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Regular Article

Professional development for open science adoption among Ukrainian educators

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HIGHLIGHTS

- Brief, targeted training can move educators toward open science practices.
- Positive attitudes alone do not yield adoption – an attitude-behavior gap.
- Prior familiarity, not quiz performance, signals who is ready to adopt.
- Distinct educator profiles call for differentiated, tailored support.
- Closing the gap requires structural support, not more awareness-raising.

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ABSTRACT

Despite growing policy emphasis on open science practices, little is known about how professional development can effectively prepare educators to adopt these practices, particularly in contexts where digital infrastructure is still developing. This study evaluated a cloud services training program for Ukrainian educators (n = 588 matched participants) using a quasi-experimental pre-post design, examining changes in open science knowledge and repository adoption intentions. Grounded in the European Framework for the Digital Competence of Educators (DigCompEdu), Rogers' Diffusion of Innovations theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT), we tested six hypotheses regarding training effectiveness, predictors of adoption, and educator response heterogeneity. Results revealed large improvements in open science familiarity (Cohen's g = 0.91) and cloud service knowledge (g = 0.93), with moderate-to-large effects on repository usage intentions (g = 0.74). However, cluster analysis identified four distinct educator profiles, including a "Supportive Non-Adopters" group (33%) who developed positive attitudes toward open access yet expressed no intention to use repositories – instantiating the attitude-behavior gap theorized in behavioral research. Prior open science familiarity emerged as the sole significant predictor of adoption intentions (OR = 2.85, $p < .001$), while quiz performance and disciplinary background showed no predictive value. These findings suggest that professional development effectively shifts knowledge and attitudes but that converting favorable attitudes into behavioral intentions requires additional intervention components targeting implementation planning. The study contributes evidence from an underexamined context where open science infrastructure and educator digital competencies are co-developing, with implications for differentiated professional development design globally.

1. Introduction

The UNESCO Recommendation on Open Science, adopted in November 2021 by 193 member states, established open science as a global policy priority and called for systematic capacity building among researchers and educators (UNESCO, 2021). This landmark agreement recognized that realizing open science principles – including open access publishing, open data sharing, and transparent research practices – requires not only infrastructure development but also workforce preparation. Yet despite this policy momentum, empirical evidence on how

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to effectively prepare educators to adopt open science practices remains limited, particularly in contexts where digital infrastructure and educator competencies are simultaneously developing.

Professional development (PD) represents the primary mechanism through which education systems attempt to shift educator practices at scale. Meta-analytic evidence indicates that well-designed PD can produce meaningful effects on teacher knowledge (pooled $g = 0.77$) and instructional practice (Kraft et al., 2018; You et al., 2025), though effects on student outcomes are typically smaller and more variable (Sims et al., 2021). However, the PD effectiveness literature has focused predominantly on core instructional practices – mathematics pedagogy, literacy instruction, classroom management – with comparatively little attention to emerging competency areas like open science. Whether the principles governing effective PD for established practices transfer to novel domains characterized by evolving norms and developing infrastructure remains an open question.

Open science adoption presents distinct challenges that may limit the applicability of general PD effectiveness findings. Unlike pedagogical practices that occur within classroom settings under educator control, open science practices often depend on institutional infrastructure (repository access, computing resources), policy environments (funder mandates, promotion criteria), and disciplinary norms (data sharing expectations, preprint culture) that vary substantially across contexts (Makel et al., 2026). Educators may develop favorable attitudes toward open science while perceiving that local conditions make adoption impractical – a pattern the attitude-behavior gap literature suggests is common when intentions require resources or conditions beyond individual control (Sheeran & Webb, 2016). Understanding whether and how PD can bridge this gap requires evidence from contexts where these challenges are salient.

Ukraine presents such a context. Following the 2014 Revolution of Dignity, Ukraine has pursued European integration across sectors including higher education, adopting EU frameworks for quality assurance, research assessment, and digital competencies (Kvit, 2020). The Ministry of Education and Science has prioritized open science as part of this integration, incorporating open access requirements into research funding and endorsing international frameworks for responsible research. Simultaneously, the country has invested in educator digital literacy, with over 300,000 educators participating in technology integration training since 2022 (Ministry of Digital Transformation of Ukraine, 2023). However, Ukraine's research infrastructure remains underdeveloped relative to Western European standards, institutional support for open science varies widely, and the disruptions of ongoing conflict have created both challenges and unexpected opportunities for digital transformation. This combination of policy commitment, active capacity building, and infrastructural constraints makes Ukraine an informative case for understanding PD effectiveness in what we term "emerging digital economy" contexts – settings where educator competencies and enabling infrastructure are co-developing rather than sequentially established.

1.1. Theoretical framework

This study integrates three theoretical frameworks to examine open science PD effectiveness: the European Framework for the Digital Competence of Educators (DigCompEdu), Rogers' Diffusion of Innovations theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT).

The European Framework for the Digital Competence of Educators (Redecker, 2017) provides a comprehensive model of educator digital competencies organized into six areas: Professional Engagement, Digital Resources, Teaching and Learning, Assessment, Empowering Learners, and Facilitating Learners' Digital Competence. For open science adoption, the Professional Engagement area – encompassing organizational communication, professional collaboration, and reflective practice – and the Digital Resources area – covering selecting, creating, and sharing resources – are particularly relevant. DigCompEdu specifies progression levels from Newcomer (A1) through Pioneer (C2), providing a developmental framework for understanding educator readiness. Prior research has demonstrated the validity of DigCompEdu as both a descriptive framework and an intervention target. Lucas et al. (2021) found that self-assessed DigCompEdu competencies predicted technology integration behaviors among Portuguese educators, while Cabero-Almenara et al. (2020) documented significant competency gains following structured digital skills training aligned with the framework. We extend this work by examining whether DigCompEdu-aligned PD can promote open science adoption specifically, treating cloud services competencies as a component of the Digital Resources area.

Rogers' (2003) Diffusion of Innovations theory provides a complementary lens focused on how new practices spread through social systems. The theory posits that adoption decisions unfold through stages – knowledge, persuasion, decision, implementation, confirmation – and that adoption rates vary systematically based on both innovation characteristics (relative advantage, compatibility, complexity, trialability, observability) and adopter characteristics. Rogers' familiar adopter categories – innovators, early adopters, early majority, late majority, laggards – suggest that populations are heterogeneous in their adoption trajectories, with implications for intervention design. For open science, Rogers' framework suggests that educators must first become aware of open science practices (knowledge stage), develop favorable attitudes toward them (persuasion), decide whether to adopt specific practices (decision), attempt implementation, and confirm the value of continued use. PD programs typically target the knowledge and persuasion stages, providing information about open science tools and their benefits. However, progression through later stages may depend on factors beyond PD content, including institutional support and peer norms. We draw on Rogers' framework to hypothesize that distinct adopter profiles will emerge in response to training, reflecting differential progression through the innovation-decision process.

