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AI adoption readiness among Ukrainian education managers: Barriers, typologies, and policy implications

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HIGHLIGHTS

- A 0.68-point gap separates personal from institutional AI readiness among Ukrainian education managers ($d = 0.73$).
- Regulatory uncertainty and digital competency gaps are the most prevalent barriers to AI adoption.
- Six distinct manager typologies identified via Latent Class Analysis reveal heterogeneous readiness profiles.
- fsQCA finds no barrier necessary/sufficient for low AI readiness, indicating diffuse rather than configurational determination.
- Policy interventions should target regulatory frameworks and differentiated training by manager typology.

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ABSTRACT

Artificial intelligence (AI) adoption in education requires strategic leadership from education managers, yet little research examines AI readiness among this stakeholder group, particularly in post-Soviet transitional contexts. As decision-makers who control whether and how AI enters educational practice, managers' readiness is essential for evidence-based policy. This study investigates (1) the current state of AI adoption readiness among Ukrainian education managers, including the gap between personal and institutional readiness; (2) the barriers and facilitators that most strongly influence AI readiness; (3) distinct manager typologies based on readiness profiles; and (4) policy implications for scaling AI in education. A cross-sectional survey was administered to 395 education managers across 23 Ukrainian regions in September 2025. The 47-variable instrument covered demographics, AI readiness (personal and system), adoption barriers, tool usage, application potential, and psychological attitudes. Analysis employed descriptive statistics, Latent Class Analysis (LCA) for person-centered typology identification, fuzzy-set Qualitative Comparative Analysis (fsQCA) for configurational analysis of barrier combinations, and exploratory structural analysis. Personal readiness ($M = 3.83$, $SD = 0.96$) significantly exceeded system readiness ($M = 3.15$,

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$SD = 0.93$), a 0.68-point personal–institutional gap confirmed by a Wilcoxon signed-rank test ($p < .001$, $d = 0.73$). Regulatory absence and digital competency gaps were the most prevalent barriers. ChatGPT was the most widely adopted tool. LCA identified six provisional manager profiles, with the Competency-constrained class being the largest. fsQCA found that no barrier was a necessary condition and no barrier configuration was sufficient for low AI readiness, indicating that low readiness is not reducible to specific barriers or their combinations. Digital competency showed the largest training gap. Ukrainian education managers demonstrate higher personal than institutional AI readiness, constrained primarily by regulatory uncertainty and competency deficits. The identification of six provisional typologies enables targeted policy interventions. Policy priorities should focus on regulatory framework development, institutional capacity building, and differentiated, typology-based training.

1. Introduction

The rapid advancement of artificial intelligence (AI) technologies offers new capabilities while posing implementation difficulties for educational systems worldwide (Holmes et al., 2019; Pedró et al., 2019). As AI tools – from generative language models to learning analytics platforms – become increasingly accessible, educational institutions now face the practical challenge of integrating AI tools into their operations (Chiu, 2024; Zhang & Aslan, 2021). Education managers – including school principals, department heads, and educational administrators – hold a distinctive position: their decisions shape whether and how AI technologies are adopted locally (Anderson & Dexter, 2005; Cheng & Wang, 2023).

Despite their strategic importance, relatively little empirical research has examined the determinants of AI adoption readiness specifically among education managers. The majority of existing studies focus on teachers' technology acceptance (López-Costa et al., 2025; Marienko et al., 2026; Masry Herzallah & Makaldy, 2025), students' AI literacy (Casal-Otero et al., 2023), or system-level policy frameworks (Pedró et al., 2019). Managers bridge national policy and local practice: they allocate training budgets, set institutional priorities, and influence staff attitudes toward technology (Cheng & Wang, 2023; Marocco et al., 2024). Their readiness – or lack thereof – directly affects AI integration at the institutional level.

The Ukrainian context provides a relevant setting for studying AI adoption in education. As a post-Soviet transitional economy, Ukraine faces challenges including legacy institutional structures from the Soviet educational model, ongoing digital transformation accelerated by European integration, and the need to modernize educational systems to meet European standards (Ovcharuk et al., 2025; Spirin et al., 2025). Since 2022, the wartime situation has further intensified digitalization pressures – remote learning requirements, disrupted infrastructure, and the need for resilient educational delivery – while simultaneously constraining resources and complicating institutional capacity building (Semerikov & Mintii, 2026; Semerikov, Nechypurenko et al., 2026). These conditions shape how education managers approach AI adoption under conditions of institutional uncertainty and resource scarcity.

Recent research has advanced understanding of AI adoption, but three limitations persist. First, most studies adopt variable-centered approaches that examine the average effects of individual predictors, overlooking the possibility that distinct subgroups of managers may follow qualitatively different adoption pathways (Collins & Lanza, 2010; Tang & Bao, 2021). Second, existing research predominantly treats barriers as independent, additive factors, whereas configurational theory suggests that barriers may combine in complex, non-linear ways to produce readiness outcomes (Ragin, 2008). Third, the post-Soviet educational context – with its distinctive institutional legacies, regulatory gaps, and digital transformation dynamics – remains understudied in the AI adoption literature (Ovcharuk et al., 2025).

This study addresses three primary research questions:

- RQ1: What is the current state of AI adoption readiness among Ukrainian education managers, and what gaps exist between personal and institutional dimensions?
- RQ2: What barriers and facilitators most strongly influence AI readiness, and how do these combine configurationally to produce readiness outcomes?
- RQ3: What distinct typologies of education managers exist based on their AI readiness profiles, and what are the policy implications of typology-based differentiation?

To address these questions, we employ a multi-method analytical approach that combines person-centered (Latent Class Analysis, LCA) and configurational (fuzzy-set Qualitative Comparative Analysis, fsQCA) methods, complemented by descriptive statistics and exploratory structural analysis. This approach complements the variable-centered approaches common in technology adoption research by enabling the identification of manager typologies and barrier configurations – insights that are directly actionable for policy design.

We contribute by integrating technology adoption theory with organizational readiness and configurational perspectives to explain the personal–institutional gap, by combining person-centered and set-theoretic methods to capture heterogeneous adoption patterns, and by providing typology-differentiated policy recommendations for a transitional educational system.

The theoretical gap addressed here is not only that Ukrainian education managers have received limited empirical attention, but also that existing AI adoption research cannot explain a policy-relevant paradox: managers may be personally willing to support AI, yet institutional readiness may remain weak. This disconnect limits the explanatory reach of individual acceptance models, which assume that stronger personal acceptance should translate into stronger adoption readiness. We address this gap by theorizing readiness as a layered phenomenon in which personal willingness, institutional capacity, and barrier configurations do not necessarily align. The theoretical novelty is a theoretical extension (Lim, 2026): the study extends AI adoption research from individual acceptance to personal–institutional misalignment among education managers. The theoretical interestingness lies in the noteworthiness and partial paradox of the findings (Lim, 2026) – the main obstacle is not reluctance to use AI, since personal readiness is relatively high, but the mismatch between individual readiness and institutional conditions. The paper thus contributes a typology-based account of readiness that explains why the same policy environment may produce different managerial profiles and intervention needs.

2. Literature review

AI technologies in education encompass intelligent tutoring systems, automated assessment, administrative automation, learning analytics, and generative AI applications (Zawacki-Richter et al., 2019; Zhang & Aslan, 2021). While evidence suggests substantial potential for personalization and efficiency gains, implementation challenges persist, including data privacy concerns, algorithmic bias, and institutional resistance (Pedró et al., 2019; Selwyn, 2019). Education managers play a critical role in mediating these tensions: their decisions shape the institutional environment within which teachers and students encounter AI tools (Cheng & Wang, 2023; Semerikov, Vakaliuk et al., 2026; Zahorodko & Semerikov, 2026).

Recent studies in the *Computers and Education: Artificial Intelligence* journal have begun examining adoption patterns across educational stakeholders. López-Costa et al. (2025) applied PLS-SEM to understand AI adoption among secondary teachers, identifying perceived usefulness and facilitating conditions as key predictors. Masry Herzallah and Makaldy (2025) found that technological self-efficacy and sense of coherence drove teachers' AI acceptance. Cheah et al. (2025) examined generative AI integration in K–12 settings, revealing significant barriers related to preparedness and institutional support. However, these studies focus on teachers rather than managers, and none employ person-centered or configurational methods.

The Technology Acceptance Model (TAM) and its extensions provide the dominant theoretical lens for understanding technology adoption in educational contexts (Davis, 1989; Venkatesh et al., 2003). TAM posits that perceived usefulness and ease of use determine behavioral intention, while the Unified Theory of Acceptance and Use of Technology (UTAUT) extends this framework with social influence and facilitating conditions (Venkatesh et al., 2003). In educational settings, Hazzan-Bishara et al. (2025) demonstrated that institutional support has both direct and indirect effects on teachers' intention to use AI, mediated by intrinsic motivation and self-efficacy.

