An integrated AI-supported model for developing digital competence in lifelong learning★

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Abstract
The article is devoted to the development and empirical testing of an integrated model for using artificial intelligence technologies to develop digital competence in adults in the context of lifelong learning. The initial problem is the fragmented implementation of digital solutions in professional development programs, where platforms, assessment tools, recommendation mechanisms, and management procedures exist separately and do not form a coherent educational environment. The proposed model considers AI not as an autonomous "teacher" but as an element of a coordinated socio-technical system, where learning outcomes are determined by the interaction of pedagogical design, technological infrastructure, learning analytics, and institutional governance. The conceptual part is based on four principles (integration, adaptability, scalasbility, accountability) and is implemented through a multi-level architecture and a cyclical mechanism. The research results were tested in control and experimental groups using mixed methods: scenario-based testing according to DigComp, questionnaires, interaction log analysis, regression modeling, and qualitative thematic analysis. The results showed a statistically significant increase in the integral index of digital competence in the experimental group compared to the control group. The most significant changes were observed in the domains of cybersecurity and information literacy. Modeling showed that the impact of AI on learning outcomes is mainly realized through engagement and self-regulation, while governance mechanisms indirectly influence trust, participation, and the nature of platform use. The scientific novelty lies in combining an ecosystem-based conceptual approach with a formalized mathematical-analytical framework for assessing competence dynamics and in empirically confirming the role of behavioral mediation and institutional regulation as key conditions for the effectiveness of AI-supported learning. The practical significance of the results lies in providing a coherent architecture for scalable digital upskilling programs and recommendations for implementing responsible AI governance necessary for trust and sustainability of educational outcomes.

Keywords
artificial intelligence in education, digital competence, adaptive learning, learning analytics, adult education. responsible ai, lifelong learning

1. Introduction

Digital technologies have become part of everyday life in ways that were difficult to imagine only a few decades ago. They affect how people work, communicate, use public services, and obtain information. In practice, this means that digital competence is no longer limited to technical specialists [1]. For most adults, it has become a necessary condition for employment, social participation, and professional development. Digital technologies have gradually become part of almost every area of professional and social life [2]. In this situation, educational institutions can no longer limit themselves to short training courses [3]. Instead, they are increasingly expected to support learning processes that develop over time and continue throughout a person's professional life [4].

In recent years, artificial intelligence has become more noticeable in everyday educational practice. Many programs now use adaptive platforms, automated feedback systems, and various data-based monitoring tools [5]. Research often points to their potential benefits for learning efficiency [6]. However, experience from schools, universities, and training centers suggests a more

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complex picture [7]. In practice, positive results do not arise automatically. In many cases, they depend not so much on technical sophistication as on how these tools are incorporated into teaching routines and organizational culture.

In a large number of programs, digital technologies are still introduced in a fragmented way. Different platforms and services are used simultaneously, but without clear coordination or common pedagogical logic. As a result, artificial intelligence is often perceived as an additional technical feature rather than as an essential part of learning design [8]. For adult learners, who differ in professional experience, motivation, and learning habits, this situation reduces the real value of training.

Similar patterns can be found in recent research. Many studies focus on specific technologies or short-term pilot projects, often carried out under relatively controlled conditions [9]. Much less attention is given to institutional contexts, governance practices, and long-term learning processes. Ethical and legal issues related to AI are also frequently discussed separately from everyday teaching, even though they strongly influence learner trust and acceptance.

From a theoretical point of view, many existing models still offer only a partial view of how education functions in real settings [10]. Some emphasize cognitive processes; others concentrate on system performance indicators [11]. Only a limited number of studies attempt to describe how pedagogical, technological, and organizational factors interact in daily institutional practice [12]. As a result, educators and policymakers often have to rely on general recommendations rather than on clearly grounded and practically tested guidance.

Taking these issues into account, the present study adopts an ecosystem perspective. In this approach, AI-supported learning is viewed as a network of interconnected processes rather than as a collection of separate tools. Particular attention is paid to the relationship between instructional design, technological infrastructure, analytical support, and governance mechanisms. On this basis, an integrated model for digital competence development in lifelong learning is developed and empirically tested.

2. Conceptual Model

Let us consider a conceptual model that aims to address the problems that exist in many existing applications of artificial intelligence used in lifelong learning. This paper proposes to consider AI not as an isolated educational tool, but rather a model that represents AI as an integrated socio-technical system with built-in pedagogical, analytical, and management structures. The development of this model was based on several iterative research cycles, which were based on design and corresponding empirical observations of pilot implementations.