The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) synthesizes elements from eight technology acceptance models, including the foundational Technology Acceptance Model (Davis, 1989), to identify core determinants of technology adoption. UTAUT posits that behavioral intention to use technology is determined by performance expectancy (perceived usefulness), effort expectancy (perceived ease of use), social influence (perceived peer and supervisor support), and facilitating conditions (perceived resource availability). Meta-analytic evidence supports UTAUT's predictive validity in educational contexts, with performance expectancy emerging as the strongest predictor across studies (Than et al., 2021; Xue et al., 2024). UTAUT provides a framework for understanding why PD might produce attitude change without corresponding behavior change. If educators develop favorable attitudes toward open science (high performance expectancy, low effort expectancy) but perceive inadequate institutional support (low facilitating conditions) or peer adoption (low social influence), UTAUT predicts that behavioral intention will not form despite positive attitudes. This prediction aligns with the attitude-behavior gap literature and motivates our examination of the discrepancy between attitude and intention outcomes.

1.2. Research questions and hypotheses

Integrating these frameworks, we address four research questions:

- RQ1: How effective is professional development in improving educators' open science knowledge and adoption intentions?
- RQ2: What factors predict adoption intentions following training?
- RQ3: Do distinct educator profiles emerge in response to training?
- RQ4: Is there evidence of an attitude-behavior gap – educators who develop positive attitudes but do not form adoption intentions?

Based on theoretical expectations and prior research, we tested six hypotheses:

- **H1 (training effectiveness):** Professional development will produce significant improvements in open science knowledge and repository adoption intentions. This hypothesis derives from general PD effectiveness evidence (You et al., 2025) and specific evidence that digital skills training improves DigCompEdu competencies (Cabero-Almenara et al., 2020).
- **H2 (prior knowledge predicts adoption):** Prior familiarity with open science will predict post-training adoption intentions. Rogers' knowledge-persuasion-decision sequence suggests that educators who have already entered the innovation-decision process (possessing prior knowledge) will be better positioned to progress to the decision stage during training.
- **H3 (profile heterogeneity):** Distinct educator profiles will emerge with different adoption patterns. Rogers' adopter categories and meta-analytic evidence of PD effect heterogeneity (Sims et al., 2021) suggest that educators will respond differently to identical training.
- **H4 (knowledge acquisition predicts adoption):** Quiz performance during training will predict adoption intentions. This hypothesis reflects the intuitive expectation that learning more should translate to greater behavior change, though UTAUT's distinction between knowledge and intention suggests that this relationship may be weak.
- **H5 (disciplinary differences):** STEM educators will show higher adoption rates than non-STEM educators. Open science norms, including data sharing and preprint posting, are more established in STEM fields (Tenopir et al., 2020), potentially creating favorable attitudes that facilitate adoption.
- **H6 (attitude-behavior gap):** Some educators may develop positive attitudes toward open science while expressing no intention to adopt repository use. This hypothesis operationalizes the attitude-behavior gap (Sheeran, 2002; Webb & Sheeran, 2006) in the open science domain.

Fig. 1 presents the conceptual model linking these theoretical frameworks to study variables and hypotheses.

1.3. Study contributions

This study makes three contributions to the literature. First, we provide evidence from an underexamined context – Ukrainian higher education – where open science infrastructure and educator digital competencies are co-developing. This "emerging digital economy" context is increasingly common globally but rarely studied in the open science adoption literature, which has focused predominantly on well-resourced Western European and North American settings. Second, we move beyond average treatment effects to identify distinct educator profiles with differential training responses, demonstrating that heterogeneity in PD outcomes is systematic rather than noise. The identification of "Supportive Non-Adopters" – educators who develop positive attitudes but not adoption intentions – operationalizes the attitude-behavior gap in the open science domain and carries implications for intervention design. Third, we establish that prior open science familiarity, rather than disciplinary background or training performance, predicts adoption intentions, suggesting that the innovation-decision process may need to be initiated before formal training can effectively advance educators toward adoption.

2. Literature review

2.1. Open science adoption: awareness, attitudes, and barriers

Open science encompasses a range of practices – open access publishing, open data sharing, open educational resources, preprint posting, and

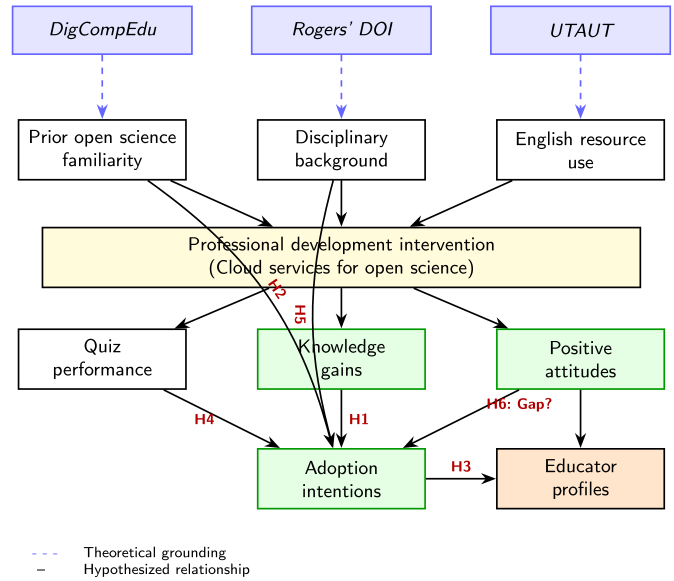

Fig. 1. Conceptual model integrating DigCompEdu, Diffusion of Innovations, and UTAUT frameworks. Hypotheses H1–H6 specify predicted relationships between pre-course characteristics, training processes, and adoption outcomes. The attitude-behavior gap (H6) is represented by the potential disconnect between positive attitudes and adoption intentions.

open peer review – united by commitments to transparency, accessibility, and collaboration in knowledge production (UNESCO, 2021). Survey research consistently documents a gap between awareness and practice: researchers and educators typically endorse open science principles while engaging in open practices at substantially lower rates (Schöpfel et al., 2017; Tenopir et al., 2020). In the most comprehensive survey to date, Tenopir et al. (2020) found that 78% of researchers expressed willingness to share data, but only 32% had actually done so.

Barriers to adoption operate at multiple levels. At the individual level, lack of time, inadequate training, and unfamiliarity with tools and platforms are consistently cited (Makel et al., 2026). At the institutional level, misaligned incentive structures, inadequate infrastructure, and absent or unclear policies impede adoption even among willing researchers (Amaral et al., 2025). At the disciplinary level, norms regarding data sharing, preprint acceptance, and methodological transparency vary substantially, creating different baseline expectations across fields. A recent scoping review of 485 open science studies identified lack of skills and infrastructure as the most frequently cited barriers, followed by concerns about data misuse and intellectual property (Makel et al., 2026).

The attitude-behavior gap documented in open science research parallels findings across behavioral domains. Sheeran (2002) meta-analyzed 10 prior meta-analyses (422 studies) and found that intentions predicted behavior with $r = .53$ – a large correlation by conventional standards, yet one that leaves nearly three-quarters of behavioral variance unexplained. Decomposing this relationship, Sheeran identified "inclined abstainers" – people who intend to act but fail to do so – as the primary source of the intention-behavior gap. In open science contexts, the analogous phenomenon may occur one step earlier: educators who develop favorable attitudes may fail to form behavioral intentions when perceived barriers loom large. Understanding this pattern requires examining not only whether PD changes attitudes but also whether attitude change translates to intention formation.

Gap 1: Most open science adoption research has focused on researchers rather than educators, and on awareness rather than the attitude-to-intention transition. Whether PD can address the attitude-behavior gap among educators remains unexplored. This gap motivates H6.