For education managers, however, these individual-level models may be insufficient. Managers operate within organizational structures where institutional capacity, regulatory environments, and resource allocation decisions shape adoption outcomes beyond individual perceptions (Weiner, 2009). The concept of organizational readiness for change (Armenakis et al., 1993; Weiner, 2009) – which encompasses both psychological readiness (commitment, efficacy) and structural readiness (resources, policies) – provides a complementary lens that captures the dual personal–institutional dimension of AI adoption.

Research consistently identifies several categories of barriers to AI adoption in education: regulatory uncertainty (absence of clear AI governance frameworks), digital competency gaps (insufficient technical skills among staff), resistance to change (psychological reluctance), and distrust of AI (concerns about reliability and bias) (Cheah et al., 2025; Cheng & Wang, 2023; Pedró et al., 2019). Cheng and Wang (2023) found that school leaders in Hong Kong identified a lack of teacher readiness and inadequate policy guidance as primary barriers. Marocco et al. (2024) synthesized facilitators and barriers to managers' AI adoption, noting the importance of organizational support and training opportunities.

A relevant limitation is that most studies examine barriers in isolation – reporting their prevalence and individual effects. This additive approach overlooks the possibility that barriers may interact: regulatory absence may amplify the effect of competency gaps, or resistance to change may be a prerequisite for distrust to emerge. Configurational theory (Ragin, 2008) offers a framework for examining such combinations.

Traditional variable-centered approaches (regression, SEM) examine how predictors relate to outcomes on average across an entire sample. While informative, they assume homogeneity – that the same relationships hold for all individuals. Person-centered approaches, such as LCA, challenge this assumption by identifying subgroups (latent classes) that differ qualitatively in their response patterns (Collins & Lanza, 2010; Nylund et al., 2007). In education research, Tang and Bao (2021) demonstrated the value of LCA for identifying teacher barrier profiles, finding distinct subgroups with differential support needs.

Configurational approaches, particularly fsQCA, examine how combinations of conditions (rather than individual predictors) produce outcomes (Ragin, 2000, 2008). fsQCA is grounded in set theory and identifies necessary conditions (factors present in all instances of the outcome) and sufficient configurations (combinations that consistently produce the outcome) (Schneider & Wagemann, 2012). Bourhim and Labti (2022) applied fsQCA to technology adoption in education, demonstrating that augmented reality adoption followed multiple equifinal pathways. This configurational logic is particularly appropriate for understanding AI adoption barriers, which likely combine in complex, non-additive ways.

Taken together, these literatures motivate a deliberate methodological choice. Variable-centered models estimate average effects and presume that a single set of predictor–outcome relations holds for all managers; yet evidence on heterogeneous teacher and leader profiles (Tang & Bao, 2021) and on conjunctural barrier effects (Ragin, 2008) points to two unmet needs. First, if managers cluster into qualitatively distinct readiness profiles, a person-centered method (LCA) is needed to recover those profiles and to differentiate interventions. Second, if barriers operate jointly rather than additively, a configurational method (fsQCA) is needed to test necessity and sufficiency directly rather than infer them from net effects. We therefore combine LCA and fsQCA with descriptive analysis, expecting that the person-centered and set-theoretic lenses yield typological and configurational insights that variable-centered methods, by construction, cannot provide.

Ukraine's education system has undergone substantial reform since independence, with recent emphasis on decentralization, competency-based curricula, and digital transformation (Kvit, 2020; Spirin et al., 2025). The Ministry of Digital Transformation has prioritized AI development, yet implementation at the institutional level remains uneven. Ovcharuk et al. (2025) documented significant digital competence gaps among Ukrainian educators, with limited readiness for AI-specific applications. The conflict situation since 2022 has created additional pressures: remote learning requirements have accelerated digitalization, while simultaneously constraining institutional resources and complicating regulatory development. This context creates a distinctive environment for studying AI adoption – one characterized by high urgency, low regulatory clarity, and resource constraints – that may differ systematically from the Western European contexts dominating the literature.

Three gaps motivate this study. Existing AI adoption research focuses predominantly on teachers and students, with limited attention to education managers as a distinct stakeholder group (Marocco et al., 2024). Variable-centered approaches dominate, overlooking the possibility that managers may follow heterogeneous adoption pathways requiring differentiated interventions (Tang & Bao, 2021). The post-Soviet educational context – with its institutional legacies, regulatory gaps, and wartime pressures – remains virtually absent from the AI adoption literature (Ovcharuk et al., 2025). By combining person-centered and configurational methods within the Ukrainian context, this study aims to provide both theoretical and practical insights that existing approaches cannot deliver.

3. Theoretical framework

We propose an integrative framework that synthesizes three theoretical perspectives to explain AI adoption readiness among education managers (Fig. 1).

The selection of UTAUT, organizational readiness theory, and configurational theory is justified through the IMPACT criteria for theory selection – interestingness, matching, parsimony, applicability, conceptual rigor, and testability (Hollebeek et al., 2025). The combination is *interesting* because it shifts the question from whether managers accept AI to why personally ready managers may remain institutionally constrained. The *match* is strong: UTAUT explains personal readiness through perceived usefulness, ease of use, social influence, and facilitating conditions; organizational readiness theory explains the institutional capacity and change readiness required for implementation; and configurational theory explains why barriers (regulatory absence, competency gaps, resistance, distrust) may combine rather than act in isolation. The framework is *parsimonious* because each theory addresses a distinct analytical layer – individual readiness, institutional readiness, and barrier configurations – without duplicating mechanisms. It is *applicable* because education managers translate national AI policy into institutional practice. It is *conceptually rigorous* and *testable* because each

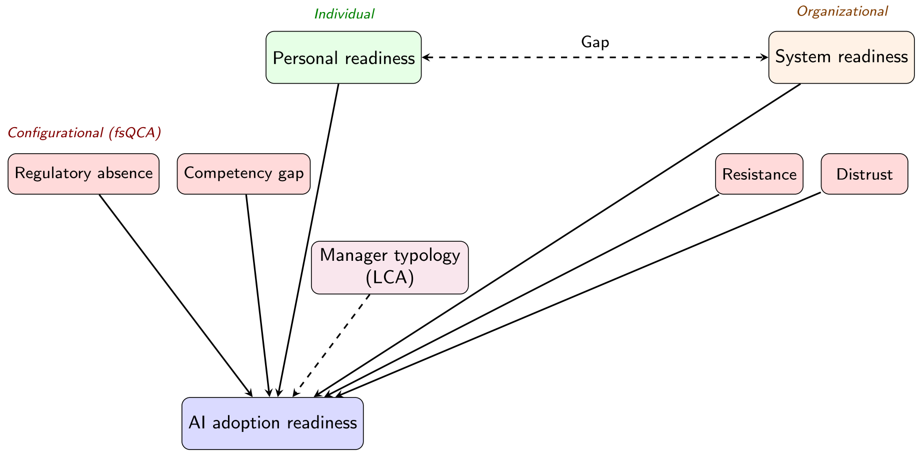

Fig. 1. Integrative theoretical framework for AI adoption readiness among education managers. Personal and system readiness represent individual and organizational dimensions (UTAUT and organizational readiness theory). Barriers are examined configurationally (fsQCA). Manager typology (LCA) is a classification (segmentation) layer that summarizes co-occurring readiness and barrier patterns; it is not tested as a statistical mediator.

element maps onto measurable readiness dimensions, barrier conditions, typologies, and hypotheses that can be examined through descriptive, person-centered, and set-theoretic analyses.

At the individual level, we draw on UTAUT (Venkatesh et al., 2003), which predicts technology adoption through performance expectancy, effort expectancy, social influence, and facilitating conditions. For education managers, personal readiness encompasses the first three constructs (perceived usefulness, perceived ease of use, and normative expectations), while system readiness aligns with facilitating conditions – the institutional infrastructure, policies, and resources that enable or constrain adoption. The personal–institutional readiness gap thus reflects the tension between individual motivation and organizational capacity.

Organizational readiness theory (Weiner, 2009) complements UTAUT by positing that adoption is not solely an individual decision but an organizational change process. Readiness for change comprises both psychological readiness (change commitment and change efficacy) and structural readiness (resource availability, policy clarity, and institutional support). Education managers occupy a unique dual role: their personal readiness shapes their individual adoption behavior, while their position as organizational leaders means their perceptions of system readiness influence institutional adoption decisions. Barriers to AI adoption – regulatory absence, competency gaps, resistance, and distrust – represent facets of organizational unreadiness.