The model was developed through iterative research cycles based on design and is based on empirical observations of pilot implementations. Its main goal is to ensure consistency between learning objectives, technological infrastructure, data-driven decision-making and learning objectives, as well as ethical responsibility.

2.1. Design Principles

The research identified key design principles. These principles were derived from both theoretical considerations and practical constraints observed in large-scale adult education initiatives. Thus, the development of an integrated AI model was based on four fundamental design principles (Figure 1): integration, adaptability, scalability, and accountability (Table 1).

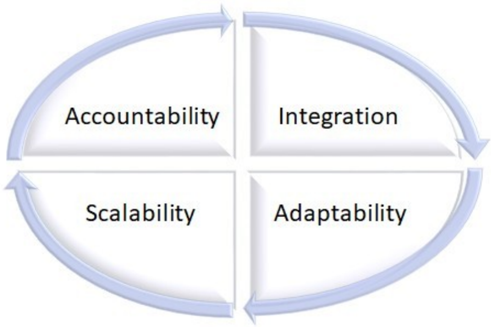

Figure 1: Design Principles

Integration in the proposed model refers to the deliberate coordination of pedagogical objectives, technological solutions, and analytical instruments. In practical terms, this means that learning content, assessment procedures, AI-based recommendations, and administrative processes are developed as parts of a unified system rather than as separate and weakly connected elements. Experience shows that isolated digital tools often lead to fragmented learning trajectories, superficial skill acquisition, and limited transfer of knowledge to real-life situations. The integrated model aims to address these issues by ensuring coherence and functional compatibility among all system components.

Table 1.
Design Principles and Their Operationalization

Principle	Pedagogical Function	Technological Mechanism	Governance Instrument
Integration	Curriculum coherence	API interoperability	Quality standards
Adaptability	Personalized instruction	Recommendation engines	Review protocols
Scalability	Mass participation	Cloud infrastructure	Resource planning
Accountability	Ethical learning management	Audit trails, explainability	Ethics committees

Adaptability reflects the capacity of the system to respond flexibly to differences in learners' competence levels, learning preferences, and personal circumstances. Adaptive mechanisms operate through the adjustment of learning content, task difficulty, feedback intensity, and learning pace. This principle is particularly important in lifelong learning contexts, where participant groups are highly heterogeneous and characterized by diverse educational backgrounds and professional experiences. Under such conditions, standardized curricula rarely meet the needs of all learners, and individualized learning pathways become essential.

Scalability refers to the ability of the model to operate effectively across institutions of different sizes, population groups, and resource conditions. The system architecture is designed to support gradual expansion without reducing instructional quality or compromising data reliability. This feature is especially important for regional and national professional development programs, where small-scale pilot initiatives must eventually be transformed into stable, long-term educational practices.

Accountability emphasizes the importance of transparency, ethical responsibility, and institutional control in AI-supported learning environments. Automated processes and algorithmic recommendations must remain subject to human supervision, documentation, and regular evaluation. This principle ensures that technological efficiency does not override pedagogical judgment, professional responsibility, or broader social values.

2.2. Structure of the Integrated AI Model

The integrated AI model was designed as a multi-level system consisting of four interdependent levels: pedagogical, technological, analytical and managerial (Table 2). Each level performs a separate function, while remaining functionally interconnected.

The pedagogical level defines learning objectives, learning strategies, assessment criteria and competence descriptors. It formalizes digital competence according to the established framework and contextual learning needs. At this level, AI serves as a pedagogical assistant, not an autonomous instructor. AI supports the implementation of the curriculum and helps in guiding students.

The technological level covers software platforms, user interfaces, cloud infrastructure and communication protocols. It provides the operational basis for other levels and is responsible for content delivery, interaction and data collection. Modular design principles allow for flexible configuration of the system and integration with external services.

The analytics layer processes learning data using statistical, machine learning, and visualization tools. The primary function of this layer is to generate actionable insights into learner progress, risk factors, and timely intervention and curriculum adjustments. Learning analytics serves as the primary feedback mechanism that connects empirical data to instructional decision-making.

The governance layer governs ethical standards, data protection, quality assurance, and strategic alignment. It helps generate accountability and ensures compliance with legal frameworks. This layer plays a critical role in maintaining trust and engagement between learners, educators, and stakeholders.