2.2. Technology acceptance in educational contexts

The technology acceptance literature provides frameworks for understanding why favorable attitudes may not translate into adoption intentions. The Technology Acceptance Model (Davis, 1989) posited that perceived usefulness and perceived ease of use determine technology adoption. UTAUT (Venkatesh et al., 2003) extended this framework to include social influence and facilitating conditions, acknowledging that adoption depends not only on individual perceptions but also on environmental factors.

Meta-analytic evidence supports UTAUT's validity in educational contexts while revealing important boundary conditions. Xue et al. (2024) systematically reviewed 162 UTAUT applications in higher education, finding that performance expectancy consistently emerged as the strongest predictor of behavioral intention, followed by social influence and effort expectancy. However, UTAUT typically explains less variance in educational settings than in corporate contexts, suggesting that educator technology adoption involves factors beyond those captured by the model. Than et al. (2021) meta-analyzed faculty technology adoption studies and found substantial heterogeneity in effect sizes across institutional types and national contexts.

For open science specifically, UTAUT suggests that educators must perceive that open practices will enhance their professional effectiveness (performance expectancy), that using repositories and other tools will not be excessively difficult (effort expectancy), that colleagues and supervisors support open practices (social influence), and that institutional resources enable participation (facilitating conditions). PD programs can address performance and effort expectancy by demonstrating benefits and teaching skills, but social influence and facilitating conditions depend on factors beyond PD content.

Gap 2: Technology acceptance research has rarely examined open science tools specifically, and has not investigated how prior knowledge interacts with training to predict adoption. This gap motivates H2.

2.3. Professional development effectiveness for technology integration

The professional development effectiveness literature has established that PD can improve educator knowledge and practice, with effect sizes varying based on program features. Darling-Hammond et al. (2017) identified seven features of effective PD: content focus, active learning, collaboration, use of models, coaching and expert support, feedback and reflection, and sustained duration. However, Kennedy (2016) challenged the evidence base for these features, noting that most studies confound multiple design elements and that experimental evidence for specific mechanisms remains weak.

Recent meta-analyses provide updated benchmarks. You et al. (2025) meta-analyzed 514 effect sizes from science teacher PD studies and found a pooled effect of $g = 0.77$ for teacher knowledge outcomes, with smaller effects for classroom practice ($g = 0.41$) and student achievement ($g = 0.23$). Sims et al. (2021) synthesized PD effects across domains and documented substantial heterogeneity, with effects ranging from near-zero to over 1.0 depending on outcome type, study design, and context. Critically, Hill et al. (2020) demonstrated that effects observed in efficacy trials often fail to replicate at scale, raising questions about generalizability.

For technology-focused PD specifically, effects tend to be moderate. Kraft et al. (2018) meta-analyzed teacher coaching interventions and found effects of $d = 0.49$ for instruction and $d = 0.18$ for student achievement. Technology integration PD shows similar patterns: knowledge gains are typically larger than practice changes, and practice changes are larger than student outcome effects. This pattern is consistent with theories suggesting that knowledge is necessary but not sufficient for behavior change (Webb & Sheeran, 2006).

Gap 3: PD effectiveness research has not examined open science as an outcome domain, and has rarely investigated how training effects vary across educator subgroups. These gaps motivate H1, H3, and H5.

Table 1
Hypotheses and theoretical grounding.

H	Prediction	Theoretical basis
H1	PD improves knowledge and intentions	PD effectiveness meta-analyses (Kraft et al., 2018; You et al., 2025); DigCompEdu training evidence (Cabero-Almenara et al., 2020)
H2	Prior familiarity predicts adoption	Rogers' knowledge-persuasion-decision sequence; UTAUT performance expectancy
H3	Distinct profiles emerge	Rogers' adopter categories; PD heterogeneity evidence (Sims et al., 2021)
H4	Quiz performance predicts adoption	Knowledge-behavior link assumption; DigCompEdu progression model
H5	STEM shows higher adoption	Disciplinary norm differences (Tenopir et al., 2020)
H6	Attitude-behavior gap exists	Intention-behavior gap literature (Sheeran, 2002; Webb & Sheeran, 2006); UTAUT facilitating conditions

2.4. The Ukrainian context: digital transformation and european integration

Ukraine's education system has undergone substantial transformation since 2014, with European integration as a guiding framework. The adoption of EU frameworks for quality assurance, research assessment, and digital competencies has created policy pressure for open science adoption while infrastructure development lags (Kvit, 2020). The Strategy for Higher Education Development 2022–2032 explicitly prioritizes open access and research transparency as components of European integration (Cabinet of Ministers of Ukraine, 2022).

Several contextual factors shape open science adoption in Ukraine. Positively, the government has invested substantially in educator digital literacy, with over 300,000 educators participating in training programs since 2022 (Ministry of Digital Transformation of Ukraine, 2023). The DigCompEdu framework has been adopted as a reference for educator competency development, creating alignment between national policy and EU standards. The disruptions of conflict have paradoxically accelerated digital transformation, as remote teaching and distributed collaboration have become necessities (Semerikov & Mintii, 2026; Semerikov, Nechypurenko et al., 2026). Negatively, research infrastructure remains underdeveloped, institutional support for open science varies widely, and competing priorities limit time available for adopting new practices.

Prior research on Ukrainian educators' digital competencies documents both substantial variation and significant gaps relative to EU benchmarks (Kuzminska et al., 2018; Spirin et al., 2024). Studies have documented low baseline familiarity with open science concepts, limited repository use, and reliance on informal information sources rather than scholarly databases. However, this research has been primarily descriptive, lacking the experimental or quasi-experimental designs necessary to evaluate intervention effectiveness.

Gap 4: No prior research has examined PD effectiveness for open science adoption in Ukraine or similar "emerging digital economy" contexts. This gap motivates the study's contextual contribution.

Table 1 summarizes the hypotheses and their theoretical grounding.

3. Methods

3.1. Research design and overview

This study employed a quasi-experimental single-group pre-post design to evaluate the effectiveness of a professional development program on Ukrainian educators' knowledge of and intentions to adopt open science cloud services. The design was selected as the most feasible approach given the training context, where random assignment to a no-training control condition would have been ethically problematic and practically difficult to implement. While this design limits causal inference, it aligns with prior research on professional development evaluation (Desimone, 2009; Guskey, 2002) and permits assessment of pre-to-post change with appropriate effect size estimation.

Table 2
Sample characteristics.

Characteristic	n	%
Sample size		
Pre-course survey	822	100.0
Post-course survey	698	84.9
Quiz assessment	905	–
Matched pre-post	588	71.5
Complete (all three)	395	48.1
Subject area		
STEM	327	39.8
Humanities	155	18.9
Primary Education	89	10.8
Other	251	30.5
Geographic location (top 5)		
Zhytomyr	151	18.4
Korosten	125	15.2
Berdychiv	41	5.0
Radomyshl	20	2.4
Kyiv	20	2.4

Note. Percentages for sample size are based on pre-course total. Participants represented over 40 cities across Ukraine.

The study addressed four research questions through distinct analytical approaches. Pre-post comparisons (McNemar tests) addressed RQ1 regarding training effectiveness. Logistic regression addressed RQ2 regarding predictors of adoption. Cluster analysis addressed RQ3 regarding educator profiles. Examination of the discordance between attitudes and behavioral intentions addressed RQ4 regarding the attitude-behavior gap. The study received ethical approval from the host institution and was conducted in accordance with the Declaration of Helsinki. All participants provided informed consent prior to enrollment.