Configurational theory (Ragin, 1987, 2008) provides the third lens, proposing that outcomes arise from specific combinations of conditions rather than from the additive effects of individual factors. This perspective suggests that: (a) the same barrier may have different effects depending on which other barriers co-occur (conjunctural causation); (b) different barrier combinations may lead to the same outcome (equifinality); and (c) some barriers may be necessary (always present when the outcome occurs) without being sufficient (their presence alone does not guarantee the outcome). We apply this logic through fsQCA to examine how barriers combine to produce low AI readiness.

Based on this framework, we derive the following hypotheses:

H1: Personal readiness for AI adoption will be significantly higher than system readiness, reflecting the personal–institutional gap.
H2: Distinct typologies of education managers will be identifiable based on their readiness and barrier profiles.
H3: Resistance to change may function as a necessary condition for low AI readiness, given its role in organizational change processes.
H4: Multiple barrier configurations will lead to low readiness (equifinality), rather than a single dominant pathway.

4. Methods

4.1. Study design and participants

This cross-sectional study employed a structured online survey administered in September 2025. The target population comprised education managers at all levels of the Ukrainian education system, including school principals, vice-principals, department heads of regional education administrations, and institutional administrators. Participants were recruited through regional education departments and professional associations using a combination of convenience and snowball sampling strategies. The final sample included $N = 395$ education managers across 23 of Ukraine's 24 administrative regions (excluding the temporarily occupied territories of Crimea and parts of Donetsk and Luhansk oblasts). The study was conducted under the ethical protocol of the National Academy of Educational Sciences of Ukraine (Protocol No. 04-25). All participants provided informed consent electronically before completing the survey.

4.2. Measures

The survey instrument comprised 47 variables organized into eight thematic blocks:

1. *Demographics.* Age, professional experience, institution type, settlement type, and region.
2. *AI readiness.* System readiness and personal readiness were measured using 5-point Likert scales (1 = strongly disagree, 5 = strongly agree) adapted from technology readiness instruments used in educational technology research (Davis, 1989; Venkatesh et al., 2003). System readiness assessed institutional capacity for AI adoption (infrastructure, policies, support), while personal readiness measured individual preparedness and willingness. Throughout, *AI readiness* is the umbrella term; *personal readiness* denotes a manager's individual willingness and preparedness to support AI, whereas *system readiness* denotes the manager's appraisal of institutional capacity to adopt AI. Each dimension was assessed with a single survey item (system readiness, Q7; personal readiness, Q25) and the two are therefore treated as separate single-item constructs rather than a combined readiness composite. Because the study's central finding concerns the *difference* between them, a composite would mask the very gap

Table 1
Psychometric properties of multi-item scales.

Scale	Items	Cronbach's α	Mean	SD
AI optimism	4	0.78	3.72	0.91
AI skepticism[a]	2	0.64	2.95	0.97

Note: N = 395. All items measured on 5-point Likert scales. [a]The AI skepticism scale shows modest reliability (α = 0.64) and should be interpreted with caution.

of interest. The two items are moderately correlated (Spearman $\rho = (.)39$, $p < (.)001$), indicating related but separable constructs. Single-item measurement of these dimensions is acknowledged as a limitation (Section 6.6).

3. *Barriers to AI adoption.* Four binary (yes/no) items assessed key barriers: digital competency gaps (self-reported insufficient digital skills for AI use), regulatory absence (lack of clear AI governance guidelines), resistance to change (psychological reluctance to adopt new technologies), and AI distrust (concerns about AI reliability and ethics).
4. *AI application potential.* Eight binary items assessed perceived AI potential across application areas: data analytics, document automation, quality monitoring, forecasting, communication, decision support, risk detection, and personalization.
5. *Psychological attitudes.* Multiple Likert-scale items assessed perceived AI accuracy, professional development value, life improvement potential, work improvement, and future use intentions. These items formed two coherent dimensions: AI optimism (work/life improvement, professional development) and AI skepticism (reliability concerns). Reliability: Cronbach's α = 0.78 for the optimism scale; the two-item AI skepticism scale showed only modest reliability (α = 0.64) and is interpreted with caution. We further distinguish *AI skepticism* – a Likert-scaled attitude about AI reliability – from *AI distrust*, a binary (yes/no) barrier item indicating distrust of AI within the pedagogical community (Block 3); the two are conceptually and operationally distinct.
6. *AI tool usage.* Respondents indicated which AI tools they had used from a list including ChatGPT, Gemini, Copilot, Grammarly, Canva, and others (binary: used/not used).
7. *Outcomes and institutional factors.* Ordinal and nominal items assessed perceived AI impact on education quality, willingness to delegate pedagogical decisions to AI, presence of AI-related initiatives within respondents' institutions, and perceived need for staff AI training. These items captured both anticipated outcomes of AI adoption and the institutional context shaping implementation decisions.
8. *Threat perception.* Two nominal items assessed managers' perceptions of risks associated with AI use by different stakeholders: threats arising from students' use of AI (e.g., academic dishonesty, reduced critical thinking, over-reliance) and threats arising from teachers' use of AI (e.g., deskilling, ethical concerns, loss of pedagogical autonomy). These items captured the risk dimension that complements the application potential and psychological attitude blocks.

The instrument was developed and administered in Ukrainian. The English version reproduced in Appendix Table 13 was produced by bilingual team members and verified through back-translation, with discrepancies reconciled by consensus; the English wording was used for reporting only, not for separate data collection.

Table 1 presents the psychometric properties of the multi-item scales.

4.3. Analytical strategy

Analysis proceeded in four phases, integrating variable-centered, person-centered, and configurational approaches:

Phase 1: *Descriptive analysis.* Frequencies, means, standard deviations, bivariate correlations (Spearman's ρ), and effect sizes (Cohen's d, Cramér's V). Readiness gap quantification and barrier prevalence with 95% confidence intervals.

Phase 2: *Latent Class Analysis.* Gaussian Mixture Model-based LCA to identify manager typologies, with optimal class selection via BIC minimization (Collins & Lanza, 2010; Nylund et al., 2007). Class range tested: 2–6 classes. Model fit was assessed using BIC, AIC, entropy, and silhouette score. Bootstrap stability analysis (100 resamples) evaluated classification reproducibility using the Adjusted Rand Index (ARI). Class profiles were interpreted and labeled based on indicator variable patterns.

Phase 3: *Fuzzy-set Qualitative Comparative Analysis.* Calibration followed Ragin's direct method (Ragin, 2008; Schneider & Wagemann, 2012). The four barrier conditions are dichotomous (present/absent) and were entered as crisp sets ($\{0, 1\}$). The outcome, low AI readiness, was the set-theoretic negation of personal readiness calibrated with anchors at 2 (full non-membership), 3 (crossover), and 4 (full membership) – the substantive disagree/neutral/agree points of the 5-point scale. Empirical quartiles were inspected but were degenerate for these discrete items (e.g., the 25th and 50th percentiles coincided), so theoretically anchored thresholds were preferred for transparency and reproducibility. Necessity was assessed for each condition (consistency $\geq$ 0.90) and sufficiency via truth-table construction across all 2^4 barrier configurations (consistency $\geq$ 0.80); all cases were retained (frequency threshold = 1).

Phase 4: *Exploratory structural analysis.* We attempted confirmatory factor analysis and structural equation modeling (SEM) to examine relationships between attitudes, barriers, and readiness. However, the small sample size (N = 395) relative to the number of measured variables and the measurement model limitations (limited indicators per latent construct) resulted in convergence difficulties. We therefore report exploratory correlation patterns and bivariate associations, treating structural inference as a limitation to be addressed in future research with larger samples.

All analyses were conducted in Python 3.11 with R integration (via rpy2) for lavaan/blavaan SEM analyses. Statistical significance was set at $\alpha = (.)05$; effect sizes are reported throughout following Cohen (1988). Bootstrap confidence intervals used the BCa method with 5000 iterations.

4.4. Sample size adequacy and measurement validity

Sample size adequacy was evaluated against each analytical purpose rather than a single universal rule (Lim, 2025). The sample of 395 education managers is adequate for descriptive estimation and exploratory pattern detection; the six-class typology, however, is interpreted cautiously given the small size of some classes and weak bootstrap stability (Section 5.6), and the configurational analysis is likewise treated as exploratory rather than confirmatory. Measurement validity was considered in a staged manner (Lim, 2024; Lim, Khatri et al., 2026). *Content* validity concerns whether the items capture readiness, barriers, application potential, and attitudes; *face* validity concerns whether the Ukrainian items were clear to education managers; *convergent* validity concerns whether related attitude items cohere empirically (e.g., the AI optimism scale, α = 0.78); *discriminant* validity concerns whether optimism, skepticism, personal readiness, and system readiness are sufficiently distinct; and *nomological* validity concerns whether readiness relates to barriers in theoretically expected directions (Appendix Table 12). *Predictive* validity is limited in this cross-sectional design and is reserved for future longitudinal work linking readiness profiles to actual AI implementation outcomes.

