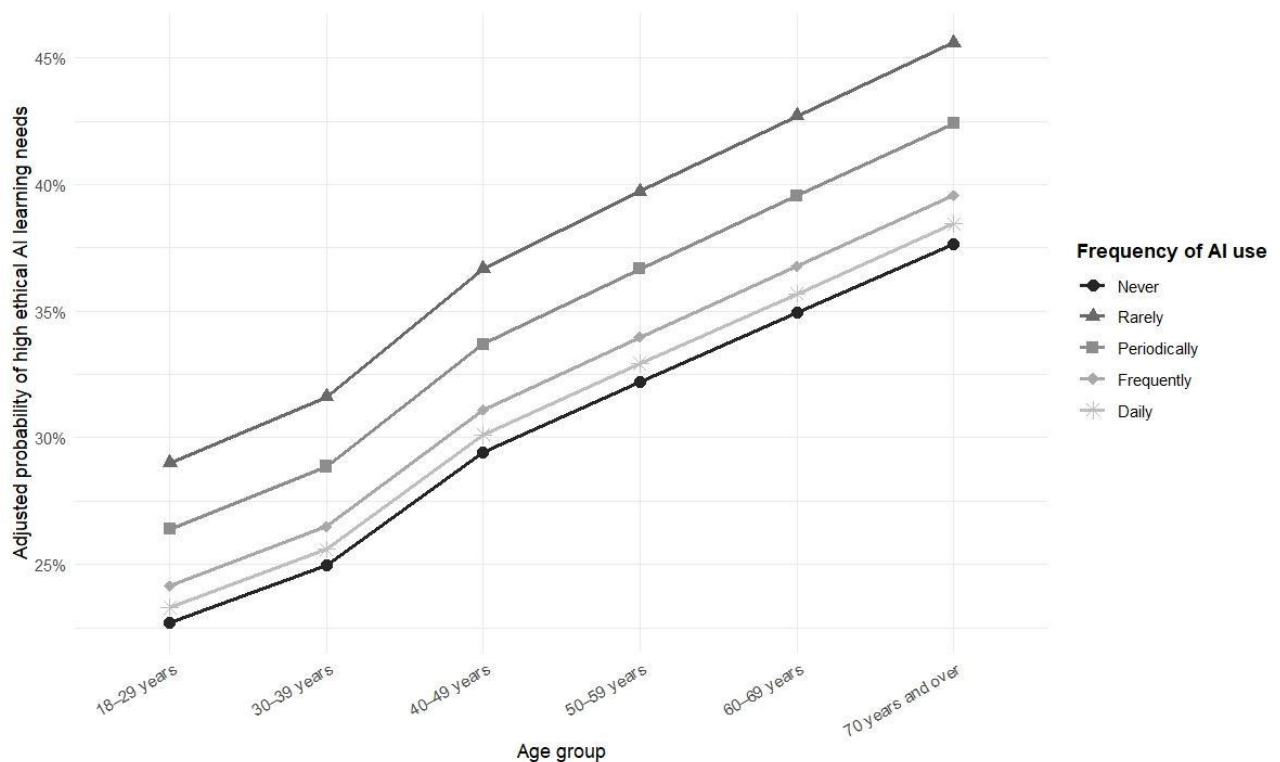


Fig. 1. Adjusted probability of high ethical AI learning needs by age group and frequency of AI use

Notes: Predicted probabilities are adjusted for gender, research experience, institutional AI policy status, and field of research. The high-need outcome combines response categories 4 and 5. The full age-by-frequency interaction was avoided because sparse cells in the oldest group produced a rank-deficient specification

The age-related increase in predicted ethical AI learning need is broadly visible across the larger AI-use categories, although the profiles are not perfectly parallel or monotonic. In particular, the Never category, which contains only 63 respondents (3.1% of the HEI sample), shows a less regular pattern and generally yields lower predicted probabilities than the other use categories. Among the more populated categories, adjusted probabilities tend to rise with age. For example, under the Rarely-use scenario, the predicted probability increases from about 29.0% among respondents aged 18–29 to 45.6% among those aged 70 years and over, while under the Daily-use scenario it rises from about 23.3% to 38.4%. The figure should therefore be interpreted as showing a broad age-related pattern rather than a perfectly smooth gradient across every AI-use category.

At a given age, a higher frequency of AI use is not associated with a higher predicted learning need in this additive specification. The isolated-case-use profile is generally the highest, while frequent and daily use are lower. This is consistent with the main ordinal result, in which frequent use was associated with lower odds of being in a higher ethical-knowledge-gap category relative to isolated-case use. The substantive message is therefore not that older respondents use AI less (Table 2 showed only a weak age association with frequency), but that older age groups report greater ethical learning needs after adjustment for how often AI is used. This distinction is important for professional development planning: an age-related preparedness gradient may persist even where access to or use of AI is already widespread.

3.6. Adjusted ethical AI learning needs by institutional policy status

Figure 2 focuses on the institutional dimension. It presents adjusted probabilities from a model that includes categorical AI-use frequency, policy status and their interaction, with age, gender, research experience and discipline included as controls. The interaction was not statistically significant overall ($\chi^2(8) = 5.51$, $p = 0.702$), so the figure should be interpreted primarily as a descriptive comparison of policy-related differences rather than as evidence that the association between AI use and learning need varies by policy status. Across most AI-use categories, respondents who reported that an institutional AI policy was in place had lower adjusted probabilities of high ethical learning need than those who reported no policy or uncertainty about policy status. The pattern was not completely uniform, however. Among the small group of respondents who never used AI ($n = 63$), the predicted probability for the no-policy group dipped slightly below that for the policy-in-place group. Given the limited size of this subgroup, the isolated reversal should be interpreted cautiously. Across the substantially larger Rarely, Periodically, Frequently and Daily categories, the broader policy-related pattern was more consistent.