3.2. Participants and recruitment

Participants were Ukrainian educators who voluntarily enrolled in a professional development course on cloud services for research and open science. Recruitment occurred through multiple channels: announcements on the university's continuing education platform, email invitations distributed through regional education networks in Zhytomyr Oblast, and promotion through professional educator associations. The course was offered free of charge and was open to educators from all disciplines, institution types, and career stages. No specific prerequisites were required beyond internet access and basic computer literacy. Reflecting this open enrollment, participants spanned both general and higher education – in-service school teachers (including primary teachers and staff at specialized science lyceums and gymnasiums) together with university and college educators.

A total of 822 educators completed the pre-course survey at enrollment. Of these, 698 (84.9%) completed the post-course survey, and 905 educators completed the knowledge assessment quiz (which was also open to some participants who had not completed the pre-course survey). Through email address matching, 588 participants (71.5% of original enrollees) were identified as having completed both pre- and post-course surveys, forming the primary analytic sample for pre-post comparisons. A subset of 395 participants (48.1% of original enrollees) completed all three instruments – pre-survey, post-survey, and quiz – enabling analyses incorporating quiz performance as a predictor.

Attrition analysis compared completers ($n = 588$) to non-completers ($n = 234$) on available pre-course characteristics. No significant differences emerged for prior open science familiarity ($\chi^2(1) = 1.24$, $p = .27$), cloud knowledge ($\chi^2(1) = 0.89$, $p = .35$), or subject area distribution ($\chi^2(3) = 5.12$, $p = .16$). The similarity between completers and non-completers on observed baseline characteristics reduces, though does not eliminate, concerns about differential attrition.

Table 2 presents detailed sample characteristics.

The matched sample ($n = 588$) represented educators from over 40 cities across Ukraine, with geographic concentration in Zhytomyr Oblast reflecting the host institution's regional focus. By subject area, STEM educators (mathematics, physics, chemistry, biology, informatics) comprised 39.8% of the sample, followed by humanities (18.9%), primary education (10.8%), and other subjects including vocational and specialized fields (30.5%). Fig. 2 illustrates the geographic distribution, while Fig. 3 shows the distribution by subject area.

3.3. Intervention: professional development program

The professional development program was designed following principles of effective teacher PD (Darling-Hammond et al., 2017; Desimone, 2009), emphasizing content focus, active learning, and practical application. The intervention description below follows the Template for Intervention Description and Replication (TIDieR) guidelines to enhance reproducibility (Hoffmann et al., 2014).

The course addressed six thematic modules delivered over approximately six weeks: (1) introduction to open science concepts and the open science ecosystem, including the UNESCO Recommendation on Open Science and European Open Science Cloud initiatives; (2) overview of cloud-based research tools and their applications across research stages; (3) practical skills for using data repositories, including Zenodo, Figshare, and institutional repositories; (4) reference management and citation tools, focusing on Mendeley, Zotero, and their integration with word processors; (5) collaborative research platforms including

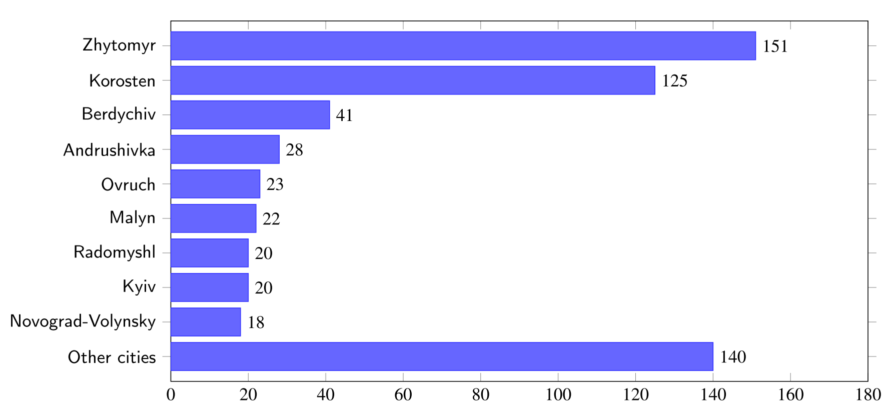

Fig. 2. Geographic distribution of participants (top 10 locations). The sample concentrated in Zhytomyr Oblast reflects the regional recruitment focus; however, participants from over 40 cities provide geographic breadth.

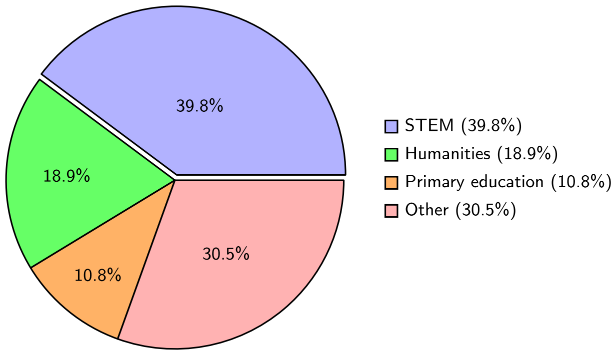

Fig. 3. Distribution of participants by subject area. STEM educators comprised the largest group (39.8%), with substantial representation from humanities, primary education, and other specialized fields.

Google Scholar profiles, ResearchGate, ORCID, and collaborative writing tools; and (6) academic integrity, ethical considerations, and responsible research practices in open science contexts.

The course was delivered asynchronously through a Moodle-based learning management system, allowing participants to progress at their own pace while maintaining structured weekly milestones. Each module included video lectures (45–60min per module, approximately 5 hours total), reading materials drawn from open access sources, guided tutorials with annotated screencasts demonstrating tool use (approximately 3 hours total), and practical exercises requiring participants to create accounts, upload sample materials, and configure profiles on target platforms. Discussion forums facilitated peer interaction and question-asking, with course facilitators responding to queries within 48 hours during business days.

Total expected engagement time was approximately 20–24 hours spread over six weeks. Participants were encouraged to complete one module per week, though the asynchronous format permitted faster or slower progression. Minimum completion requirements for receiving a certificate included viewing all video lectures (tracked via Moodle analytics), completing at least four of six practical exercises, and passing the knowledge assessment quiz with a score of at least 50% (4 out of 7 questions correct).

The course was developed by faculty members with expertise in educational technology and open science practices. Two facilitators monitored discussion forums and provided technical support throughout the course period. The instructional approach combined direct instruction (video lectures explaining concepts) with guided discovery (tutorials walking through procedures) and experiential learning (practical exercises requiring authentic tool use). Participants were encouraged to apply learned concepts to their own research or teaching contexts, with optional advanced exercises inviting them to deposit an actual work product in a repository.

3.4. Instruments and measures

Three instruments were developed for this study: a pre-course survey, a post-course survey, and a knowledge assessment quiz. Survey items were developed in Ukrainian based on constructs from the DigCompEdu framework and adapted from prior studies on open science awareness (Tenopir et al., 2020) and technology adoption (Davis, 1989). Content validity was assessed through expert review by three faculty members with expertise in educational technology, and items were pilot-tested with a small group of educators ($n = 15$) prior to deployment.