Table 2
AI readiness score statistics (N = 395).

Variable	Mean	SD	Median	Top-2 box (%)
System readiness	3.15	0.93	3	32.9
Personal readiness	3.83	0.96	4	67.3

Note: Measured on 5-point Likert scales (1 = strongly disagree, 5 = strongly agree). Top-2 box = percentage scoring 4 or 5.

5. Results

5.1. Sample characteristics

The sample comprised 395 education managers (Table 2). Regional representation was led by Odesa (18.7%), Kirovohrad (10.1%), and Dnipro (8.6%). Kyiv City contributed 8.1% of respondents. Fig. 2 displays the geographic distribution across Ukrainian regions.

5.2. Personal–institutional readiness gap

A significant gap emerged between personal readiness (M = 3.83, SD = 0.96) and system readiness (M = 3.15, SD = 0.93). Personal readiness showed 67.3% in the top-2 box (scores of 4 or 5), compared to only 32.9% for system readiness. A Wilcoxon signed-rank test for paired samples confirmed that personal readiness significantly exceeded system readiness (W = 3538, p < (.)001, rank-biserial r = 0.77; n = 395). This 0.68-point mean difference (d = 0.73, large effect) represents a substantial discrepancy between individual preparedness and perceived institutional capacity, supporting H1. Fig. 3 illustrates the distribution of readiness scores.

5.3. Barrier prevalence

Table 3 presents barrier prevalence rates. Regulatory absence was the most frequently cited barrier (58.5%, 95% CI [53.6%, 63.2%]), followed by digital competency gaps (53.9%, 95% CI [49.0%, 58.8%]). AI distrust affected 44.8% of respondents, while resistance to change was reported by 24.6%. The prevalence hierarchy – regulatory > competency > distrust > resistance – suggests that systemic and skill-related barriers outweigh attitudinal ones (Fig. 4).

5.4. AI tool adoption

ChatGPT demonstrated dominant market penetration at 69.4% (95% CI [64.7%, 73.7%]) adoption. This was followed by Gemini and Canva (see Fig. 5 for the complete distribution). The high ChatGPT adoption

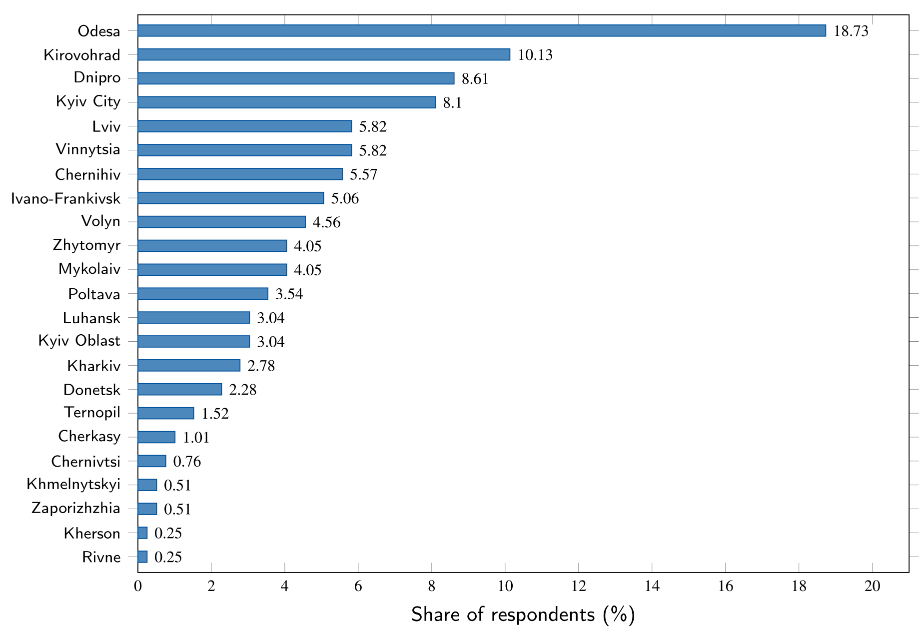

Fig. 2. Geographic distribution of education manager respondents across Ukrainian regions. The sample represents 23 of Ukraine's administrative regions, with the largest concentrations in Odesa (18.7%), Kirovohrad (10.1%), and Dnipro (8.6%).

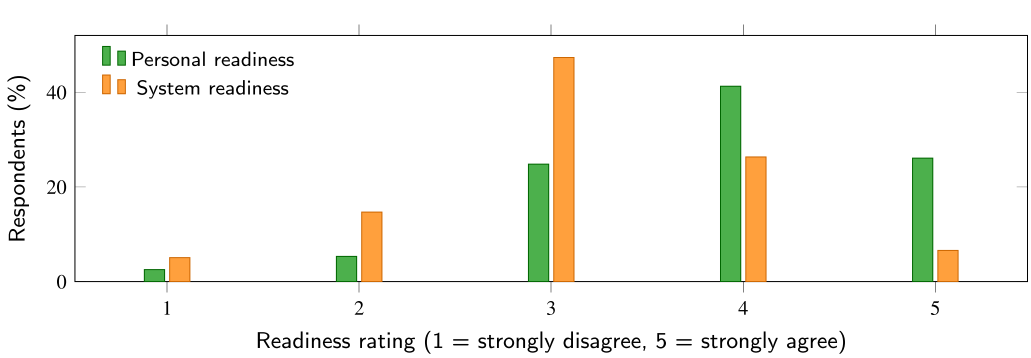

Fig. 3. Distribution of readiness ratings among education managers. Personal readiness scores are notably higher and more positively skewed than system readiness scores, indicating that individuals feel more prepared for AI adoption than they perceive their institutions to be.

Table 3
Barrier prevalence among education managers.

Barrier	Prevalence (%)	95% CI lower	95% CI upper
Regulatory absence	58.5	53.6	63.2
Digital competency gaps	53.9	49.0	58.8
AI distrust	44.8	40.0	49.7
Resistance to change	24.6	20.6	29.0

Note: CI = confidence interval. N = 395. Binary items (yes/no).

rate suggests that education managers are primarily familiar with conversational AI interfaces rather than specialized educational AI tools.

5.5. AI application potential

Managers perceived the greatest AI potential for data analytics (61.0%), document automation (58.0%), and quality monitoring (53.4%). Lower perceived potential was reported for personalization (29.4%) and risk detection (34.9%). Table 4 presents the full range of perceived AI applications.

5.6. Latent class analysis

LCA identified six provisional manager classes, supporting H2. Across the 2–6 class range, BIC decreased monotonically (Table 5; Fig. 6) without reaching a clear minimum, so the six-class solution is best understood as the most granular interpretable partition examined rather than a BIC-identified optimum; solutions with more classes were not pursued because they produced substantively redundant profiles. The uniformly high entropy (1.00) reflects the near-deterministic component separation that Gaussian-mixture estimation yields with largely binary indicators and should not be read as perfect classification certainty. Bootstrap stability analysis indicated poor classification stability (mean ARI = 0.385, 95% CI [0.184, 0.702]), so the typology is interpreted throughout as exploratory and provisional, requiring confirmation with larger samples and categorical-indicator latent-class models (Table 6).

Table 7 and Fig. 7 present the class profiles. Classes differed in system readiness and all barrier variables, producing six interpretable typologies:

Table 4
Perceived AI application potential among education managers.

Application area	Prevalence (%)	95% CI lower	95% CI upper
Data analytics	61.0	56.1	65.7
Document automation	58.0	53.1	62.7
Quality monitoring	53.4	48.5	58.3
Forecasting	41.8	37.0	46.7
Communication	38.2	33.6	43.1
Decision support	37.0	32.3	41.8
Risk detection	34.9	30.4	39.8
Personalization	29.4	25.1	34.0

Note: CI = confidence interval. N = 395. Respondents could select multiple applications.

Table 5
LCA model comparison across class solutions.

N classes	BIC	AIC	Log-likelihood	Entropy	Silhouette
2	3977.37	3623.25	−1722.62	1.00	0.158
3	113.45	−419.72	343.86	1.00	0.160
4	−1906.72	−2618.94	1488.47	1.00	0.139
5	−3690.61	−4581.88	2514.94	1.00	0.148
6	**−4851.91**	**−5922.23**	**3230.12**	**1.00**	**0.152**

Note: Bold indicates the selected model. BIC = Bayesian Information Criterion; AIC = Akaike Information Criterion. Lower BIC values indicate a better fit.

Class 1 *(15.7%): Change-resistant automators* exhibited universal resistance to change combined with high digital competency barriers, yet showed strong interest in document automation (100%). These managers recognize AI potential for routine tasks but face both psychological and skill barriers.

Class 2 *(18.2%): Regulation-blocked* faced universal regulatory barriers (100%) with no competency deficits, moderate readiness, and no interest in personalization. These managers are capable but constrained by the absence of governance frameworks.