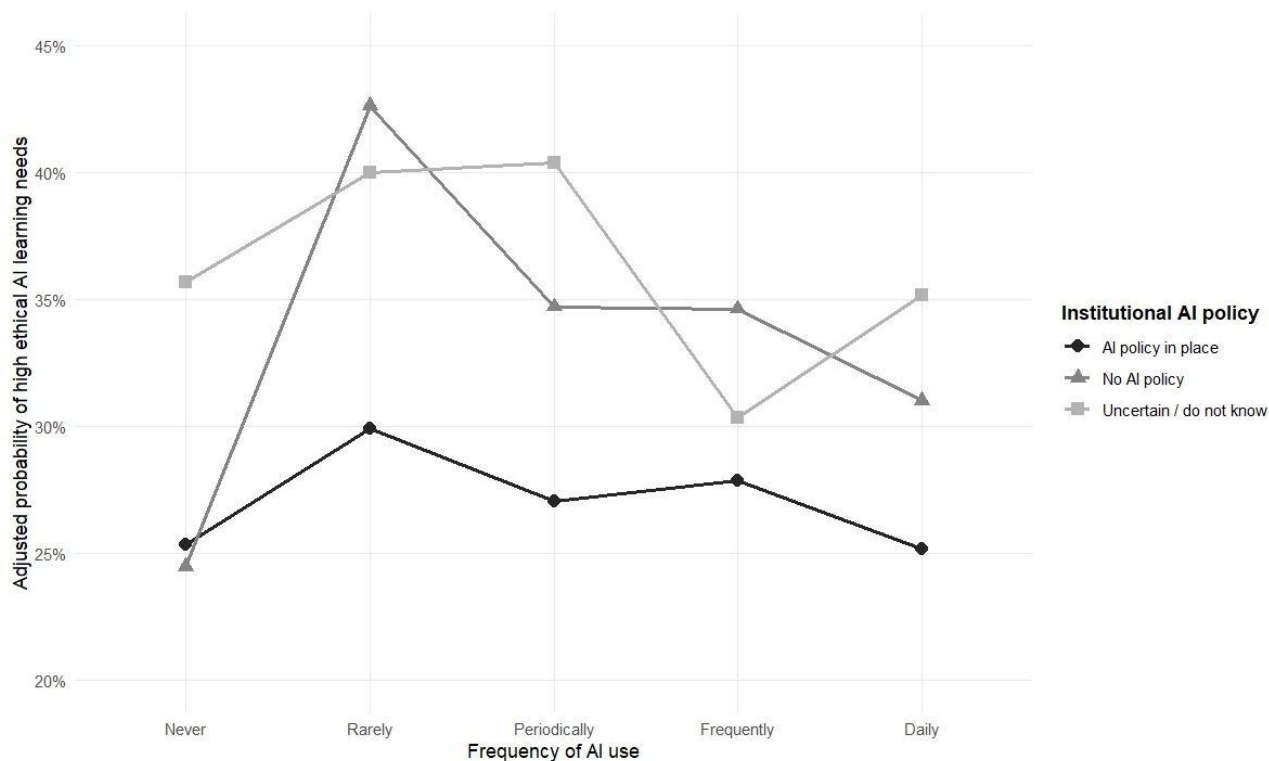


Fig. 2. Adjusted probability of high ethical AI learning needs by frequency of AI use and institutional AI-policy status

Note: Predicted probabilities are adjusted for age, gender, research experience and field of research. The figure is presented descriptively because the overall institutional AI-policy status $\times$ AI-use frequency interaction was not

statistically significant ($\chi^2(8) = 5.51, p = 0.702$). Differences in the trajectories should therefore not be interpreted as evidence of moderation

The policy-in-place group generally remained within a comparatively narrow range of approximately 25–30% predicted high need. Corresponding probabilities were often appreciably higher among respondents reporting no policy or uncertainty about policy status. For the rarely used, the adjusted probability was approximately 42.6% in the no-policy group and 40.0% among those uncertain about policy, compared with about 29.9% where a policy was reported to be in place. For periodic use, the corresponding values were approximately 34.7%, 40.4% and 27.0%. Although the exact ordering of the no-policy and uncertain groups varied across AI-use categories, both generally showed higher predicted learning needs than the policy-in-place group.

The graphical pattern reinforces the interpretation of Table 3. Institutional policy status is associated with a lower overall perceived need for ethical learning, whereas the evidence does not support a stable moderation of the AI-use gradient. The more pronounced policy coefficients in the rules-gap model further suggest that institutional policies operate most directly through clarity and guidance. A formal policy may therefore be associated not only with a lower perceived absence of rules but also with a lower perceived ethical knowledge deficit, potentially because policies signal organisational attention, provide access to guidance, or clarify acceptable practice. The cross-sectional design cannot identify which of these mechanisms is responsible, but the association is robust to the demographic, experience, use-frequency, and discipline controls included.

3.7. Identifying active but underprepared AI users

The training-priority classification provides a direct estimate of the scale of professional learning need among existing AI users. Of the 2,004 HEI respondents, 1,483 (74.0%) met the definition of active AI use. Among these active users, 472 reported an ethical knowledge gap score of 4 or 5. Thus, 31.8% of active AI users (and 23.6% of the full HEI sample) were classified as active but underprepared. Prepared active users were the largest group ($n = 1,011$; 50.4% of the HEI sample). A further 192 respondents (9.6%) were potential learners who combined low AI engagement with high perceived need, and 329 (16.4%) were in the low-engagement/low-need group.

The policy distribution of these groups is substantively revealing. In institutions where respondents reported an AI policy, 57.4% were prepared active users, and 20.4% were active but underprepared. Where no policy was reported, the prepared-active share fell to 49.8%, and the active-but-underprepared share increased to 26.5%. Among respondents uncertain about policy, only 42.4% were prepared active users, 25.3% were active but underprepared, and 13.3% were potential learners. These descriptive results indicate that policy uncertainty is associated with both reduced preparedness among active users and a larger group of less-engaged respondents who nevertheless recognise a substantial learning need.

Tab. 5

Binary logistic regression for high ethical learning need among active AI users ($N = 1,483$)

Predictor	OR [95% CI]	p
Age 30–39 vs 18–29	1.20 [0.71, 2.03]	0.498
Age 40–49 vs 18–29	1.41 [0.83, 2.42]	0.209
Age 50–59 vs 18–29	1.72 [0.98, 3.04]	0.061
Age 60–69 vs 18–29	1.86 [0.95, 3.65]	0.070
Age ≥ 70 vs 18–29	1.73 [0.52, 5.26]	0.347
Women vs men	1.00 [0.76, 1.34]	0.979
Experience 1–5 vs <1 year	0.89 [0.49, 1.62]	0.692
Experience 5–10 vs <1 year	0.72 [0.38, 1.37]	0.314
Experience >10 vs <1 year	0.59 [0.33, 1.09]	0.089

Predictor	OR [95% CI]	p
No AI policy vs policy in place	1.47 [1.11, 1.95]	0.007
Uncertain/do not know vs policy in place	1.64 [1.26, 2.14]	<0.001

Notes: The model is restricted to respondents who report periodic, frequent, or daily AI use and includes field-of-research controls. The outcome equals 1 for ethical-learning-need scores of 4–5. Discipline coefficients are omitted because the field of research is included as an adjustment rather than a focal explanatory variable