The pre-course survey (19 items) assessed participants' baseline characteristics and prior knowledge. Contextual items captured subject area taught, institution, and geographic location; to limit respondent burden and preserve the anonymity of voluntary registration, the instruments did not record personal demographic attributes such as age, gender, academic degree, rank, or employment status. Knowledge items assessed prior familiarity with open science concepts ("Before this course, were you familiar with the concept of open science?") and cloud services for research ("Before this course, did you know what the 'open science cloud' is?"), with binary yes/no response options. Additional items assessed current practices including use of English-language resources (binary) and methods for searching scientific literature (multiple response options).

The post-course survey (22 items) assessed acquired knowledge, attitudes, and behavioral intentions. Knowledge items assessed understanding of cloud service definitions, awareness of specific tools, and familiarity with FAIR principles. Attitude items assessed support for open access ("Do you support the idea of open access for scientific publications?") with binary response options. Behavioral intention items assessed repository usage intentions ("Do you plan to use educational repositories for placing your work?") and intentions to adopt specific services covered in the course. Knowledge, attitude, and behavioral-intention constructs were each measured with single dichotomous (yes/no) items rather than multi-item Likert scales; the implications of this measurement choice are considered in the Limitations.

The knowledge assessment quiz consisted of 11 multiple-choice items designed to evaluate comprehension of key course concepts. Seven items were scored as correct/incorrect, yielding a maximum score of 7 points. Internal consistency for the 7 scored items was acceptable (KR-20 = .68).

3.5. Data analysis

Data were analyzed using Python 3.11 with pandas, scipy, statsmodels, and scikit-learn libraries. Each analytical approach was selected to address specific research questions and test corresponding hypotheses.

To address H1 regarding pre-post changes, McNemar's test was used to compare binary outcomes for matched participants (McNemar, 1947). Effect sizes were calculated using Cohen's g (Cohen, 1988):

$$g = \frac{b - c}{b + c} \tag{1}$$

where b represents cases changing from negative to positive and c represents cases changing from positive to negative. Values were interpreted as small (0.05–0.15), medium (0.15–0.25), and large (>0.25) effects.

For predictive modeling addressing H2, H4, and H5, logistic regression predicted binary adoption outcomes (repository usage intention) from pre-course characteristics, subject area, and quiz performance. This approach permits estimation of odds ratios with confidence intervals. Model fit was assessed using Nagelkerke pseudo-R^2.

To identify distinct educator profiles (H3), K-means clustering was applied to pre-course knowledge indicators and post-course adoption variables. The optimal number of clusters ($k = 4$) was determined through silhouette analysis. To validate the K-means solution, Latent Profile Analysis using Gaussian Mixture Models was also conducted (reported in Supplementary Materials).

4. Results

Results are organized according to the study's hypotheses. We first present preliminary analyses establishing baseline characteristics and course performance, then address each hypothesis in turn. Supplementary analyses are reported in the supplementary materials.

4.1. Preliminary analyses

At baseline, most participants were unfamiliar with open science concepts. Only 26.8% reported prior familiarity with open science, and 23.1% indicated knowing what the "open science cloud" is. Approximately one-third (31.6%) reported using English-language resources in their professional work. For literature searching, the dominant approach was general search engines (98.9%), followed by electronic libraries (67.0%) and printed materials (51.5%). Only 14.0% reported

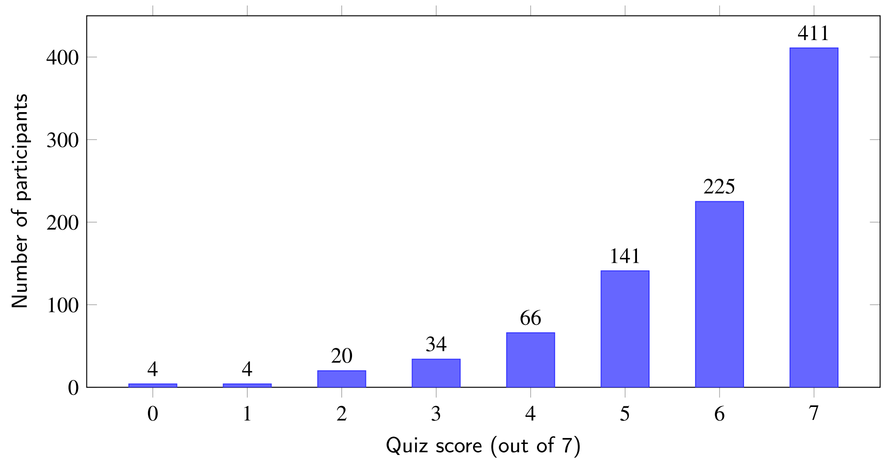

Fig. 4. Distribution of quiz scores (n = 905). The distribution shows strong performance overall (M = 5.9, SD = 1.36) with negative skew, indicating that most participants demonstrated adequate comprehension of course content.

using journal database systems, indicating limited prior engagement with formal academic search infrastructure.

Participants demonstrated strong comprehension of course content. The mean quiz score was 5.9 (SD = 1.36) out of 7 possible points, with 45.4% achieving perfect scores and 93.1% passing the minimum threshold (score ≥ 4). The negatively skewed distribution (Fig. 4) indicates that course content was accessible to most participants.

4.2. Hypothesis 1 (training effectiveness)

H1 predicted that the professional development program would produce significant improvements in open science knowledge and adoption intentions. McNemar tests comparing matched pre-post responses (n = 588) supported this hypothesis across all three primary outcomes (Table 3; Figs. 5 and 6).

Open science familiarity increased from 28.2% to 92.2%, representing a net change of 63.9 percentage points (g = 0.91, OR = 21.9). Cloud service knowledge increased from 24.8% to 92.2% (g = 0.93, OR = 27.4). Repository usage intentions increased from 24.8% to 60.7% (g = 0.74, OR = 6.7). While the effect for intentions remains large by conventional standards, the smaller magnitude compared to knowledge outcomes is consistent with theoretical expectations that behavioral intentions are more resistant to change than knowledge (Webb & Sheeran, 2006).

4.3. Hypothesis 2 (prior knowledge predicts adoption)

H2 predicted that prior open science familiarity would predict post-course adoption intentions. Logistic regression tested this hypothesis while controlling for subject area, English resource use, and quiz performance (n = 395; Table 4).

The model was statistically significant (LR χ^2 = 25.95, $p < .001$), though it explained only 4.9% of variance (Nagelkerke pseudo-R^2 = 0.049). Prior open science familiarity emerged as the only significant predictor (B = 1.05, SE = 0.27, OR = 2.85, 95% CI [1.67, 4.87], $p < .001$). Participants who reported familiarity with open science concepts before the course were nearly three times more likely to express repository usage intentions afterward. No other predictors reached significance.

4.4. Hypothesis 3 (distinct educator profiles)

H3 predicted that distinct educator profiles would emerge. K-means clustering (k = 4, silhouette score = 0.55) identified four profiles (Table 5; Fig. 7).

Table 3
Pre-post changes in knowledge and intentions.

Variable	Pre %	Post %	Δ%	χ^2	p	Cohen's g
Open science familiarity	28.2	92.2	+63.9	355.4	<.001	0.91
Cloud service knowledge	24.8	92.2	+67.3	368.2	<.001	0.93
Repository usage intention	24.8	60.7	+35.9	156.2	<.001	0.74

Note. n = 588 matched participants. McNemar's test for paired proportions. Effect size interpretation: small (0.05–0.15), medium (0.15–0.25), large (>0.25).