Class 3 *(25.6%): Competency-constrained* (largest class) showed universally high digital competency barriers (100%) with the lowest AI distrust, suggesting willingness but lacking

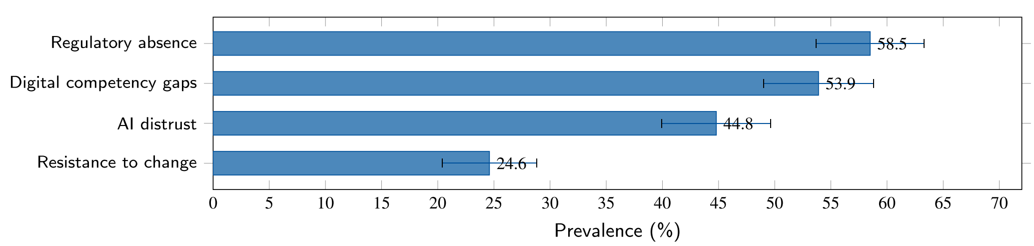

Fig. 4. Barrier prevalence among education managers (bars: %; whiskers: 95% Wilson confidence intervals). Regulatory absence and digital competency gaps were the most frequently cited barriers to AI adoption.

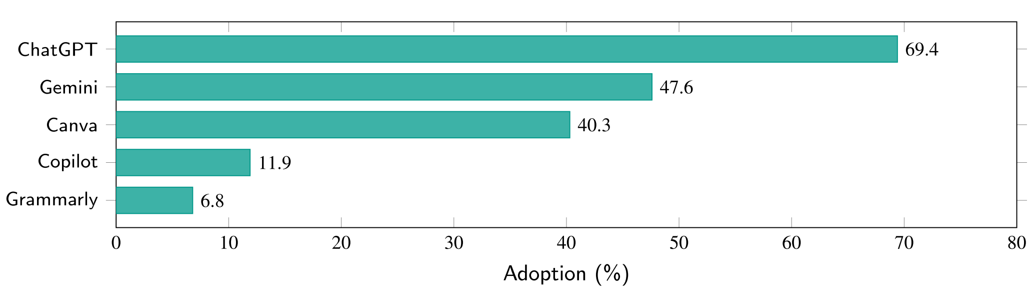

Fig. 5. AI tool usage rates among education managers. ChatGPT dominates with 69.4% adoption, followed by other generative AI and productivity tools. The high adoption of conversational AI suggests familiarity with natural language interfaces.

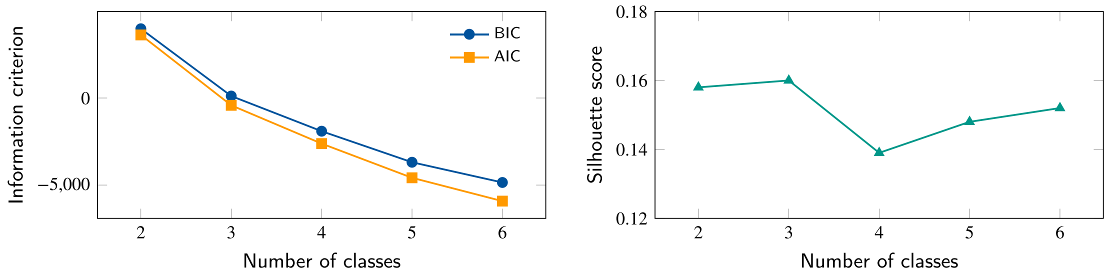

Fig. 6. Model-selection diagnostics for the LCA. BIC and AIC (left) decrease monotonically across the 2–6 class range without a clear minimum, so the six-class solution is the most granular interpretable partition examined rather than a BIC-identified optimum. Silhouette scores (right) remain low (≈ 0.15) throughout. The typology is therefore treated as exploratory.

Table 6
LCA bootstrap stability analysis.

Metric	Value
Number of bootstrap samples	100
Number of classes	6
Mean Adjusted Rand Index (ARI)	0.385
Standard deviation (ARI)	0.143
95% CI lower bound	0.184
95% CI upper bound	0.702
Minimum ARI	0.113
Maximum ARI	0.781
Stability interpretation	Poor

Note: ARI values range from −1 to 1, with 1 indicating perfect agreement. Values > 0.65 suggest good stability. The poor stability suggests that the 6-class solution should be treated as exploratory.

Table 7
Latent class profiles of education managers.

Variable	Class 1 15.7%	Class 2 18.2%	Class 3 25.6%	Class 4 10.6%	Class 5 8.9%	Class 6 21.0%
System readiness	3.23	3.17	2.89	3.52	2.74	3.36
Digital competency barrier	0.65	0.00	1.00	0.00	0.69	0.58
Regulatory barrier	0.50	1.00	0.55	0.00	0.43	0.69
Resistance to change	1.00	0.00	0.00	0.00	1.00	0.00
AI distrust	0.60	0.39	0.34	0.74	0.43	0.39
Document automation potential	1.00	0.53	0.59	0.50	0.00	0.58
Personalization potential	0.39	0.00	0.00	0.00	0.26	1.00

Note: Values are means. Binary barriers coded 0 = absent, 1 = present. Class labels: 1 = Change-resistant automators; 2 = Regulation-blocked; 3 = Competency-constrained; 4 = Barrier-free skeptics; 5 = Doubly-constrained; 6 = Personalization champions.

skills. This class represents the primary target for training interventions.

Class 4 *(10.6%): Barrier-free skeptics* demonstrated the highest readiness (3.52) with no barriers, yet paradoxically reported the highest AI distrust (74%). These informed skeptics require evidence-based trust-building rather than training.

Class 5 *(8.9%): Doubly-constrained* (smallest class) exhibited the lowest readiness (2.74) with both resistance to change (100%) and competency barriers, and no interest in document automation. This class requires intensive, multi-faceted support.

Class 6 *(21.0%): Personalization champions* showed the highest interest in personalization (100%) with moderate barriers and above-average readiness. These innovation-oriented managers could serve as peer mentors.

Fig. 8 provides a visual comparison of the class profiles across key indicator variables.

5.7. Fuzzy-set qualitative comparative analysis

Necessity analysis (Table 8) found that *no* barrier reached the 0.90 consistency threshold for necessity. Low system readiness was the strongest candidate (consistency = 0.84) but still fell short, and resistance to change – contrary to the expectation in H3 – showed low necessity (consistency = 0.24): the large majority of managers with low AI readiness did not report resistance to change. H3 is therefore *not* supported.

Sufficiency analysis examined all $2^4 = 16$ configurations of the four barriers against the low-readiness outcome (Table 9). No configuration met the 0.80 consistency threshold; the highest consistency was only 0.33 (competency, regulatory, and distrust barriers jointly present). H4 is therefore *not* supported. This null result should not be read as equifinality, which would require multiple *sufficient* pathways. The defensible interpretation is that, under the present calibration and the four measured barriers, low AI readiness is not consistently produced by any single barrier or barrier combination – it appears diffusely rather than configurationally determined. This redirects explanatory weight to the personal–institutional readiness gap and the manager typologies. The null configurational result may also reflect the modest number of conditions examined; richer condition sets (e.g., institutional type, regional development level, leadership tenure) could reveal structure that the present four-barrier design cannot detect.

5.8. Psychological attitudes

Fig. 9 presents the correlation matrix for psychological attitude variables. The structure reveals moderate positive associations among optimistic AI attitudes (work improvement, life improvement, professional development), suggesting a coherent positive orientation factor. Reliability doubts show weaker associations with other variables, indicating a partially independent skepticism dimension. This two-dimensional structure – optimism versus skepticism – aligns with the psychological readiness component of our theoretical framework.

5.9. Policy gap analysis

Because the readiness indicators (5-point Likert) and the competency indicator (a binary barrier) lie on different scales, gaps are computed on a common 0–1 metric: each indicator is divided by its scale maximum and compared against a target of 0.80 (the "agree"/4 level). On this common metric (Table 10), digital-competency adequacy shows the largest shortfall (42.4%), followed by system readiness (21.3%), while personal readiness is close to the target (4.2%). The previously reported 86.5% competency gap was an artifact of comparing a 0–1 barrier proportion against a 5-point target of 4.0 and is not retained. Consistent with the manager typologies, the competency shortfall is concentrated in the Competency-constrained and Doubly-constrained classes (Classes 3 and 5), which together define the primary training audience, whereas the system-readiness shortfall reflects institutional constraints shared across classes.