Table 2.
Structural Levels of the Integrated AI Model

Level	Core Function	Key Actors	Outputs
Pedagogical	Learning design	Educators, experts	Competence models
Technological	System operation	IT specialists	Platform services
Analytical	Evidence generation	Data analysts	Performance indicators
Governance	Regulation and control	Administrators	Policy instruments

The functioning of the integrated model is based on coordinated interactions between its structural layers. This inter-layer interaction forms a continuous regulatory cycle. The main goal of this is to correlate the student's behavior with adaptation to learning and adjustment of learning plans.

The operational logic can be summarized in five main mechanisms:

- Competency profiling. Initial and ongoing assessments allow to identify and generate multidimensional profiles of students, reflecting the strengths and weaknesses of the subject area.
- Adaptive recommendations. Based on the obtained profiles, artificial intelligence algorithms offer individual learning paths, resources and task sequences.
- Intelligent learning. Using AI to process natural language and provide contextual explanations, prompts and feedback.
- Learning analytics. Formation of interaction logs and various performance indicators, which are used to predict and diagnose the state of learning.
- Human mediation. Educators systematically review the results of the system, intervene in difficult cases, and adjust teaching strategies.

These mechanisms significantly assist in shaping and supporting the learning trajectory, but do not completely replace the presence of educators.

At the operational core of the integrated system lies the AI-Enabled Digital Competence Development Cycle (AIDCDC). This cycle emphasizes that learning is a recursive process driven by feedback and adaptation (Table 3).

The cycle should begin with a diagnostic assessment, followed by the development of personalized learning and task-oriented practice. Feedback allows learners to analyze errors, while performance evaluation confirms the acquisition of competence. System adjustments close the loop by updating the learning and analytical parameters.

This cyclic structure prevents stagnation and supports continuous competence refinement.

Table 3.
AIDCDC Learning Cycle Components

Stage	Objective	AI Function	Human Role
Diagnosis	Baseline measurement	Profiling algorithms	Validation
Personalization	Path design	Recommender systems	Supervision
Practice	Skill development	Tutoring systems	Facilitation
Reflection	Metacognitive growth	Feedback analysis	Mentoring
Evaluation	Outcome verification	Analytics models	Interpretation
Adjustment	System optimization	Model retraining	Strategic decisions

The integrated conceptual framework combines design principles, structural levels, functional mechanisms, and the learning cycle into a single framework (Figure 2). The purpose of the integrated conceptual framework is to support the sustainable development of digital competence throughout life. It combines pedagogical goals, technological infrastructure, analytical processes, and management structures.

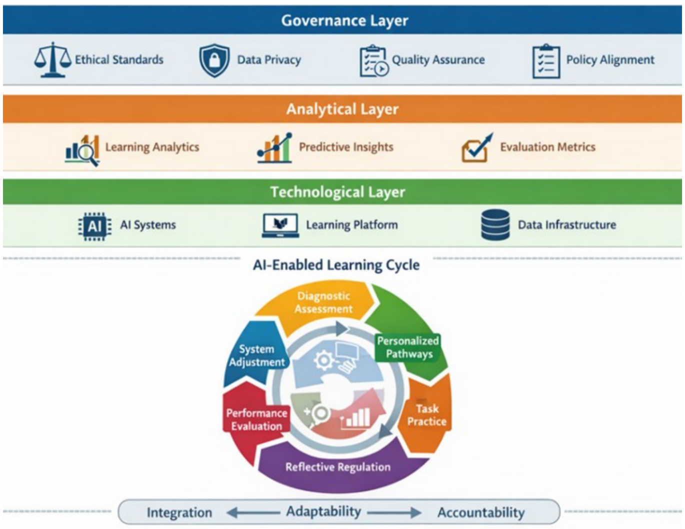

Figure 2: Integrated AI model for developing digital competence in lifelong learning

The integrated framework demonstrates that effective lifelong learning supported by artificial intelligence does not require isolated technological solutions, but a coordinated ecosystem capable of continuous adaptation and ethical regulation.

The proposed integrated AI model represents digital competence development as a dynamic, regulated, and socially embedded process. Its originality lies in the systematic combination of adaptive technologies, learning analytics, human mediation, and institutional governance within a unified conceptual architecture.