The largest group (40.0%, n = 158), *Converted Adopters*, entered with minimal prior knowledge (5% open science familiarity) but showed complete post-course adoption – 100% expressed both repository usage intentions and open access support. The second group (33.2%, n = 131), *Supportive Non-Adopters*, had similar baseline characteristics but none expressed repository usage intentions despite 100% open access support. The third profile (23.5%, n = 93), *Experienced Practitioners*, entered with high prior knowledge (97% familiarity) and maintained high adoption (84% repository intention). A small fourth group (3.3%, n = 13), *Skeptics*, was the only cluster not supporting open access post-course.

Read as emergent themes, these four profiles map onto the study's guiding frameworks and research questions. In Rogers' diffusion terms, the *Experienced Practitioners* resemble early adopters who had entered the innovation-decision process before the course, whereas the *Converted Adopters* behaved as an early majority for whom the training supplied the persuasion and decision stages. The *Supportive Non-Adopters* occupy the persuasion stage without progressing to a decision – the configuration H6 anticipated – while the *Skeptics* approximate late or non-adopters. The same gradient is legible through DigCompEdu, ranging from newcomer-level participants who gained foundational awareness to integrator- and expert-level Experienced Practitioners already depositing work. In UTAUT terms, the sharp divergence in intention between Converted and Supportive Non-Adopters despite identical open access attitudes points to facilitating conditions and social influence, rather than performance expectancy, as the operative constraint. Interpreted this way, the profiles answer RQ3 by showing that response heterogeneity is structured rather than random, and they locate the attitude-behavior gap (H6) in a specific and sizeable subgroup rather than treating it as a sample-wide average.

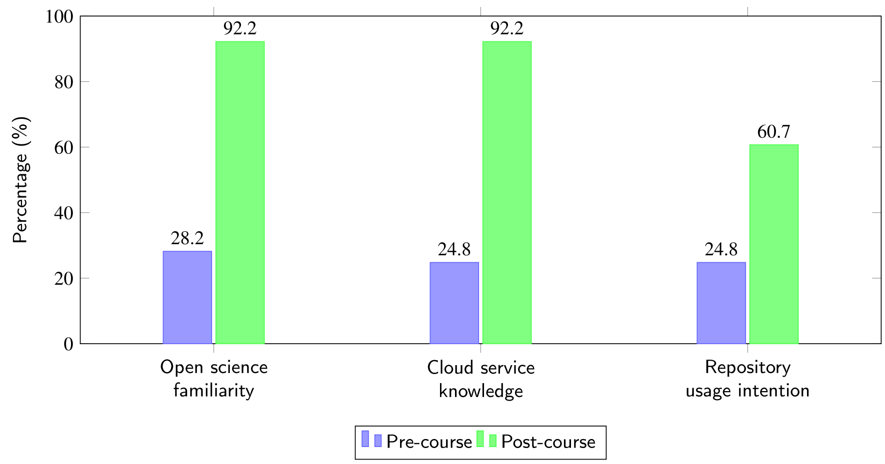

Fig. 5. Pre-post comparison of key outcomes showing percentage of participants responding positively before and after the intervention. All changes were statistically significant ($p < .001$). The gap between knowledge gains (exceeding 90%) and behavioral intention (61%) illustrates the attitude-behavior discrepancy examined under H6.

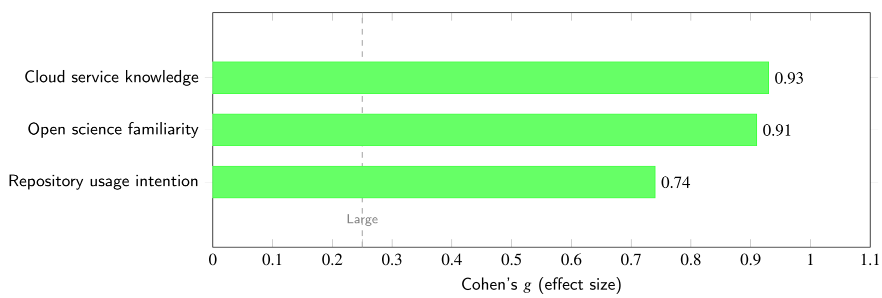

Fig. 6. Effect sizes (Cohen's g) for pre-post changes. All effects exceed the large threshold (0.25), with knowledge outcomes showing effects above 0.90. The relatively smaller effect for repository usage intentions reflects the greater difficulty of changing behavioral intentions compared to knowledge.

Table 4
Logistic regression predicting repository usage intentions.

Predictor	B	SE	OR	95% CI	z	p
Intercept	−0.63	0.75	0.54	[0.12, 2.32]	−0.84	.404
Subject: Other	−0.09	0.33	0.92	[0.48, 1.76]	−0.26	.793
Subject: Primary education	−0.48	0.42	0.62	[0.27, 1.42]	−1.13	.259
Subject: STEM	0.12	0.31	1.13	[0.61, 2.09]	0.38	.702
Quiz score	0.12	0.11	1.13	[0.91, 1.39]	1.11	.267
Prior OS familiarity	1.05	0.27	2.85	[1.67, 4.87]	3.84	<.001
English resources	0.28	0.23	1.32	[0.84, 2.09]	1.20	.230

Note. $n = 395$. Pseudo $R^2 = 0.049$. Reference category for subject area: Humanities. OR = odds ratio. OS = open science.

Table 5
Educator profile characteristics from k-means clustering.

Profile	n (%)	Prior OS	Prior Cloud	English	Repository	OA support
Converted Adopters	158 (40.0)	0.05	0.01	0.30	1.00	1.00
Supportive Non-Adopters	131 (33.2)	0.05	0.04	0.26	0.00	1.00
Experienced Practitioners	93 (23.5)	0.97	0.90	0.66	0.84	1.00
Skeptics	13 (3.3)	0.23	0.31	0.38	0.46	0.00

Note. Values are proportions (means) for binary variables. OS = open science. OA = open access. Silhouette coefficient = 0.55.

4.5. Hypothesis 4 (knowledge acquisition predicts adoption)

H4 predicted that quiz performance would predict adoption intentions. Contrary to this hypothesis, quiz scores did not significantly predict repository usage intentions (OR = 1.13, 95% CI [0.91, 1.39], p =.27). The null finding persisted across analytical approaches including mediation analysis (Supplementary materials). The failure of quiz performance to predict adoption suggests that knowing about open science is insufficient for intending to practice it.

4.6. Hypothesis 5 (disciplinary differences)

H5 predicted that STEM educators would show higher adoption. Mann-Whitney U tests revealed no significant differences between STEM ($n = 172$) and non-STEM ($n = 223$) educators on any outcome (Table 6).

4.7. Hypothesis 6 (attitude-behavior gap)

H6 predicted an attitude-behavior gap. The cluster analysis provides direct evidence: the Supportive Non-Adopters (33.2%) unanimously endorsed open access support yet uniformly declined repository usage intention. Comparing this cluster to Converted Adopters – who shared similar baselines but expressed complete adoption – illuminates the gap. Both had near-zero prior familiarity (5%), yet their behavioral intentions diverged entirely (100% vs. 0% repository intention) despite identical attitudes (100% open access support). Approximately one-third of educators who developed supportive attitudes did not translate them into adoption intentions.

Table 7 summarizes hypothesis testing results.