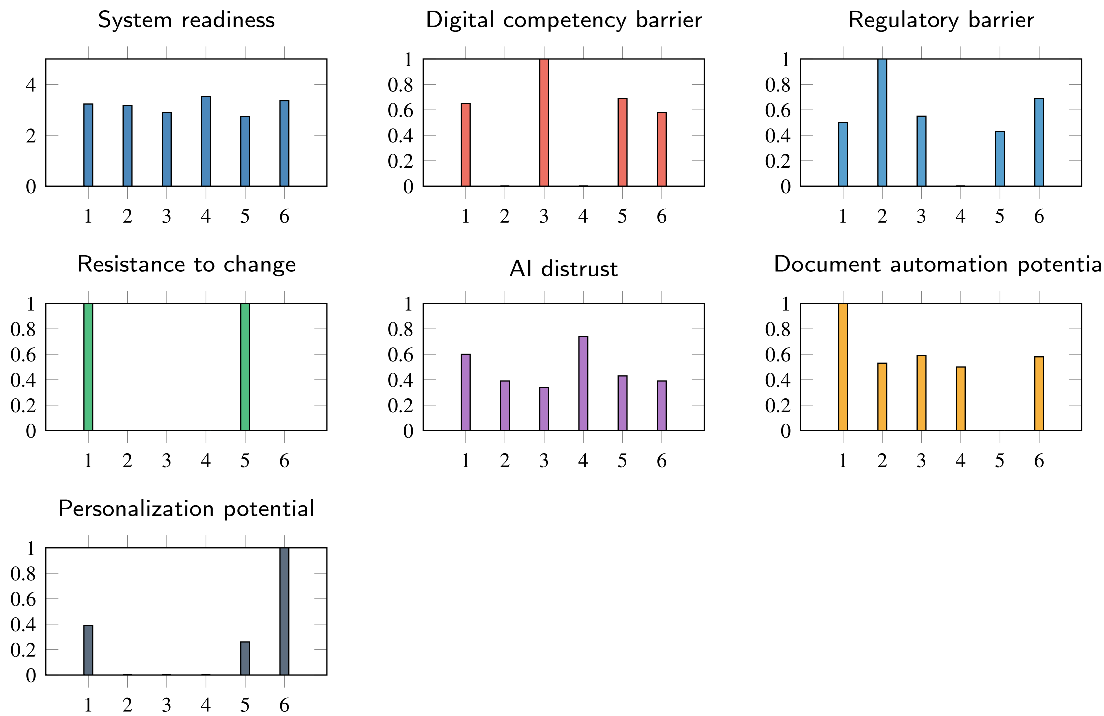

Fig. 7. Latent class profile visualization showing mean values for each indicator variable across the six identified manager classes. Each subplot represents a different variable, with bars indicating class-specific means.

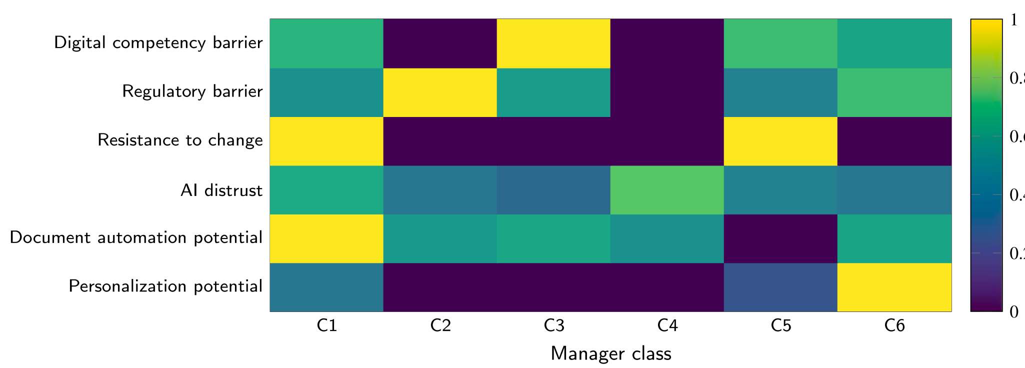

Fig. 8. Comparison of latent class profiles across key indicator variables. The visualization highlights the distinctive patterns that differentiate each manager typology, particularly the contrast between Competency-constrained (Class 3) and Barrier-free skeptics (Class 4).

Table 8
FsQCA necessity analysis results.

Condition	Consistency	Coverage	Necessary?
Low system readiness	0.838	0.391	No
Digital competency barrier	0.600	0.225	No
Regulatory absence	0.537	0.186	No
AI distrust	0.494	0.223	No
Resistance to change	0.237	0.196	No

Note: A condition is considered necessary if consistency ≥ 0.90 (Ragin, 2008; Schneider & Wagemann, 2012).

6. Discussion

6.1. Key findings

This study provides one of the first systematic analyses of AI adoption determinants among Ukrainian education managers. Four principal findings emerge, each corresponding to our hypotheses; two hypotheses are supported and two are not.

First, the substantial personal–institutional readiness gap confirms H1: individual managers are more prepared for AI adoption than their institutions can support. This gap reflects a structural deficit – managers who believe in AI's potential find themselves in organizations that lack the infrastructure, policies, and technical support to act on that belief. This finding is consistent with Weiner (2009)'s distinction between psychological and structural readiness for change. The direction of the gap is plausibly shaped by the Ukrainian context: a post-Soviet administrative legacy of centralized, compliance-oriented governance concentrates decision authority and resources above the institutional level, so individual managers can develop personal readiness faster than their institutions acquire infrastructure, budgets, and AI governance. Wartime conditions sharpen this asymmetry, raising the urgency and salience of digital tools (lifting personal readiness) while damaging infrastructure and diverting resources (depressing institutional readiness).

Second, the identification of six distinct manager typologies via LCA supports H2 and reveals that education managers are not a homogeneous group. The typology ranges from the Competency-constrained – willing but lacking skills – to the Barrier-free skeptics – capable but

Table 9
fsQCA truth table: barrier configurations and their consistency with low AI readiness.

Digital competency	Regulatory absence	Resistance to change	AI distrust	*N*	Consistency
1	1	0	1	29	0.328
1	0	1	0	16	0.281
1	0	0	0	42	0.250
0	0	0	1	37	0.243
1	0	1	1	15	0.233
1	0	0	1	19	0.211
1	1	1	1	22	0.205
0	0	1	0	15	0.200
1	1	0	0	59	0.178
0	1	0	1	40	0.175
0	1	1	0	3	0.167
0	1	1	1	10	0.150
0	1	0	0	57	0.149
0	0	0	0	15	0.133
0	0	1	1	5	0.100
1	1	1	0	11	0.091

Note: 1 = barrier present, 0 = absent. *N* = managers with that barrier pattern (total 395). Consistency = mean membership in the low-AI-readiness outcome among those managers; sufficiency requires consistency ≥ 0.80. No configuration meets this threshold.

distrustful. This heterogeneity has direct implications for intervention design: one-size-fits-all training programs will underserve some classes while overserve others.

Third, contrary to H3, resistance to change was *not* a necessary condition for low AI readiness (consistency = 0.24): the majority of low-readiness managers did not report resistance, and no other barrier met the necessity threshold. The expectation that resistance gates low readiness – plausible under organizational change theory (Armenakis et al., 1993) – is not borne out in these data, indicating that low readiness arises through routes other than overt attitudinal resistance.

Fourth, contrary to H4, no barrier configuration was sufficient for low AI readiness (highest configuration consistency = 0.33). This is not evidence of equifinality, which would require multiple *sufficient* pathways; rather, low readiness is not consistently produced by any combination of the four measured barriers. Explanatory weight therefore rests on the personal–institutional gap and the manager typologies rather than on a configurational barrier structure, and future configurational work will need richer condition sets to detect any latent structure.

Table 10
Readiness gap analysis.

Area	Current	Target	Gap	Priority
Digital competency (adequacy)	0.46	0.80	0.34 (42.4%)	High
System readiness	0.63	0.80	0.17 (21.3%)	Medium
Personal readiness	0.77	0.80	0.03 (4.2%)	Low

Note: All indicators are rescaled to a common 0–1 metric (raw value / scale maximum); competency adequacy = 1− barrier prevalence. Target = 0.80 (the "agree"/4 level on the 5-point scale). Gap = Target − Current; percentage gap relative to target.

6.2. Theoretical implications

These findings extend technology adoption theory in educational leadership contexts in three ways. First, the personal–institutional gap demonstrates that individual-level TAM/UTAUT predictors are insufficient without organizational capacity considerations (Davis, 1989; Venkatesh et al., 2003). The personal readiness dimension (analogous to performance expectancy) is high, but facilitating conditions are inadequate – a mismatch that TAM alone cannot explain.

Second, the configurational findings caution against treating any single barrier – including resistance to change – as a prerequisite for low readiness. Although prior research identifies resistance as a barrier (Cheah et al., 2025; Cheng & Wang, 2023), our analysis does not establish it as necessary or sufficient. This suggests that, for education managers in this context, low readiness is better explained by the structural personal–institutional mismatch than by attitudinal resistance, refining how organizational readiness theory (Weiner, 2009) applies to AI adoption.