By linking theoretical foundations with empirical design principles, the model provides a robust framework for both scientific analysis and practical implementation in lifelong learning systems.

3. Mathematical Modeling of AI-Supported Digital Competence Development

The development of digital competence in lifelong learning settings is a complex and multidimensional process influenced by cognitive, technological, behavioural and institutional factors. Often, such processes cannot be fully represented by formal models. However, a partial mathematical representation is an important analytical tool for understanding learning dynamics, assessing the effectiveness of interventions and supporting evidence-based decision-making.

In this study, mathematical modelling is used not as an abstract theoretical model, but as an additional methodological layer that represents the proposed conceptual framework and allows for its empirical validation. The strategy chosen to formalise the model includes index-based measurements, dynamic modelling and causal analysis to capture both structural and temporal aspects of competence development.

3.1. Composite Measurement of Digital Competence

Digital competence is presented as an integrated construct consisting of several interrelated domains. To ensure comparability across learners and learning contexts, these domains are combined into a composite digital competence index.

Let $D_i(t)$ denote the standardized performance score of the *i*-th competence domain at time t, where the domains correspond to information literacy, communication, digital content creation, cybersecurity, and problem-solving. The overall competence level is expressed as:

$$CCI(t)=\sum_{i=1}^{5} w_i D_i(t). \quad (1)$$

The weighting coefficients w_i reflect the relative contribution of each domain to overall digital functioning. These weights were determined using principal component analysis and expert assessment procedures. The integration of statistical and expert weighting should ensure both empirical robustness and pedagogical relevance.

The composite index serves as a central analytical variable throughout the study. It allows for monitoring of individual learning trajectories and supports comparative analysis between experimental and control groups.

3.2. Modeling Temporal Learning Dynamics

Digital competence does not emerge instantaneously, but develops gradually, through repeated learning cycles. To explore this temporal dimension, competence development is modeled as a dynamic process influenced by both prior learning outcomes and contextual factors.

Let $CCI(t)$ represent the competence level at learning stage *t*. The progression to the subsequent stage is formalized as:

$$CCI_{t+1}=\alpha\cdot CCI_t+\beta\cdot AI_t+\gamma\cdot SR_t+\delta\cdot E_t+\lambda\cdot F_t+\varepsilon_t \quad (2)$$

where AI_t represents the intensity of interaction with AI-supported learning tools, SR_t denotes self-regulation capacity, E_t reflects learner engagement, and F_t corresponds to feedback quality. The parameter α reflects learning persistence, while the other coefficients quantify the contribution of each variable.

The inclusion of the term CCI_t is justified by empirical evidence indicating strong continuity in learning behavior. Previous levels of competence significantly influence subsequent performance, especially in adult learning contexts characterized by gradual and cumulative skill development.

The stochastic component ε_t accounts for unobserved contextual factors such as health conditions, occupational workload, or technological disruptions.

Parameter estimation was conducted using panel regression techniques with fixed and random effects specifications. Stability conditions requiring $0<\alpha<1$ were verified empirically, ensuring convergence of learning trajectories.

3.3. Formalization of Adaptive Learning Pathways

Personalization constitutes a core element of the proposed integrated model. From an analytical perspective, personalized learning pathways can be interpreted as adaptive trajectories that evolve in response to performance feedback and instructional recommendations.

Let $P_i(t)$ denote the learning pathway state of learner i at time *t*. Pathway evolution is expressed as:

$$P_i(t+1)=f\left(P_i(t),R_i(t),F_i(t),CCI_i(t)\right), \tag{3}$$

where $R_i(t)$ represents the system-generated recommendation vector and $F_i(t)$ denotes feedback information.

The function f is implemented using reinforcement learning algorithms that iteratively update pathway parameters based on observed learning outcomes. This model demonstrates the assumption that effective personalization requires continuous exploration and use of instructional alternatives.

To balance learning efficiency and learning, sustainability path optimization, we introduce the objective function:

$$J=\sum_{t=1}^{T}\Delta CCI_t+\omega_2 S_t-\omega_3 L_t, \tag{4}$$

where ΔCCI_t denotes competence gains, S_t learner satisfaction, and L_t cognitive load. This formulation ensures that short-term performance improvement does not occur at the expense of long-term motivation or well-being.