5. Discussion

This study investigated whether professional development can promote open science adoption among Ukrainian educators and identified

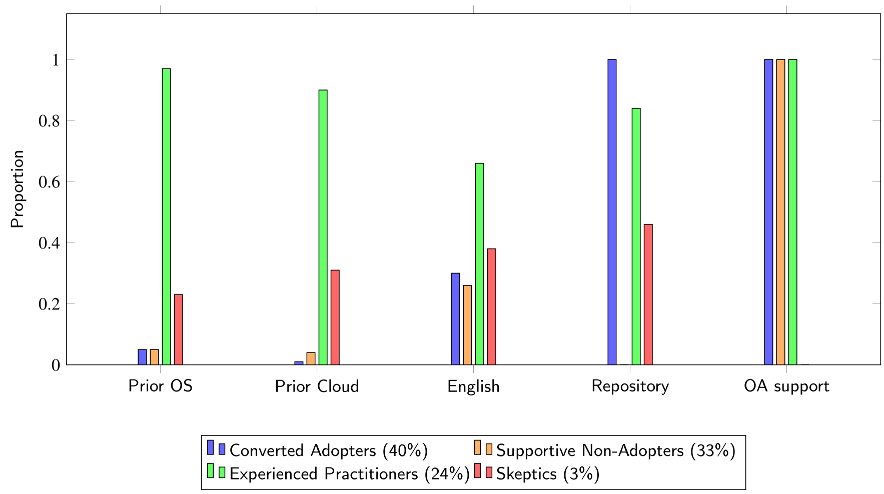

Fig. 7. Cluster profiles showing mean values on pre-course knowledge indicators (Prior OS, prior Cloud, English) and post-course outcomes (Repository intention, OA support). The Supportive Non-Adopters (Orange) show identical OA support to Converted Adopters (blue) but zero repository intention, illustrating the attitude-behavior gap.

Table 6
Subgroup comparison: STEM vs. non-STEM educators.

Variable	STEM *M*	Non-STEM *M*	*U*	*p*	*r*
Prior OS familiarity	0.26	0.28	19,579	.645	−0.02
Prior cloud knowledge	0.23	0.25	19,560	.646	−0.02
English resources	0.35	0.40	20,056	.352	−0.05
Repository intention	0.64	0.59	18,265	.336	0.05
OA support	0.97	0.96	19,048	.708	0.01
Quiz score	6.29	6.34	18,956	.825	0.01

Note. STEM $n = 172$; Non-STEM $n = 223$. Mann-Whitney *U* test. r = rank-biserial correlation.

Table 7
Summary of hypothesis tests.

Hypothesis	Prediction	Result	Key statistic
H1	PD improves knowledge and intentions	Supported	$g = 0.74$–0.93
H2	Prior familiarity predicts adoption	Supported	OR = 2.85***
H3	Distinct profiles emerge	Supported	4 clusters, $\bar{s} = 0.55$
H4	Quiz performance predicts adoption	Not supported	OR = 1.13, $p = .27$
H5	STEM shows higher adoption	Not supported	$p = .34$, $r = 0.05$
H6	Attitude-behavior gap exists	Supported	33.2% in gap cluster

Note. *** $p < .001$. $\bar{s}$ = silhouette coefficient.

factors predicting differential responses to training. While the large pre-post effects confirm that well-designed PD can shift knowledge and intentions, the study's most distinctive contribution lies in identifying a substantial subgroup – one-third of participants – who developed positive attitudes toward open science yet expressed no intention to adopt repository use. This pattern, which we term the Supportive Non-Adopters profile, instantiates the attitude-behavior gap documented across domains (Sheeran, 2002; Webb & Sheeran, 2006) and carries implications for both theory and practice.

5.1. Training effectiveness in comparative perspective

The observed effect sizes for knowledge outcomes (Cohen's g = 0.91–0.93) substantially exceed those typically reported in professional development research. The meta-analysis by You et al. (2025) of science teacher PD found an average effect of $g = 0.77$ across 514 effect sizes, while Kraft et al. (2018) reported pooled effects of $d = 0.49$ for in-service teacher training. The larger effects in the present study likely reflect the targeted nature of the intervention and the low baseline familiarity, which created substantial room for improvement.

The smaller but still substantial effect for behavioral intentions ($g = 0.74$) aligns with theoretical expectations that intentions are more resistant to change than knowledge (Webb & Sheeran, 2006). In their meta-analysis of intention-change interventions, Webb and Sheeran (2006) found that a medium-to-large change in intention strength ($d = 0.66$) produced only a small-to-medium change in subsequent behavior ($d = 0.36$). This asymmetry frames the central challenge that the Supportive Non-Adopters profile illuminates.

5.2. The attitude-behavior gap: theoretical contribution

The identification of Supportive Non-Adopters (33.2%) advances understanding of professional development outcomes by documenting the attitude-behavior gap in the open science domain. These educators entered the course with minimal prior knowledge, developed unanimously positive attitudes toward open access, yet uniformly declined to express repository usage intentions.

Sheeran (2002) decomposed intention-behavior relations into a 2×2 matrix distinguishing those who intend and act, intend but do not act, do not intend but act, and neither intend nor act. The critical cell is "inclined abstainers" – people with positive intentions who fail to act. Our Supportive Non-Adopters represent an analogous phenomenon one step earlier: they developed positive attitudes but did not form adoption intentions.

Several mechanisms may explain this pattern. First, perceived behavioral control may be insufficient – educators may endorse open science while perceiving that institutional conditions make adoption impractical. Second, intentions may require specific action plans; Gollwitzer and Sheeran (2006) demonstrated that implementation intentions substantially improve intention-to-behavior translation ($d = 0.65$). Third, Supportive Non-Adopters may have formed goal intentions ("I want to contribute to open science") without forming behavioral intentions ("I will deposit my next publication").

5.3. Prior knowledge as the key predictor

The finding that prior open science familiarity predicted adoption intentions (OR = 2.85), while quiz performance did not, integrates with Rogers' (2003) framework in unexpected ways. We propose that this reflects a distinction between declarative knowledge (measured by quiz) and prior entry into the innovation-decision process (indexed by familiarity). For participants who entered with prior familiarity, the course may have advanced them from persuasion to decision. For those without, six weeks may have been insufficient to progress through all stages.

5.4. The Ukrainian context as an emerging digital economy case

While conducted in Ukraine, these findings have implications for contexts where open science infrastructure and educator competencies are co-developing. The Supportive Non-Adopters profile may be particularly prevalent where positive attitudes toward international research norms outpace institutional support for implementing them. This interpretation suggests that PD alone cannot produce behavior change without concurrent attention to enabling conditions.

The null finding for disciplinary differences (H5) warrants comment. Although open science norms are more established in STEM fields globally (Tenopir et al., 2020), this advantage did not translate to higher adoption intentions in our sample. The course addressed general open science competencies applicable across disciplines rather than discipline-specific applications such as data sharing protocols or preprint practices. Additionally, Ukrainian educators may face similar institutional barriers regardless of field, attenuating any disciplinary differences that might emerge in contexts with more developed research infrastructure.