The binary logistic model restricted to active AI users confirms the central role of institutional policy in perceived underpreparedness. Relative to active users in institutions where an AI policy was reported to be in place, those reporting no AI policy had 47.3% higher odds of a high ethical AI learning need (OR = 1.47, 95% CI [1.11, 1.95], $p = 0.007$). Active users who were uncertain or did not know whether such a policy existed had 64.2% higher odds of reporting a high ethical AI learning need (OR = 1.64, 95% CI [1.26, 2.14], $p < 0.001$). The age coefficients for respondents aged 50–59 and 60–69 years were positive but did not reach the 5% significance threshold, while more than ten years of research experience was associated with a non-significant tendency towards lower odds. Gender remained essentially unrelated to the outcome. Overall, the binary model reproduces the substantive pattern observed in the whole-sample ordinal model within a more targeted subgroup: the absence of or uncertainty about institutional AI policy is associated with a greater perceived need for ethical AI learning among respondents who already actively use AI.

3.8. Four-group robustness analysis and integrated results

The supplementary multinomial logistic model was re-estimated using prepared active users as the reference outcome category and Education, the largest disciplinary category, as the reference field. Because the field of research served as an adjustment variable rather than a focal explanatory factor, four comparatively small disciplinary categories were combined into an ‘Other fields’ category. This re-specification removed the zero-cell problem present in the initial model and yielded interpretable estimates across all training-priority groups.

The revised multinomial results confirmed the main institutional-policy pattern. Relative to prepared active users, respondents reporting no institutional AI policy were more likely to belong to the active-but-underprepared group (RRR = 1.49, 95% CI [1.13, 1.98], $p = 0.005$), while uncertainty about policy status was associated with an even higher relative risk (RRR = 1.65, 95% CI [1.27, 2.14], $p < 0.001$). The corresponding associations were stronger for potential learners: RRR = 1.96 (95% CI [1.28, 3.00], $p = 0.002$) when no policy was reported, and RRR = 2.73 (95% CI [1.86, 4.00], $p < 0.001$) when respondents were uncertain about policy status. Policy uncertainty was also associated with a higher relative risk of belonging to the low-engagement/low-need group rather than the prepared-active group (RRR = 1.44, 95% CI [1.08, 1.93], $p = 0.014$).

Career-stage differences were also evident. Respondents aged 60–69 were more likely than those aged 18–29 to belong to the potential-learner group rather than the prepared-active group (RRR = 3.22, 95% CI [1.37, 7.58], $p = 0.008$), whereas more than 10 years of research experience was associated with a lower relative risk of the potential-learner profile (RRR = 0.45, 95% CI [0.21, 0.95], $p = 0.036$). Longer research experience was also associated with a lower relative risk of the low-engagement/low-need profile: RRR = 0.49 for 5–10 years ($p = 0.031$) and RRR = 0.43 for more than 10 years ($p = 0.006$). These results complement the significant AI-intensity-by-experience interaction in the ordinal model and suggest that career stage is related not simply to whether AI is used, but to how AI engagement combines with perceived preparedness.

Some field-of-research contrasts were statistically significant in the revised multinomial model; however, because discipline was included solely as an adjustment covariate and the pooled ‘Other fields’ category is substantively heterogeneous, these coefficients are reported in the supplementary table and are not interpreted as central findings.

3.9. Summary of empirical findings

Across the analyses, five results are particularly consistent. First, AI use is already normalised in this HEI sample: three-quarters of respondents use AI at least periodically, and fewer than one in thirty report never using it. Second, widespread use coexists with substantial learning needs. One-third of all HEI respondents report a high need for ethical AI learning, and almost one-third of active users are classified as active but underprepared. Third, institutional policy status is the most stable correlate of preparedness. Reporting no policy or uncertainty about policy is associated with higher ethical-learning-need categories, substantially higher institutional-rules gaps and higher odds of underpreparedness among active users. Fourth, age matters primarily for perceived ethical preparedness rather than for institutional rules: adjusted probabilities of high ethical learning need rise across age groups even though the age association with AI-use frequency itself is small. Fifth, research experience moderates the relationship between AI-use intensity and perceived ethical learning need. Among respondents with more than 10 years of research experience, greater AI use intensity is associated with a lower reported need. In contrast, the pattern is weaker or runs in the opposite direction among less-experienced groups.

The results support a differentiated view of responsible AI professional learning. A sizeable group already uses AI regularly while perceiving a lack of ethical knowledge, and this group is more common where institutional policy is absent or unclear. Older respondents also exhibit higher adjusted learning needs, while the career stage shapes the relationship between repeated AI use and preparedness. The evidence, therefore, favours accessible institutional guidance combined with career-sensitive professional learning, without causal claims beyond the cross-sectional design.

3.10. Discussion

The findings indicate that widespread AI adoption in Ukrainian higher education should not be equated with responsible AI preparedness. Although 74.0% of respondents used AI at least periodically, one-third reported high ethical AI learning needs, and almost one-third of active users were classified as active but underprepared. This finding supports the broader shift in the literature from viewing AI competence as operational familiarity towards understanding it as a multidimensional combination of technical, cognitive, behavioural and ethical capabilities (Ng et al., 2023; Ng et al., 2024; Wang et al., 2023). It is also consistent with arguments that the normalisation of generative AI in universities creates new tensions around critical evaluation, integrity and responsible academic practice rather than resolving them through greater use alone (Adamakis & Rachiotis, 2025; Francis et al., 2025; Walter, 2024). The present results extend this literature by identifying a sizeable group whose active engagement with AI coexists with substantial perceived ethical-learning needs. Thus, repeated use may generate practical familiarity, but it should not be interpreted as evidence of responsible AI preparedness.

Institutional policy emerged as the most consistent correlate of preparedness across the complementary model specifications. In the cumulative-link ordinal models for the full HEI sample, respondents reporting no institutional AI policy or uncertainty about policy status had higher odds of being in higher ethical-learning-need and institutional-rules-gap categories. Consistently, in the binary logistic model restricted to active AI users, the odds of reporting a high ethical AI learning need were 47.3% higher when no policy was reported (OR = 1.47, 95% CI [1.11, 1.95]) and 64.2% higher when respondents were uncertain whether a policy existed (OR = 1.64, 95% CI [1.26, 2.14]) than when a policy was reported to be in place. These findings align with research arguing that responsible AI implementation requires governance arrangements combining formal rules, legal awareness, ethical literacy and accessible institutional guidance (Chan, 2023; Chumachenko et al., 2025; Oncioiu & Bularca, 2025), and with evidence that Ukrainian universities differ in the maturity of their institutional AI policies (Suchikova & Omelchuk, 2026). At the same time, the non-significant AI-use-by-policy interaction indicates that policy status does not substantially alter the association between increasing AI use and perceived learning need. Rather, policy presence appears to be associated with a generally

lower level of perceived learning and guidance gaps. This suggests that the visibility, communication and practical interpretation of institutional policy may be as important as its formal existence, particularly given that more than one-third of respondents were uncertain whether such rules were in place.