3.4. Predictive Modeling of Learning Risks

Continuous engagement in learning is a critical condition for developing competence in lifelong learning programs. To identify learners at risk of disengagement, a logistic regression model was developed:

$$P(D=1)\frac{1}{1+e^{-(\theta_0+\theta_1 CCI+\theta_2 E+\theta_3 F)}}. \tag{5}$$

This model estimates the probability of student disengagement as a function of competence level, engagement, and quality of feedback. Its integration into the learning platform allows for early warning mechanisms, retention, and targeted support interventions.

3.5. System-Level Application of the Mathematical Framework and Limitations of the Formalization Approach

The mathematical components described above are embedded in an integrated AI platform as interconnected analytical modules. A competency index provides diagnostic assessment, a dynamic regression model informs progress monitoring, an adaptive pathway model enables personalized exploration, and a risk prediction module provides proactive support for students throughout their learning journey.

Teachers and administrators access these analytical outputs through visual dashboards that translate complex model results into actionable insights. This integration ensures that mathematical formalization directly contributes to pedagogical decision-making rather than remaining an abstract analytical layer.

Despite its analytical utility, the proposed mathematical framework has several limitations. Cognitive and motivational variables can only be observed partially, and their formalization involves approximation. Moreover, the stability of the parameters can be affected by changes in the institutional context and technological infrastructure.

Therefore, the ongoing calibration and contextual interpretation of important components of the model remains a pressing issue. Thus, at this stage, the proposed mathematical model cannot serve as a universal tool and requires responsible application of the model, but in this study, it is key to obtaining analytical data.

The mathematical framework developed in this study provides a coherent formal representation of the development of digital competence in lifelong learning environments supported by artificial intelligence. It offers a sound methodological basis for both scientific research and practical implementation.

4. Methodology

The methodological framework of this study was developed to ensure coherence between the integrated conceptual-analytical model and its empirical validation. Given the complexity of lifelong learning systems supported by artificial intelligence, a purely experimental or purely qualitative approach will be insufficient to capture both learning outcomes and underlying mechanisms.

The study therefore uses a quasi-experimental mixed-methods design, supported by learning analytics and process-oriented qualitative research. This design allows for a systematic assessment of causal relationships while remaining sensitive to contextual and empirical factors.

4.1. Research Design

The study follows a quasi-experimental pretest–posttest control group design integrated within a mixed-methods research strategy (Figure 3). Full randomization was not feasible due to institutional and ethical constraints typical of adult education programs. Consequently, intact learning groups were assigned to experimental and control conditions using matched-pair procedures.

The experimental group participated in the integrated AI-supported learning environment, while the control group followed conventional instructor-led digital competence training. The quantitative assessment of outcomes was complemented by qualitative process analysis, which strengthened validity.

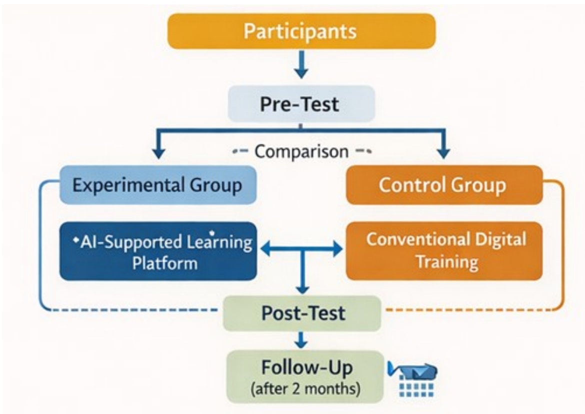

Figure 3: Overall Research Design

This structure supports both short-term impact analysis and medium-term retention assessment.

4.2. Participants and Sampling Strategy

Participants were recruited from different groups of educational centers and companies in Kyiv, formed on the basis of lifelong learning and advanced training programs. The target group consisted of adult learners engaged in advanced training and digital literacy development, both on their own initiative and groups formed by companies to improve the digital literacy of employees.

The final sample included 128 participants aged 23–64. To ensure representativeness, stratified sampling was used based on age, education, employment status, and access to digital technologies (Table 4).

Within each stratum, students were selected according to baseline competency scores and then assigned to experimental or control conditions.

This procedure minimized selection bias and facilitated generalization to the population level.