5.5. Practical implications

For professional development designers, the findings translate into specific design choices rather than general encouragement. First, embedding implementation-intention prompts – having participants write a dated plan naming the next manuscript or dataset they will deposit, the repository they will use, and the week they will do so – targets the exact point at which the Supportive Non-Adopters stalled, and such if–then plans reliably improve goal enactment (Gollwitzer & Sheeran, 2006; Sheeran & Webb, 2016). Second, replacing the optional final exercise with a required capstone that culminates in an actual deposit (a DOI serving as evidence) converts intention into a completed first act before the course ends. Third, a brief intake diagnostic – two items on prior familiarity – can route participants into differentiated tracks, so that newcomers receive foundational scaffolding while Experienced Practitioners move to discipline-specific applications. Fourth, short follow-up "booster" contacts at one and three months can sustain momentum beyond the course window, where intentions otherwise decay.

For institutions and policymakers, attitudinal gains will not become practice unless the surrounding incentives change. Recognising open outputs in hiring, promotion, and evaluation – and signalling that recognition through low-cost mechanisms such as open-practice badges, which measurably increase data sharing (Kidwell et al., 2016) – addresses the facilitating conditions that the Supportive Non-Adopters profile implicates. Aligning institutional policy with transparency and openness standards (Nosek et al., 2015), providing library-mediated deposit support, and maintaining a functioning institutional repository with persistent identifiers together lower the practical barriers that favorable attitudes alone cannot overcome. The recurring implication is that professional development should be resourced as one component of a system that also reforms incentives and infrastructure, not as a standalone intervention.

5.6. Strengths

Several features strengthen confidence in these findings. The design integrated three complementary frameworks – DigCompEdu (Redecker, 2017), Diffusion of Innovations (Rogers, 2003), and UTAUT (Venkatesh et al., 2003) – into an explicit set of hypotheses and a conceptual model, answering calls for theory-driven rather than atheoretical technology-adoption research (Xue et al., 2024). The matched pre-post sample ($n = 588$) is large relative to typical professional development studies (Sims et al., 2021), affording adequate power to detect the reported effects (Cohen, 1988). The analytic strategy paired confirmatory tests with convergent person-centred methods: the k-means solution was cross-validated with latent profile analysis (Spurk et al., 2020) and evaluated with silhouette analysis (Rousseeuw, 1987), reducing the likelihood that the profiles are artefacts of a single algorithm. The intervention is reported in full following the TIDieR guideline (Hoffmann et al., 2014), supporting replication and appraisal of fidelity.

5.7. Limitations

The quasi-experimental design without control limits causal inference, though large effect sizes reduce plausibility of regression to the mean. The reliance on intentions rather than observed behavior is a second limitation – even Converted Adopters may not ultimately translate intentions into repository use. Longitudinal follow-up assessing actual deposits would provide stronger evidence. The modest explained variance (pseudo-$R^2 = 0.049$) indicates substantial unmeasured factors. Geographic concentration in Zhytomyr Oblast may limit generalizability.

Three further limitations concern measurement and sampling. First, the constructs were assessed with single dichotomous self-report items rather than multi-item scales. Dichotomous items cannot capture gradations of knowledge or attitude, are prone to ceiling effects (post-course endorsement was uniformly high), and preclude internal-consistency estimates for the survey constructs; like all self-reports, they are also susceptible to social-desirability responding, which can inflate endorsement of normatively approved practices such as open access (Akbulut, 2025; van de Mortel, 2008). Reported intentions were not validated against observed deposit behavior. Second, enrollment was voluntary and free, so the sample over-represents educators already inclined toward open science; the effects therefore describe educators who self-select into such training rather than a mandated population. Third, because registration was anonymous, no personal demographic data (age, gender, academic degree, rank, or employment status) were collected, which prevents demographic subgroup and moderator analyses and constrains description of the sample beyond discipline and region.

An additional theoretical limitation concerns our use of UTAUT as a framing device without directly measuring its core constructs. While we interpreted the Supportive Non-Adopters profile through the lens of facilitating conditions and social influence, we did not assess these constructs directly. Future research should incorporate validated UTAUT measures to determine whether perceived barriers to adoption (low facilitating conditions) or absence of peer support (low social influence) explain why educators who developed favorable attitudes did not form behavioral intentions.

5.8. Future research directions

Several directions warrant investigation: longitudinal designs tracking actual repository deposits, experimental tests of implementation intention interventions, qualitative research illuminating barriers preventing intention formation, comparative research across emerging digital economy contexts, and fuller integration of UTAUT constructs. Mixed-methods designs would be especially valuable: pairing the surveys with classroom observation, focus groups, or interviews, and with repository deposit logs, would triangulate self-reports against behavioral evidence and help explain why favorable attitudes do not always become intentions (Akbulut, 2025).

6. Conclusion

Professional development can effectively shift educators' knowledge and attitudes toward open science, but shifting attitudes does not guarantee adoption. This study's most consequential finding is that one-third of participants who developed favorable views of open science nonetheless expressed no intention to use repositories – a pattern we term

Supportive Non-Adopters. This attitude-behavior gap, well-documented in health and environmental domains but underexplored in open science education, suggests that evaluations measuring only attitude change may substantially overestimate intervention success.

What this pattern asks us to accept is that the conventional marker of professional development success – demonstrable gains in knowledge and attitude – can be fully met while the behavior the training exists to promote remains absent. Heterogeneity is central rather than incidental here: the average treatment effect concealed a sizeable group whose response inverts the implicit theory of change, and what separated those who formed intentions from those who did not was prior entry into the innovation-decision process, not disciplinary background or course performance. The lesson is not that training works or fails, but that it accomplishes one particular task – moving educators from unawareness to informed endorsement – while a second and distinct task, converting endorsement into action, depends on instruments the course did not contain and on institutional conditions it could not supply.

For practitioners, these findings suggest that professional development should incorporate implementation intention interventions and that converting favorable attitudes into behavioral intentions requires explicit attention to action planning and barrier reduction. For the substantial proportion of educators who develop supportive attitudes without forming adoption intentions, follow-up interventions targeting implementation support may be more valuable than additional persuasion.

As open science mandates expand globally, understanding how to bridge the gap between endorsing open science and practicing it becomes urgent. The Supportive Non-Adopters identified here are not opponents to be persuaded but allies awaiting the conditions – institutional, practical, and psychological – that will enable them to act on their convictions.

CRediT authorship contribution statement

Maiia V. Marienko: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Mariya P. Shyshkina:** Writing – original draft, Methodology, Investigation. **Serhiy O. Semerikov:** Writing – review & editing, Software, Investigation, Formal analysis, Visualization.

Informed Consent

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

Ethics approval

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of the Institute for Digitalisation of Education of the National Academy of Educational Sciences of Ukraine (Protocol No. 9, dated 2021-09-13). All participants provided informed consent prior to enrollment in the professional development program. Participation was voluntary, and educators could withdraw at any time without consequence. Survey responses were collected anonymously and stored securely. No personally identifiable information beyond email addresses (used solely for matching pre-post responses) was retained, and email addresses were deleted following data linkage.

Studies in Human

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was conducted in accordance with Declaration of Helsinki. This study was approved by the Ethics Committee of the Institute for Digitalisation of Education of the National Academy of Educational Sciences of Ukraine (Approval No. Protocol No. 9, dated 2021-09-13).

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

During the preparation of this work, the authors used Claude Opus 4.5 to improve readability and language of the manuscript. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix A. Supplementary data

Supplementary data for this article can be found online at doi:10.1016/j.ssaho.2026.103394.

Data availability

The anonymized data supporting the findings of this study are available from the corresponding author upon reasonable request. Survey instruments are provided in the Supplementary Materials.

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