The age and research-experience findings further support a differentiated rather than uniform model of professional learning. In the whole-sample cumulative-link ordinal model, respondents aged 50–59 and 60–69 had significantly higher odds of reporting greater ethical AI learning needs than those aged 18–29, although age differences in AI-use frequency itself were weak. The relevant divide therefore appears to concern perceived preparedness rather than simply access to or frequency of AI use. Research experience added further nuance: the significant AI-intensity-by-experience interaction showed that, among respondents with more than ten years of research experience, greater AI-use intensity was associated with lower perceived ethical learning needs, whereas the relationship was weaker or absent among less-experienced groups. This pattern is compatible with research suggesting that AI-related professional learning, workforce adaptation and digital self-efficacy develop differently across professional contexts and career stages (Hart, 2025; Lamichhane et al., 2026; Mamdouh et al., 2025). In the Ukrainian context, where higher education is simultaneously adapting to rapid technological change and broader pressures on institutional and intellectual capacity, such heterogeneity strengthens the case for career-sensitive and institutionally supported professional development rather than one-size-fits-all AI training (Iurchenko & Ponomarenko, 2025; Yeremenko, 2026).

A further interpretive caution concerns the negative association between AI-use frequency and perceived ethical learning need. In the cumulative-link ordinal model for the full HEI sample, frequent users had lower odds of reporting a higher ethical-learning-need category than rare users ($OR = 0.77$, $p = 0.046$), and Figure 1 shows a broadly similar descriptive pattern. One interpretation is that researchers who are better prepared for responsible AI use are more likely to adopt these tools intensively, or that repeated use contributes to greater familiarity with ethical and procedural requirements. However, the opposite interpretation is equally plausible. Because the outcome measures perceived rather than objectively demonstrated competence, intensive users who are highly confident in their AI practices may underestimate ethical risks or fail to recognise gaps in their own knowledge. A lower self-reported learning need therefore does not necessarily indicate greater objective preparedness and may instead reflect limited recognition of ethical complexity. The cross-sectional and self-reported design cannot distinguish between these explanations. The negative AI-use gradient should therefore be interpreted as an association with perceived learning need rather than as evidence that intensive AI use produces or necessarily reflects greater ethical competence. The significant interaction with research experience requires the same caution: among respondents with more than ten years of experience, greater AI-use intensity was associated with lower perceived learning needs, but this may reflect either accumulated competence or greater confidence in existing practices. Objective or performance-based measures of AI literacy and ethical competence would be required to distinguish preparedness from perceived preparedness.

4. CONCLUSIONS

The study examined responsible AI preparedness as an element of continuous digital professional learning in Ukrainian higher education, with particular emphasis on how perceived ethical AI learning needs differ across career stages and patterns of AI use, and how these needs relate to the institutional policy environment. Rather than treating AI adoption itself as evidence of readiness, the research focused on the extent to which practical use of AI is accompanied by perceived ethical preparedness and sufficiently clear institutional guidance.

The analysis used cross-sectional survey data collected in Ukraine between 29 November and 8 December 2025, restricting the analytical sample to 2,004 respondents representing higher education

institutions. The empirical strategy combined descriptive statistics, chi-squared tests and Cramér's V, cumulative-link ordinal logistic regression, interaction models, adjusted predicted probabilities, and a binary logistic model of active-but-underprepared AI users, supplemented by an exploratory multinomial classification.

AI use was already widespread in the HEI sample, with 74.0% of respondents using AI at least periodically. At the same time, 33.1% reported a high ethical AI learning need, indicating that adoption and responsible preparedness should not be treated as equivalent. Among active AI users, 472 respondents were classified as active but underprepared, corresponding to 31.8% of active users and 23.6% of the full HEI sample. Institutional policy status was the most consistent correlate of perceived preparedness. In the binary logistic model restricted to active AI users, respondents reporting no institutional AI policy had 47.3% higher odds of a high ethical AI learning need (OR = 1.47, 95% CI [1.11, 1.95]), while those uncertain about whether such a policy existed had 64.2% higher odds (OR = 1.64, 95% CI [1.26, 2.14]) than respondents reporting a policy in place. The whole-sample ordinal analyses further showed that perceived ethical learning needs tended to be higher among older respondents, whereas gender showed little systematic association with underpreparedness. Research experience significantly moderated the relationship between AI-use intensity and perceived ethical learning need, suggesting that career stage shapes how repeated AI use relates to preparedness. By contrast, institutional policy did not significantly moderate the AI-use gradient, indicating that policy presence is associated primarily with lower overall levels of perceived learning and guidance gaps rather than with different effects of increasing AI use.

From a higher-education policy perspective, the findings indicate that responsible AI development should not be limited to issuing formal institutional regulations or encouraging the adoption of new digital tools. Universities should combine visible, accessible, and practically interpretable AI policies with continuous professional learning opportunities that address ethical decision-making, academic integrity, transparency in AI use, responsible verification of AI-generated outputs, and appropriate research practice. Particular attention should be given to academic staff who already use AI regularly yet continue to perceive substantial ethical knowledge gaps, as this group accounts for almost one-third of active users in the sample. Professional development should also be differentiated by career stage rather than delivered through a uniform model: older, more experienced researchers may require different forms of support from early-career researchers, whose AI use and perceptions of preparedness develop under different professional conditions. Importantly, the relatively high level of uncertainty about whether institutional AI policies exist suggests that policy communication itself should be considered part of institutional digital education; a policy that is formally adopted but poorly communicated is unlikely to provide effective guidance. Such measures would position responsible AI competence as part of continuous professional learning in higher education. They could contribute to broader objectives of digital education, institutional innovation and quality lifelong learning.