Table 4.
Sample Characteristics (Summary)

Variable	Category	Percentage
Gender	Female / Male	38 / 62
Residence	Urban / Rural	73 / 27
Education	Secondary / Higher	28 / 72
Employment	Employed / Unemployed	81 / 19

4.3. Research Instruments and Data Sources

To capture multiple dimensions of digital competence development, the study used a framework that combines performance measurement, self-report data, and behavioral analytics (Figure 4):

- Standardized scenario-based tests were developed according to the DigComp framework. The tests measured information evaluation, cybersecurity awareness, digital content creation, and problem-solving skills.
- Reliability analysis showed Cronbach's $\alpha = 0.87$, indicating satisfactory internal consistency.
- Validated questionnaires were used to assess student engagement, perceived usefulness of AI support, and technology acceptance.
- Automated system interaction logs were implemented to record task completion time, feedback use, navigation patterns, and recommendation acceptance. These data provided objective measures of learning behavior.

Figure 4: Data Collection Architecture

This architecture ensures continuous and synchronized data acquisition.

Here is the study procedure. The empirical study was conducted over a 16-week period and followed a structured multi-phase protocol aligned with the AIDCDC learning cycle (Table 5).

Table 5.
Intervention Timeline

Phase	Duration	Activities
Baseline Diagnostics	Weeks 1–2	Participants completed initial competency tests and surveys. Individual learning profiles were created using AI-based profiling algorithms.
Intervention Implementation	Weeks 3–12	Over a 10-week period, participants used personalized learning paths, intelligent learning systems, and analytics-based feedback mechanisms. The control group followed standardized curricula without adaptive AI support.
Post-Intervention Evaluation	Weeks 13–14	Post-intervention tests, surveys, and interviews were conducted to assess the immediate learning effect and user experience.
Retention Evaluation	Weeks 15–16	A delayed test tested retention and transferability of competencies.

4.4. Data Analysis and Integration Strategy

Data analysis procedures were aligned with the multi-layer architecture of the integrated AI model (Figure 5):

- **Quantitative Analysis.** Descriptive statistics were used to summarize baseline characteristics. Dynamic regression models and structural equation modeling were applied to analyze learning trajectories and causal relationships.
- **Qualitative Analysis.** Interview transcripts and reflective journals were analyzed using thematic coding. An inductive–deductive strategy enabled identification of both theory-driven and emergent patterns.
- **Mixed-Methods Integration.** Quantitative and qualitative findings were integrated through joint display matrices and narrative synthesis.

The methodology implemented combines experimental evaluation, learning analytics, and qualitative process analysis within a coordinated mixed-methods design.

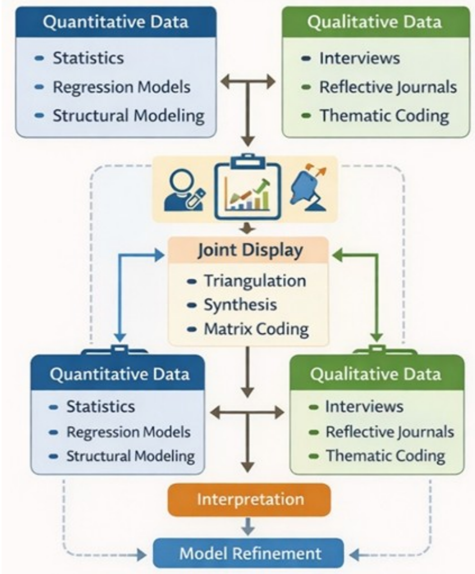

Figure 5: Analytical Integration Framework

The inclusion of visualized workflows and analytical architectures enhances methodological transparency and supports reproducibility.

5. Results

Let us consider empirical evidence for the effectiveness of the proposed integrated model for developing digital competence based on artificial intelligence.

Quantitative indicators are complemented by qualitative findings to provide a comprehensive explanation of learning dynamics in the context of lifelong learning.

5.1. Baseline Analysis

Before the intervention was introduced, a baseline analysis was carried out to examine whether the experimental and control groups were comparable in terms of their initial levels of digital competence (Table 6). This step was necessary to ensure that any subsequent differences could be attributed to the intervention rather than to pre-existing disparities.

Table 6.
Baseline Digital Competence Indicators

Domain	Experimental (M)	Control (M)	p-value
Information literacy	56,1	55,8	0,61
Communication	59,4	60,2	0,48
Content creation	52,7	53,3	0,55
Cybersecurity	47,9	48,5	0,62
Problem solving	55,4	56,1	0,51

The results of the pre-test indicated that participants in both groups demonstrated generally moderate levels of digital competence. No statistically significant differences were identified between the groups ($p > 0{,}05$). The mean value of the composite competence index at baseline was 54,3 (SD = 11,2) in the experimental group and 55.1 (SD = 10,9) in the control group, suggesting a high degree of initial similarity.