Third, the absence of necessary or sufficient barrier conditions indicates that low AI readiness is diffusely determined rather than driven by specific barrier configurations. For theory, this implies that barrier-centric accounts – whether variable-centered or configurational – may be insufficient when the dominant signal is a structural gap between individual and institutional readiness; integrating readiness-gap constructs into adoption models may be more productive than enumerating barrier combinations.

6.3. Implications for educational theory and pedagogy

Although the analysis centers on managers, its implications are fundamentally pedagogical, because managers shape the conditions under which teachers and learners encounter AI. First, the application

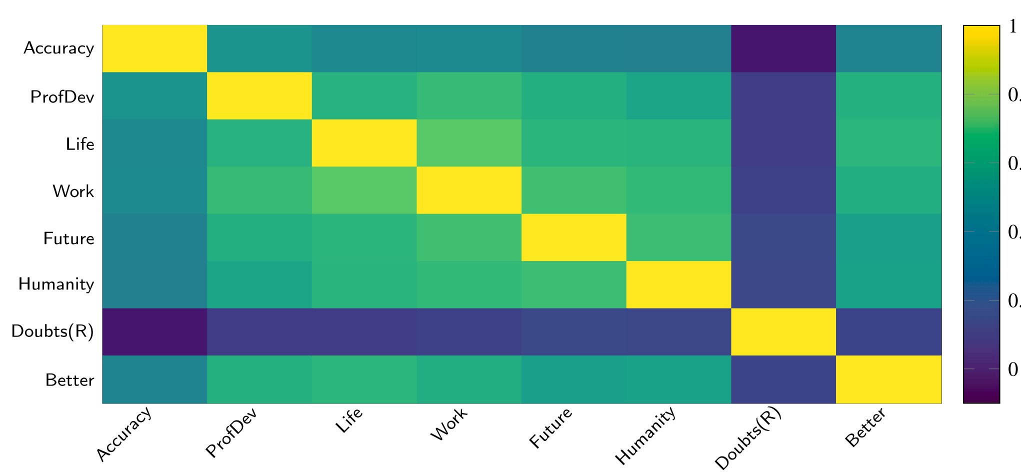

Fig. 9. Correlation matrix for psychological attitude variables toward AI. Warmer colors indicate stronger positive correlations. The pattern suggests two underlying dimensions: general AI optimism (upper-left cluster) and reliability concerns (partially independent). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

areas managers prioritized – educational data analytics (61.0%), document automation, and quality monitoring – locate AI within *data-driven decision-making* and *learning analytics*, where managerial readiness is a precondition for the institutional adoption of analytics that ultimately inform teaching and assessment. Second, the personal–institutional gap is a leadership-for-learning problem: technological-pedagogical leadership presumes that leaders' own readiness and their provision of facilitating conditions jointly determine whether pedagogical innovation diffuses; our results show the institutional component lagging behind the individual one, predicting uneven classroom uptake even where managers are personally willing. Third, the typology implies differentiated professional learning rather than uniform training – competency-constrained managers need data- and AI-literacy capability building, regulation-blocked managers need governance scaffolding, and personalization-oriented managers can seed peer-learning networks. Framing AI adoption as pedagogical innovation, rather than mere administrative automation, positions education managers as mediators between AI policy and classroom practice and clarifies why institutional readiness – not individual acceptance alone – is decisive for educational outcomes.

6.4. Comparison with existing literature

Our findings are consistent with and extend recent CAEAI research. The regulatory barrier dominance echoes Cheng and Wang (2023), who found that policy guidance is a primary enabler for AI integration. The competency gap parallels Kim and Kwon (2023) and Ovcharuk et al. (2025), who documented digital competence deficits among educators. ChatGPT's dominance among available tools is consistent with Cheah et al. (2025) observation of generative AI concentration among teachers.

However, our person-centered findings add a dimension absent from these studies. While López-Costa et al. (2025) used PLS-SEM to model average effects, and Masry Herzallah and Makaldy (2025) examined self-efficacy as a continuous predictor, our LCA reveals that these "average" relationships mask substantial heterogeneity. The Competency-constrained and Barrier-free skeptics classes would respond to opposite interventions, a distinction invisible to variable-centered approaches.

6.5. Practical implications

Because the latent classes are exploratory and only modestly stable (Section 5.6), the typology-differentiated recommendations below should be read as provisional hypotheses for intervention design rather than fixed policy segments. The regulatory and institutional capacity-building priorities, which rest on the more robust prevalence and gap findings, are firmer than the class-specific tailoring, which should be piloted and validated before large-scale rollout. The findings suggest four priority levels of policy intervention, differentiated by manager typology:

1. **Regulatory framework development (high priority).** The regulatory barrier prevalence and the Regulation-blocked class indicate that clear AI governance guidelines – addressing data protection, algorithmic transparency, and ethical use – are the most urgent policy need. This requires ministerial action rather than institutional initiative.
2. **Differentiated training programs (high priority).** Given the heterogeneity revealed by LCA, one-size-fits-all training is suboptimal:
   - *Competency-constrained (Class 3, 25.6%)*: Intensive digital skills training
   - *Regulation-blocked (Class 2, 18.2%)*: Policy advocacy and compliance guidance
   - *Change-resistant classes (1 and 5, 24.6%)*: Change management and psychological support
   - *Barrier-free skeptics (Class 4, 10.6%)*: Evidence-based trust-building through peer testimony and demonstration projects
3. **Institutional capacity building (medium priority).** Closing the personal–institutional gap requires investment in infrastructure, technical support, and organizational change processes rather than individual training alone. System readiness gaps (21.3%) address structural barriers that training cannot resolve.
4. **Peer learning networks (low priority but high impact).** Personalization champions (Class 6, 21.0%) can be leveraged as innovation champions and mentors within regional peer networks, given their advanced vision for AI applications and above-average readiness.

6.6. Limitations

Several limitations warrant consideration. First, the cross-sectional design precludes causal inference; longitudinal research could track readiness trajectories and test whether the identified typologies are stable over time. Second, the measures are self-reported and may be subject to social desirability bias – managers may overstate personal readiness and willingness given the policy salience of AI and their leadership role. Self-report also entails subjective interpretation: "AI," "readiness," and individual barriers may be construed differently across respondents, adding measurement noise that anonymous administration mitigates but cannot eliminate. Several core constructs, moreover, were measured with single items – personal and system readiness with one item each, and the four barriers as single binary (yes/no) indicators – which cannot capture the facets of complex constructs or support internal-consistency estimation; multi-item, validated scales are needed in future work (Section 4.4).

Third, the LCA stability analysis yielded poor results (mean ARI = 0.385), indicating that the 6-class solution should be treated as exploratory. The instability may reflect the relatively small sample size for LCA with eight indicator variables, and future research with larger samples is needed to confirm the typology. We note, however, that the theoretical interpretability of the six classes and their consistency with organizational change theory provide some confidence in their substantive meaning.

Fourth, the fsQCA found no necessary condition and no sufficient barrier configuration for low AI readiness. We interpret this as low readiness being diffusely rather than configurationally determined, but it may also reflect the modest number of conditions examined (four binary barriers) and the calibration strategy. Future research should include additional, finer-grained conditions (e.g., institutional type, regional development level, leadership tenure) and explore alternative calibrations.

Fifth, confirmatory factor analysis and structural equation modeling could not be successfully estimated due to the small sample size relative to the number of measured variables, preventing the examination of latent variable relationships. Future studies with larger samples should revisit the structural relationships between attitudes, barriers, and readiness.

Sixth, the sample, while covering 23 regions, may not fully represent all educational contexts, particularly smaller rural institutions. Finally, the wartime context may have affected response patterns in ways not captured by our measures – heightened digitalization urgency may inflate readiness reports, while resource constraints may depress them.

6.7. Future research directions

Future research should examine how manager typologies relate to actual AI implementation outcomes over time, using longitudinal designs that can establish causal pathways. Qualitative research could deepen understanding of barrier mechanisms and successful adoption strategies from the manager's perspective. Comparative research across post-Soviet and Western European contexts would illuminate the role of institutional legacies in shaping adoption patterns. Studies with larger samples should confirm the LCA typology and enable robust structural modeling. Finally, intervention studies testing typology-differentiated training programs would provide the strongest evidence for the practical utility of the person-centered approach.

7. Conclusion

This study demonstrates that Ukrainian education managers exhibit substantial personal readiness for AI adoption but face institutional and regulatory constraints that create a significant personal–institutional readiness gap. The identification of six provisional manager typologies – ranging from Competency-constrained to Barrier-free skeptics – reveals heterogeneity that enables targeted intervention strategies. Configurational analysis found no barrier to be necessary or sufficient for low readiness, indicating that low readiness is diffusely determined and that the personal–institutional gap, rather than any single barrier, is the central lever for policy.