Several limitations should be considered when interpreting these findings. First, the study is based on cross-sectional, self-reported survey data and therefore identifies associations rather than causal effects; for example, institutions with clearer AI policies may differ from other institutions in ways that are not fully captured by the available covariates. Second, participation was voluntary and based on non-probability recruitment, creating a potential risk of self-selection bias. Respondents with greater interest in, familiarity with, or stronger views about AI may have been more likely to participate. This concern is particularly relevant given the composition of the HEI analytical sample: 76.3% of respondents were women, 69.3% had more than ten years of research experience, and only 3.1% reported never using AI. Moreover, no survey weights were available. Consequently, the observed prevalence of AI use and the distribution of preparedness profiles should not be interpreted as nationally representative population estimates for Ukrainian higher education. Third, both focal outcomes were measured using single questionnaire items, so internal-consistency reliability could not be estimated. In addition, the two outcomes and institutional AI-policy status were obtained from the

same self-reported questionnaire at the same point in time; consequently, common-method variance cannot be excluded. The measures, therefore, capture perceived rather than objectively demonstrated preparedness and institutional guidance. The active-but-underprepared category is likewise an analytically constructed classification rather than a validated diagnostic measure of AI competence. Fourth, respondents' reports of institutional AI policy status do not establish the actual content, quality, implementation, visibility, or enforcement of those policies. Fifth, the supplementary multinomial analysis required four comparatively small disciplinary categories to be pooled into an 'Other fields' category to reduce sparse-cell instability. Although this produced a stable specification, the heterogeneous composition of the pooled category limits discipline-specific interpretation of the multinomial results. Future research should combine longitudinal or institutionally stratified designs with objective or performance-based measures of AI literacy and ethical competence. Scenario-based assessments of academic integrity, verification, transparency and responsible AI decision-making could help determine whether lower reported learning needs among intensive users reflect genuine competence, overconfidence or limited recognition of ethical risks. Further studies should also verify the characteristics of institutional AI policies and test whether targeted professional development reduces the identified preparedness gaps.

Author Contributions:

Conceptualization: Artem Artyukhov, Dmytro Chumachenko, Denys Babaiev, Artem Koldovskiy, Victor Chentsov.

Data curation: Artem Artyukhov, Denys Babaiev, Victor Chentsov.

Formal analysis: Dmytro Chumachenko, Artem Koldovskiy, Victor Chentsov.

Investigation: Dmytro Chumachenko.

Methodology: Dmytro Chumachenko.

Project administration: Artem Artyukhov.

Supervision: Artem Artyukhov.

Validation: Denys Babaiev, Artem Koldovskiy, Victor Chentsov.

Visualization: Denys Babaiev, Artem Koldovskiy, Victor Chentsov.

Writing – original draft: Artem Artyukhov, Dmytro Chumachenko, Denys Babaiev, Artem Koldovskiy, Victor Chentsov.

Writing – review & editing: Artem Artyukhov, Dmytro Chumachenko, Denys Babaiev, Artem Koldovskiy, Victor Chentsov.

Acknowledgment: The research did not receive any outside support, including financial support.

Conflict of interest: The authors declare no conflict of interest.

REFERENCES

- [1] Adamakis, M., & Rachiotis, T. (2025). Artificial Intelligence in Higher Education: A State-of-the-Art Overview of Pedagogical Integrity, Artificial Intelligence Literacy, and Policy Integration. *Encyclopedia*, 5(4), 180. <https://doi.org/10.3390/encyclopedia5040180>
- [2] Alakoum, A., Nica, E., & Abiad, M. (2025). AI and algorithmic governance in public administration: implications for faculty satisfaction, HR strategies, and performance systems in higher education. *Administratie si Management Public*, 44, 6-22. <https://doi.org/10.24818/amp/2025.44-01>
- [3] Artyukhov, A., Chumachenko, D., Babaiev, D., Koldovskiy, A., & Chentsov, V. (2026). From ai use to responsible ai preparedness: professional learning needs in Ukrainian higher education [Dataset]. Zenodo. <https://doi.org/10.5281/zenodo.22706501>
- [4] Bilan, S., Šuleř, P., Skrynnyk, O., Krajňáková, E., & Vasilyeva, T. (2022). Systematic bibliometric review of artificial intelligence technology in organizational management, development, change and culture. *Business: Theory and Practice*, 23(1), 1–13. <https://doi.org/10.3846/btp.2022.13204>
- [5] Cela, E., Vajjhala, N. R., & Fonkam, M. M. (Eds.). (2025). *Next-Generation AI Methodologies in Education*. IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3693-7220-3>