A more detailed domain-level examination showed that cybersecurity awareness and information verification skills were comparatively weak in both groups. This pattern is consistent with previous observations in adult education contexts, where such competencies often represent persistent challenges.

Taken together, these results indicate that the two groups were well matched at the outset of the study. This provided a solid basis for the subsequent analysis of intervention effects and strengthened the internal validity of the research design.

5.2. Learning Outcomes

Learning outcomes were evaluated by comparing participants' performance before and after the intervention and by monitoring changes in competence levels over time. This approach made it possible to capture both immediate learning effects and their subsequent development.

The analysis showed clear and consistent improvement in the experimental group across all competence domains (Table 7). These changes were statistically significant ($p < 0{,}001$). On average, the composite competence index increased from 54,3 at the beginning of the study to 78.6 after the intervention, which corresponds to a mean gain of 24,3 points. By comparison, participants in the control group demonstrated a much smaller increase, from 55,1 to 63,4.

Effect size calculations further confirmed the practical relevance of these results. The obtained value of Cohen's d (0,82) indicates that the observed improvements were not only statistically reliable but also educationally meaningful and closely related to the use of the AI-supported learning model.

Table 7.
Pre–Post Learning Outcomes

Group	Pre-test	Post-test	Gain (Δ)	Cohen's d
Experimental	54,3	78,6	+24,3	0,82
Control	55,1	63,4	+8,3	0,29

Follow-up assessment conducted two months after the completion of the program revealed that most of the achieved progress was retained. Approximately 87% of the competence gains were preserved, suggesting that the intervention led to relatively stable changes in learners' digital practices rather than short-term performance fluctuations.

5.3. Domain-Level Effects

To better understand how learning outcomes differed across specific competence areas, a separate analysis was carried out for each DigComp domain. This made it possible to identify which types of skills were most strongly influenced by the intervention (Table 8).

Table 8.
Domain-Level Competence Gains

Domain	Experimental Δ (%)	Control Δ (%)
Information literacy	+21	+7
Communication	+14	+5
Content creation	+19	+6
Cybersecurity	+28	+9
Problem solving	+18	+6

The largest improvements were recorded in cybersecurity and information literacy, with increases of 28% and 21%, respectively. These gains appear to be closely related to the use of AI-based simulations and adaptive feedback, which allowed participants to practice typical problem situations and receive immediate guidance. Noticeable progress was also observed in content creation and problem-solving skills. In contrast, competencies related to communication developed more slowly and showed more moderate changes over the same period.

Overall, these results indicate that AI-supported learning environments are particularly well suited for domains that require repeated practice, step-by-step guidance, and rapid feedback. In such areas, technological support seems to reinforce learning processes more effectively than in domains that depend primarily on social interaction and collaborative experience.

5.4. Predictive Factors of Competence Development

To better understand which factors played the most important role in competence development, the data were analyzed using regression methods and structural equation modeling. This made it possible to examine both direct and indirect relationships between different learning variables.

The results of multiple regression analysis showed that learner engagement, self-regulation, and the quality of feedback provided by the AI system were strongly associated with learning outcomes. (Table 9) Together, these factors explained a substantial proportion of the observed variance ($R^2 = 0{,}67$). Among them, the intensity of AI use demonstrated the strongest direct influence on competence development.

Further insights were obtained from the structural equation model. The analysis indicated that engagement functioned as a key mediating factor between AI support and self-regulatory behavior. In practice, this means that technological support first increased learners' involvement in learning activities, which then promoted more effective self-regulation and, ultimately, higher levels of digital competence.

Table 9.
Regression Model Results

Predictor	β	SE	p-value
AI usage	0,41	0,05	<0,001
Engagement	0,33	0,06	<0,001
Self-regulation	0,19	0,07	0,004
Feedback quality	0,15	0,06	0,018

The results of the study suggest that the influence of technological tools on learning is largely indirect and operates mainly through changes in learners' behavior and thinking patterns. In other words, technology itself does not automatically lead to better outcomes, but works through the ways in which learners engage with content, reflect on their progress, and organize their learning activities.