Policy priorities should focus on regulatory framework development as the most urgent need, followed by differentiated capacity building approaches tailored to manager profiles, and leveraging personalization champions as peer mentors for scaling AI adoption. The personal–institutional readiness gap indicates that systemic capacity building – infrastructure, technical support, and organizational change processes – must complement individual training programs. These findings contribute to both technology adoption theory and educational policy practice, demonstrating that understanding manager typologies and barrier configurations yields insights unavailable from additive models.

CRediT authorship contribution statement

Vasyl G. Kremen: Supervision, Conceptualization. **Oleh M. Spirin:** Writing – original draft, Supervision, Methodology, Conceptualization. **Oleksandr I. Liashenko:** Investigation, Data curation, Conceptualization. **Svitlana H. Lytvynova:** Writing – review & editing, Methodology, Investigation. **Yurii I. Malovanyi:** Writing – review & editing, Investigation. **Olha P. Pinchuk:** Writing – original draft, Formal analysis, Data curation. **Oleksandra M. Sokolyuk:** Writing – review & editing, Investigation. **Serhiy O. Semerikov:** Writing – review & editing, Writing – original draft, Visualization, Software.

Ethics statement

The study was approved by the Ethics Committee of the Institute for Digitalisation of Education of the NAES of Ukraine (Protocol No.04-25). Informed consent was obtained electronically from all participants before the survey, and their privacy rights were strictly observed: participation was voluntary and anonymous, no directly identifying information was collected, and responses were stored and analyzed only in aggregate. Given the wartime context, additional safeguards were applied to protect participants in conflict-affected regions: no data on precise location, institution name, or other potentially sensitive information were collected; regional identifiers were retained only at the oblast level; participation imposed no obligation and any item could be skipped; and no data were collected from the temporarily occupied territories.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used generative AI tools in the following ways:

1. Analytical pipeline development: Claude (Anthropic, model Claude Opus 4) was used to assist in writing Python code for data analysis, including latent class analysis, fuzzy-set QCA (fsQCA) calibration, and bootstrap regression procedures. All statistical outputs were independently verified by the authors against the raw data.
2. Manuscript preparation: Claude was used to assist with drafting and revising sections of the manuscript, including literature review synthesis, restructuring of the discussion, and improving clarity of expression. The authors reviewed, edited, and approved all AI-generated text, taking full responsibility for the final content.
3. Translation assistance: Claude was used to assist with translating survey items from Ukrainian to English for the instrument appendix. Translations were verified against the original instrument by bilingual team members.

The authors affirm that all substantive intellectual contributions–including study design, interpretation of results, theoretical framing, and policy recommendations–are their own. AI tools were employed as productivity aids under direct human supervision and editorial control.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary tables

A.1. Detailed latent class profiles

Table 11 presents the complete latent class profiles with means and standard deviations for all indicator variables.

Table 11
Detailed latent class profiles with standard deviations.

Variable	Class 1 ($n=62$) 15.7%	Class 2 ($n=72$) 18.2%	Class 3 ($n=101$) 25.6%	Class 4 ($n=42$) 10.6%	Class 5 ($n=35$) 8.9%	Class 6 ($n=83$) 21.0%
System readiness	3.23 (1.01)	3.17 (0.82)	2.89 (0.80)	3.52 (0.83)	2.74 (1.07)	3.36 (0.94)
Digital competency barrier	0.65 (0.48)	0.00 (0.00)	1.00 (0.00)	0.00 (0.00)	0.69 (0.47)	0.58 (0.50)
Regulatory barrier	0.50 (0.50)	1.00 (0.00)	0.55 (0.50)	0.00 (0.00)	0.43 (0.50)	0.69 (0.47)
Resistance to change	1.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	1.00 (0.00)	0.00 (0.00)
AI distrust	0.60 (0.49)	0.39 (0.49)	0.34 (0.47)	0.74 (0.45)	0.43 (0.50)	0.39 (0.49)
Document automation	1.00 (0.00)	0.53 (0.50)	0.59 (0.49)	0.50 (0.51)	0.00 (0.00)	0.58 (0.50)
Data analytics	0.65 (0.48)	0.64 (0.48)	0.53 (0.50)	0.57 (0.50)	0.57 (0.50)	0.69 (0.47)
Personalization	0.39 (0.49)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.26 (0.44)	1.00 (0.00)

Note: Values are means with standard deviations in parentheses. Binary variables are coded as 0 = absent, 1 = present. Class labels: 1 = Change-resistant automators; 2 = Regulation-blocked; 3 = Competency-constrained; 4 = Barrier-free skeptics; 5 = Doubly-constrained; 6 = Personalization champions.

A.2. Variable correlation matrix

Table 12 presents the Spearman correlation coefficients among key study variables.

Table 12
Spearman correlation matrix for key variables.

	1	2	3	4	5	6
1. System readiness	–					
2. Digital competency barrier	−.223***	–				
3. Regulatory barrier	−.163**	−.037	–			
4. Resistance to change	−.050	.138**	−.128*	–		
5. AI distrust	(.)005	−.107*	−.026	.101*	–	
6. Personal readiness	.390***	−.004	.024	.012	−.052	–

Note: * $p <$ (.)05, ** $p <$ (.)01, *** $p <$ (.)001. $N = 395$.

A.3. Survey instrument items

Table 13 lists the survey items organized by thematic block. The original instrument was administered in Ukrainian; English translations are provided below. The full Ukrainian-language instrument is available from the corresponding author upon request.

Table 13
Survey instrument items (English translation).

Code	Type	Item (English translation)
Block 1: Demographics		
REGION	Nominal	Region of employment
SETTLE	Binary	Settlement type (Urban / Rural)
GENDER	Binary	Gender
AGE	Ordinal	Age group
ROLE	Nominal	Management role (Director, Deputy, Specialist, etc.)
Block 2: Readiness		
Q7	Likert 1–5	How do you rate the readiness of Ukraine's education system to implement AI technologies?
Q25	Likert 1–5	How personally ready are you to support and implement AI technologies in your professional activity?
Q28	Ordinal	How do you rate the readiness of teaching staff to use AI? (Low/Medium/High/Hard to assess)
Q29	Ordinal	How do you rate the readiness of your institution to use AI? (Low/Medium/High/Hard to assess)
Block 3: Barriers (binary, select all that apply)		
BAR1	Binary	Insufficient digital competency of educators
BAR2	Binary	Absence of regulatory framework
BAR3	Binary	Resistance to change in the pedagogical community
BAR4	Binary	Distrust of AI among educators
Block 4: AI potentials (binary, select all that apply)		
POT1	Binary	Document automation
POT2	Binary	Educational data analytics
POT3	Binary	Personalization of learning
POT4	Binary	Education quality monitoring
POT5	Binary	Prediction of educational outcomes
POT6	Binary	Decision-making support
POT7	Binary	Communication with educational stakeholders
POT8	Binary	Detection of educational risks
Block 5: Psychological perceptions (Likert 1–5)		
PSY1	Likert 1–5	How accurate do you think AI is in its responses?
PSY2	Likert 1–5	Does AI help you develop professionally?
PSY3	Likert 1–5	I believe AI will improve my life
PSY4	Likert 1–5	I believe AI will improve my work
PSY5	Likert 1–5	I think I will use AI technology in the future
PSY6	Likert 1–5	I consider AI technologies positive for humanity
PSY7	Likert 1–5	I have doubts about the reliability of AI-provided information^{R}
PSY8	Likert 1–5	I believe AI will make me a better professional in my field
Block 6: AI tools (binary, select all that apply)		
TOOL1–5	Binary	ChatGPT, Gemini, Copilot, Grammarly, Canva
Block 7: Outcomes and institutional factors		
Q38	Ordinal	How do you rate the potential impact of AI on education quality?
Q47	Ordinal	Are you ready to delegate pedagogical decisions to AI?
Q_INIT	Nominal	Are AI-related initiatives being implemented in your institution?
Q_TRAIN	Nominal	Is AI training needed for staff?
Block 8: Threat perceptions		
THREAT1	Nominal	What threats do you see in students' use of AI?
THREAT2	Nominal	What threats do you see in teachers' use of AI?

Note: ^{R} = reverse-coded item. Likert scales range from 1 (strongly disagree / very low) to 5 (strongly agree / very high). Binary items are coded as 0 (not selected) / 1 (selected). Barrier, potential, and tool items allow multiple selections. The coded dataset contains 47 binary/ordinal columns derived from these items; multi-select questions generate one column per response option.

Data availability

The dataset is available on Zenodo: https://doi.org/10.5281/zenodo.17768693. The analysis code is available from the corresponding author upon request.

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