- [6] Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, 20, Article 38. <https://doi.org/10.1186/s41239-023-00408-3>
- [7] Chugh, R., Turnbull, D., Cowling, M. A., & others. (2023). Implementing educational technology in higher education institutions: A review of technologies, stakeholder perceptions, frameworks and metrics. *Education and Information Technologies*, 28, 16403–16429. <https://doi.org/10.1007/s10639-023-11846-x>
- [8] Chumachenko, D., Fitz-Gerald, A., Artyukhov, A., & Lyeonov, S. (2025). Governing AI in education: A cross-organization analysis of international policy, law, and standards. *CEUR Workshop Proceedings*, 4164, 389–400. URL: <https://ceur-ws.org/Vol-4164/>
- [9] Domina, O., Andriushchenko, K., Liezina, A., Tsymbalenko, Y., Titova, O., Kyryliuk, O., & Vylgin, Y. (2025). The Impact of Artificial Intelligence on the Formation of a Teacher's Digital Twin in the Metaverse. *Journal of Vasyl Stefanyk Precarpathian National University*, 12(3), 169–185. <https://doi.org/10.15330/jpnu.12.3.169-185>
- [10] European Commission, Directorate-General for Education, Youth, Sport and Culture. (2026). *Guidelines on the ethical use of artificial intelligence and data in teaching and learning for educators* (Updated ed.). Publications Office of the European Union. <https://doi.org/10.2766/7967834>
- [11] Francis, N. J., Jones, S., & Smith, D. P. (2025). Generative AI in higher education: Balancing innovation and integrity. *British Journal of Biomedical Science*, 81, Article 14048. <https://doi.org/10.3389/bjbs.2024.14048>
- [12] Frimpong, V. (2025). Not All That Can Be Automated Should Be Automated – Strategic Minimalism as a Disciplined and Ethically Grounded Approach to AI Adoption. *Business Ethics and Leadership*, 9(4), 57–66. [https://doi.org/10.61093/bel.9\(4\).57-66.2025](https://doi.org/10.61093/bel.9(4).57-66.2025)
- [13] Haley, P., & Burrell, D. N. (2025). Integrating Artificial Intelligence into Law Enforcement: Socioeconomic and Ethical Challenges. *SocioEconomic Challenges*, 9(2), 60–77. [https://doi.org/10.61093/sec.9\(2\).60-77.2025](https://doi.org/10.61093/sec.9(2).60-77.2025)
- [14] Hayes, R. D., & Burrell, D. N. (2026). Reasonable Oversight of the Practical, Legal, and Ethical Boundaries Impacting Human Factors Trust in Automated Decision-Making. *Public Governance, Regulation and Law*, 2(1), 33–50. [https://doi.org/10.61093/pgrl.2\(1\).33-50.2026](https://doi.org/10.61093/pgrl.2(1).33-50.2026)
- [15] Hart, G. (2025). Navigating AI Implementation in Healthcare Retail: A Case Study on Leadership, Workforce Adaptation, and Digital Transformation. *Health Economics and Management Review*, 6(3), 1–16. <https://doi.org/10.61093/hem.2025.3-01>
- [16] Iurchenko, M., & Ponomarenko, M. (2025). Ukrainian Educational and Scientific Potential After the Full-Scale Invasion: Socioeconomic Challenges and Prospects. *SocioEconomic Challenges*, 9(1), 21–38. [https://doi.org/10.61093/sec.9\(1\).21-38.2025](https://doi.org/10.61093/sec.9(1).21-38.2025)
- [17] Koibichuk, V., Samoilikova, A., & Vasylieva, T. (2023). Digitalization and Innovation Transfer as a Leadership Trend in Education: Bibliometric Analysis and Social Analytics. In: Strielkowski, W. (eds) *Leadership, Entrepreneurship and Sustainable Development Post COVID-19. NILBEC 2022*. Springer Proceedings in Business and Economics. Springer, Cham. https://doi.org/10.1007/978-3-031-28131-0_17
- [18] Kot, S., Kaur, H., & Haque, A. U. (2026). Embracing vulnerability in AI mediated coaching: A developmental pathway for ethical HRD. *Journal of International Studies*, 19(2), 31–46. <https://doi.org/10.14254/2071-8330.2026/19-2/2>
- [19] Kritikos, I., Sarantopoulos, A., Roumeliotis, A., Vasiliades, J., & Matsinas, I. (2025). Unlocking the Potential of Artificial Intelligence in Pharma Research and Development: Insights from Investor and Researcher Perspectives. *Health Economics and Management Review*, 6(2), 1–16. <https://doi.org/10.61093/hem.2025.2-01>
- [20] Kuzior, A., Marszałek-Kotzur, I., Sansyzbayeva, K. N., & Lukács, E. (2025). From AI vibrancy to labour market outcomes: Testing displacement across education groups. *Economics and Sociology*, 18(4), 131–159. <https://doi.org/10.14254/2071-789X.2025/18-4/7>
- [21] Lamichhane, B. D., Chalise, M., Dhungana, B. R., Neupane, D., Kayastha, M., & Rai, K. (2026). Socio-economic challenges of leadership-driven learning strategies in management education. *SocioEconomic Challenges*, 10(2), 71–85. [https://doi.org/10.61093/sec.10\(2\).71-85.2026](https://doi.org/10.61093/sec.10(2).71-85.2026)
- [22] Lyeonov, S., Artyukhov, A., Bilan, S., & Bács, Z. (2026). How university staff evaluate generative AI: Cognitive and ethical perspectives on teaching, trust, and academic integrity. *Human Technology*, 22(1), 68–97. <https://doi.org/10.14254/1795-6889.2026.22-1.4>
- [23] Mamdouh, A., Adel, R., Khourshed, N., & Ragheb, M. A. (2025). Impact of Digital Leadership on Employee Performance with Mediation Roles of Digital Self-Efficacy and Employee Motivation. *Business Ethics and Leadership*, 9(3), 109–129. [https://doi.org/10.61093/bel.9\(3\).109-129.2025](https://doi.org/10.61093/bel.9(3).109-129.2025)

- [24] Miao, F., & Holmes, W. (2023). *Guidance for generative AI in education and research*. UNESCO. <https://doi.org/10.54675/EWZM9535>
- [25] Miao, F., & Cukurova, M. (2024). *AI competency framework for teachers*. UNESCO. <https://doi.org/10.54675/ZJTE2084>
- [26] Molina, E., & Medina, E. (2025). AI Revolution in Higher Education. What you need to know. In *Digital Innovations in Education*. World Bank. World Bank. URL: <https://documents1.worldbank.org/curated/en/099757104152527995/pdf/IDU-b1e5ef00-75ff-4ba4-a4b6-84899c3ea968.pdf>
- [27] Mura, L., & Stehlíková, B. (2025). The ethics of artificial intelligence: Safeguarding human dignity, social justice and environmental stability in the age of AI. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 20(2), 479-507. <https://doi.org/10.24136/eq.3743>
- [28] Ng, D. T. K., Leung, J. K. L., Su, J., Ng, R. C. W., & Chu, S. K. W. (2023). Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Education and Information Technologies*, 71, 137–161. <https://doi.org/10.1007/s11423-023-10203-6>
- [29] Ng, D. T. K., Wu, W., Leung, J. K. L., Chiu, T. K. F., & Chu, S. K. W. (2024). Design and validation of the AI literacy questionnaire: The affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology*, 55, 1082–1104. <https://doi.org/10.1111/bjet.13411>
- [30] OECD. (2024). *Education Policy Outlook 2024: Reshaping Teaching into a Thriving Profession from ABCs to AI*. OECD Publishing, Paris. <https://doi.org/10.1787/dd5140e4-en>
- [31] OECD. (2025). *Results from TALIS 2024: The State of Teaching*. TALIS, OECD Publishing, Paris. <https://doi.org/10.1787/90df6235-en>
- [32] Okulich-Kazarin, V., & Artyukhov, A. (2025). (Un)invited Assistant: AI as a Structural Element of the University Environment. *Societies*, 15(11), 297. <https://doi.org/10.3390/soc15110297>
- [33] Oncioiu, I., & Bularca, A. R. (2025). Artificial Intelligence Governance in Higher Education: The Role of Knowledge-Based Strategies in Fostering Legal Awareness and Ethical Artificial Intelligence Literacy. *Societies*, 15(6), 144. <https://doi.org/10.3390/soc15060144>
- [34] Pilny, J., & Postrzednik-Lotko, K. (2025). The Use of New Technologies and Artificial Intelligence in Language Learning and Corporate Discourse. *Knowledge Economy and Lifelong Learning*, 1(2), 50-76. [https://doi.org/10.61093/kell.1\(2\).50-76.2025](https://doi.org/10.61093/kell.1(2).50-76.2025)
- [35] Popova, L. (2024). The Phenomenon of “Artificial Intelligence” in the Formation of Transversal Competencies of the Future Teacher: Pros and Cons. *Journal of Vasyl Stefanyk Precarpathian National University*, 11(1), 86–93. <https://doi.org/10.15330/jpnu.11.1.86-93>
- [36] Rahmanov, F., Ganiyeva, S., Aliyeva, N., Neymatova, L., & Aghazada, T. (2025). The impact of education digitalization on achieving SDG4: A comparative assessment of Azerbaijan and SDG4 leaders. *Problems and Perspectives in Management*, 23(2), 634–650. [https://doi.org/10.21511/ppm.23\(2\).2025.46](https://doi.org/10.21511/ppm.23(2).2025.46)
- [37] Salas-Pilco, S. Z., Xiao, K., & Hu, X. (2022). Artificial Intelligence and Learning Analytics in Teacher Education: A Systematic Review. *Education Sciences*, 12(8), 569. <https://doi.org/10.3390/educsci12080569>
- [38] Sarwar, U., Sanhong, T., Waheed Akhtar, M., & Aamir, M. (Eds.). (2025). *Navigating Barriers to AI Implementation in the Classroom*. IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3373-1827-1>
- [39] Schinello, S. (2025). Challenges and opportunities in the use of artificial intelligence in creative economy: Insights from expert interviews. *Economics and Sociology*, 18(1), 199-216. <https://doi.org/10.14254/2071-789X.2025/18-1/10>
- [40] Sieciński, K., & Oliński, M. (2026). ChatGPT as a knowledge-support tool: Perceptions of its professional use among working students in Poland. *Knowledge and Performance Management*, 10(3), 80–99. [https://doi.org/10.21511/kpm.10\(3\).2026.06](https://doi.org/10.21511/kpm.10(3).2026.06)
- [41] Škare, M., Porada-Rochon, M., & Veselica Celić, R. (2025). Total factor productivity dynamics and the artificial intelligence paradox: Evidence from longmemory analysis. *Journal of International Studies*, 18(4), 218-242. <https://doi.org/10.14254/2071-8330.2025/18-4/11>
- [42] Skrynnyk, O., Lyeonov, S., Lenska, S., Litvinchuk, S., Galaieva, L., & Radkevych, O. (2022). Artificial intelligence in solving educational problems. *Journal of Information Technology Management*, 14(Special Issue: Digitalization of Socio-Economic Processes), 132–146. <https://doi.org/10.22059/jitm.2022.88893>
- [43] Springs, D. (2025). Smart Leadership Adaptations in Artificial Intelligence Dual Use Functions and Ethical Implications in Healthcare Organizations and Biotechnology Innovations. *Health Economics and Management Review*, 6(3), 28-37. <https://doi.org/10.61093/hem.2025.3-03>

- [44] Stolpe, K., & Hallström, J. (2024). Artificial Intelligence Literacy for Technology Education. *Computers and Education Open*, 6, 100159. <https://doi.org/10.1016/j.caeo.2024.100159>
- [45] Suchikova, Y., & Omelchuk, S. (2026). Institutional AI policies in Ukrainian higher education: A thematic analysis and assessment using the taxonomy of institutional AI policy maturity. *Knowledge and Performance Management*, 10(2), 1–19. [https://doi.org/10.21511/kpm.10\(2\).2026.01](https://doi.org/10.21511/kpm.10(2).2026.01)
- [46] Szeberényi, A. (2026). From compliance to accountability in digital globalization: The ethical friction threshold model for artificial intelligence-enabled business leadership. *Business Ethics and Leadership*, 10(2), 228–243. [https://doi.org/10.61093/bel.10\(2\).228-243.2026](https://doi.org/10.61093/bel.10(2).228-243.2026)
- [47] Vorontsova, A., Tarasenko, S., Duranowski, W., Durasiewicz, A., Soss, J., & Bilovol, A. (2025). A bibliometric analysis of the economic effects of using artificial intelligence and ChatGPT tools in higher education institutions. *Problems and Perspectives in Management*, 23(1), 101–114. [https://doi.org/10.21511/ppm.23\(1\).2025.08](https://doi.org/10.21511/ppm.23(1).2025.08)
- [48] Walter, Y. (2024). Embracing the future of artificial intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, 21, Article 15. <https://doi.org/10.1186/s41239-024-00448-3>
- [49] Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, 42(9), 1324–1337. <https://doi.org/10.1080/0144929X.2022.2072768>
- [50] World Bank. (2025). Digital Progress and Trends Report 2025: Strengthening AI Foundations. Washington, DC: World Bank. <https://doi.org/10.1596/978-1-4648-2264-3>
- [51] World Bank, EdTech Hub, & AI Observatory. (2026). Preparing tertiary institutions for an AI-driven world: An artificial intelligence in education Community of Interest event (January 22, 2026). World Bank. URL: <https://documents1.worldbank.org/curated/en/099728105012642727/pdf/IDU-fc687a85-fee7-4c00-a760-0f344888c704.pdf>
- [52] Yarovenko, H., Kuzior, A., Norek, T., & Lopatka, A. (2024). The future of artificial intelligence: Fear, hope or indifference?. *Human Technology*, 20(3), 611–639. <https://doi.org/10.14254/1795-6889.2024.20-3.10>
- [53] Yeremenko, O. (2026). Retraining and Lifelong Learning as an Anti-Crisis Tool: Preserving Ukraine's Intellectual Capital in Times of War. *Knowledge Economy and Lifelong Learning*, 2(1), 48–66. [https://doi.org/10.61093/kell.2\(1\).48-66.2026](https://doi.org/10.61093/kell.2(1).48-66.2026)
- [54] Zimosz, P., & Ober, J. (2025). Impact of Artificial Intelligence on Education. *Knowledge Economy and Lifelong Learning*, 1(2), 77–98. [https://doi.org/10.61093/kell.1\(2\).77-98.2025](https://doi.org/10.61093/kell.1(2).77-98.2025)
- [55] Żulicki, R. (2026). Negative relationship between cultural individualism and ChatGPT usage. Sociological analysis across 21 countries. *Human Technology*, 22(1), 139–157. <https://doi.org/10.14254/1795-6889.2026.22-1.7>

Artem Artyukhov, Doctor of Economics, Associate Professor, Senior Researcher, Assistant Professor in the Department of International Trade, Bratislava University of Economics and Business, Bratislava, Slovakia; Associate Professor in the Department of Marketing, Sumy State University, Sumy, Ukraine;

ORCID ID: 0000-0003-1112-6891

Address: Department of International Trade, Bratislava University of Economics and Business, Dolnozemska cesta 1, Bratislava, 852 35 Slovakia.

Department of Marketing, Sumy State University, Kharkivska Street 116, Sumy, 40007, Ukraine.

E-mail: artem.artiukhov@euba.sk

Dmytro Chumachenko, PhD in Technical Sciences, Associate Professor, Visiting Associate Professor in the Gillmore Centre for Financial Technologies, University of Warwick, Coventry, UK;

Associate Professor in the Department of Mathematical Modelling and Artificial Intelligence, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine;

ORCID ID: 0000-0003-2623-3294

Address: Gillmore Centre for Financial Technologies, University of Warwick, CV4 7AL, Coventry, UK;

National Aerospace University "Kharkiv Aviation Institute", Vadym Manko Street 17, Kharkiv, 61070, Ukraine.

E-mail: dichumachenko@gmail.com

Denys Babaiev, M.B.A., CEO, Co-founder, Scale Your Web LLC, Philadelphia, PA, USA;

ORCID ID: 0009-0000-5052-9939

Address: 570 N 5th St, Philadelphia, PA 19123.

Email: denis@scaleyourweb.com

Artem Koldovskiy, PhD in Economics, Associate Professor, Higher Education Institution "Open International University of Human Development 'Ukraine", Kyiv, Ukraine; Humboldt International University, Miami, Florida, USA;

ORCID ID: 0009-0009-5827-4649

Address: Higher Education Institution "Open International University of Human Development 'UKRAINE", 23 Lvivska Street, Kyiv, 03115, Ukraine;

Humboldt International University, 4000 West Flagler Street, 5th Floor, Miami, FL 33134, USA.

E-mail: akoldovskiy.pa@gmail.com

Victor Chentsov, D. Sc. (History), D. Sc. (Public Management and Administration), First Vice-Rector, University of Customs and Finance, Dnipro, Ukraine;

ORCID ID: 0000-0002-1109-8168

Address: University of Customs and Finance, Volodymyr Vernadsky street, 2/4, 49000, Dnipro, Ukraine.

E-mail: chentsov61@gmail.com

Received: July 18, 2026; **revised:** September 9, 2026; **accepted:** September 26, 2026; **published:** September 30, 2026.

Арте́м Артю́хов, Дми́тро Чу́маченко, Де́нис Баба́єв, Арте́м Колдо́вський, Ві́ктор Ченцо́в. Від використання штучного інтелекту до відповідальної готовності до його застосування: потреби у професійному навчанні в українській вищій освіті. *Журнал Прикарпатського університету імені Василя Стефаника*, **13** (3) (2026), 164-185.

Швидка інтеграція штучного інтелекту у вищу освіту посилила потребу розмежовувати рутинне використання ШІ та готовність викладачів і науковців застосовувати його відповідально й етично за належного інституційного супроводу. Мета дослідження – проаналізувати готовність до відповідального використання ШІ як складову безперервного цифрового професійного навчання в українській вищій освіті, виявивши відмінності у потребах щодо етичного використання ШІ за етапами кар'єри та рівнями його використання, а також їхній зв'язок з інституційною політикою щодо ШІ. Використано дані поперечного опитування 2 004 представників українських закладів вищої освіти та описову статистику, критерій хі-квадрат, V Крамера, порядкову логістичну регресію, моделі взаємодії, скориговані прогнозовані ймовірності й бінарну логістичну регресію. ШІ принаймні періодично використовували 74,0 % респондентів; 33,1 % повідомили про високі потреби в навчанні щодо етичного використання ШІ, а 42,2 % – про значні прогалини в інституційних правилах або рекомендаціях. Серед активних користувачів 472 особи були класифіковані як активні, але недостатньо підготовлені, що становило 31,8 % активних користувачів і 23,6 % вибірки ЗВО. Порівняно з респондентами, які повідомили про наявність інституційної політики щодо ШІ, активні користувачі в установах без такої політики мали на 47,3 % вищу ймовірність високої потреби в етичному навчанні (OR = 1,47; 95 % ДІ [1,11; 1,95]), а невизначеність щодо політики була пов'язана з на 64,2 % вищими шансами (OR = 1,64; 95 % ДІ [1,26; 2,14]). Потреби були вищими серед респондентів віком 50–59 років (OR = 1,64) і 60–69 років (OR = 1,86), ніж серед 18–29-річних. Досвід наукової роботи значуще модифікував зв'язок між інтенсивністю використання ШІ та потребою в навчанні (LR $\chi^2(3) = 8,82$; $p = 0,032$).

Ключові слова: штучний інтелект, вища освіта, етична підготовка, професійне навчання, політика у сфері штучного інтелекту, науково-педагогічний персонал, цифрова компетентність.

Appendix A. Questionnaire items used in the principal analyses

The items below are reproduced from the original Ukrainian-language survey instrument. English translations are provided for transparency. The two preparedness outcomes were measured using single items; therefore, internal-consistency reliability coefficients are not applicable

Analytical construct	Questionnaire item	Response options and analytical coding
Ethical AI learning need	<i>I feel I lack the knowledge required to use artificial intelligence tools ethically in research.</i>	Five-point ordered response scale: 1–5. Higher values indicate a greater perceived need for AI learning in ethics. The full 1–5 scale was retained in the ordinal models; scores 4–5 were classified as high need for descriptive, predicted-probability and training-priority analyses.
Institutional-rules gap	<i>I lack clear rules and/or official policies concerning the use of artificial intelligence in research at my institution.</i>	Five-point ordered response scale: 1–5. Higher values indicate a greater perceived institutional-rules gap. The full 1–5 scale was retained in the ordinal model; scores 4–5 were classified as a high gap for descriptive analyses.
AI-use frequency	<i>How often do you use artificial intelligence tools in your research work?</i>	Never; Rarely; Periodically; Frequently; Daily. In the interaction models, these categories were coded 0–4, respectively. For the training-priority classification, Periodically, Frequently and Daily were defined as active AI use.
Institutional AI-policy status	<i>Does the educational institution or research institution where you work, or study, have an official policy on the use or implementation of AI in research activities?</i>	Yes, as a separate document; Yes, as part of a broader document on AI implementation in the institution; No; Difficult to say / Do not know. The two affirmative responses were combined into the AI policy in place. The remaining analytical categories were "No AI policy" and "Uncertain /do not know".

Notes: The original questionnaire was administered in Ukrainian. For transparency and readability, the items reproduced in this appendix are English translations of the original Ukrainian wording. The translation preserves the substantive meaning and response structure of the original instrument. For consistency throughout the manuscript, the five AI-use categories are reported as Never, Rarely, Periodically, Frequently, and Daily. The two preparedness outcomes are single-item measures rather than multi-item psychometric scales; therefore, internal-consistency reliability coefficients are not applicable.