Qualitative data helped to clarify how these processes unfolded in practice. Interviews and open-ended responses showed that many participants gradually became more independent in their use of digital resources and more confident in online environments. They also reported a better understanding of cybersecurity risks and a stronger ability to evaluate the reliability of information. At the same time, learners frequently pointed to the motivational role of personalized feedback and the feeling of security created by simulated learning situations. For many of them, individualized recommendations played an important role in maintaining engagement and structuring daily learning routines.

Teachers and instructors provided a complementary perspective. They emphasized the practical value of learning analytics dashboards, especially for monitoring student progress and detecting emerging difficulties. According to their experience, these tools made it easier to intervene at an early stage and to adjust instructional strategies to individual needs. As a result, support measures became more timely and more precisely targeted.

When considered together, the qualitative and quantitative findings present a coherent picture of the learning process. They indicate that observed improvements were not limited to technical skills, but were also accompanied by changes in attitudes, self-confidence, and self-regulatory behavior. Overall, the evidence shows that the integrated AI-supported model contributed to meaningful and sustainable development of digital competence in lifelong learning settings. The combination of general progress, domain-specific improvements, high learner engagement, and positive user experiences provides strong support for the proposed conceptual–analytical framework.

6. Discussion

6.1. Interpretation of Findings

The results of the study show that the proposed AI-supported model led to clear and stable improvements in the digital competence of adult learners. The size of the observed effect indicates that these changes were not only statistically reliable but also meaningful in practical educational terms.

Further analysis suggests that these improvements did not result simply from the use of new technologies. Instead, they were largely linked to higher levels of learner engagement and more developed self-regulation skills. In this sense, artificial intelligence functioned mainly as a supportive tool that helped participants reflect on their learning and take greater responsibility for their progress.

The follow-up assessment provides additional evidence in this regard. Most of the acquired skills were retained over time, which indicates that learners did not merely adapt temporarily to the training format. Rather, they developed more stable digital practices and greater confidence in working in online environments. This interpretation is also supported by qualitative data.

Overall, the findings confirm the main assumption of the AIDCDC model: sustainable competence development depends on the continuous interaction between diagnostic assessment, adaptive support, reflective learning processes, and analytical feedback.

Previous research indicates that institutional and managerial support plays a significant role in shaping learners' and employees' attitudes toward continuous professional development and technology-supported learning. Visible commitment from organizational leadership reduces uncertainty and increases motivation to engage in long-term competence development and reskilling initiatives [13], [14], [15]. The present findings confirm that individuals are more willing to invest effort in AI-supported learning and lifelong upskilling when they perceive consistent institutional support, which directly corresponds to the second objective of this study, aimed at identifying organizational conditions that facilitate sustainable AI-enabled learning environments.

6.2. Alternative Interpretations and Robustness of Findings

Although the results provide strong support for the proposed model, it is important to consider other possible explanations. One potential interpretation is that the observed improvements were caused mainly by more intensive instruction rather than by the use of AI technologies. However, the comparison of teaching time and curriculum content between the experimental and control groups does not support this assumption.

Another possible factor is the so-called novelty effect. New technologies often increase motivation in the early stages of learning simply because they are unfamiliar and attractive. While such an effect was observed at the beginning of the program, follow-up results indicate that learning gains were largely preserved over time. This suggests that the improvements cannot be explained by short-term enthusiasm alone.

Participation in the study was voluntary, which raises the possibility of self-selection bias. To reduce this risk, baseline equivalence and stratified matching procedures were applied. Although this does not eliminate all sources of bias, it increases confidence in the validity of the findings.

Taken together, these considerations indicate that the observed effects are relatively stable and cannot be attributed solely to methodological artifacts or temporary motivational factors.

6.3. Comparison with Prior Research

Most previous studies on AI-supported learning have focused on individual technological tools, such as intelligent tutoring systems, recommender platforms, or analytics dashboards. While these studies often report positive learning effects, they rarely examine how such tools are integrated into broader institutional and organizational contexts.

In contrast, the present study adopts a systemic perspective that emphasizes the interaction between pedagogical design, analytical support, and governance structures. This approach differs from tool-centered models by treating AI as part of a coordinated learning ecosystem rather than as an isolated technical solution.

In addition, many earlier investigations were based on relatively small samples and short-term interventions. The present study extends this line of research by demonstrating sustained effects in heterogeneous adult learner populations, thereby strengthening the external validity of existing findings.

From a methodological standpoint, the combination of regression analysis, structural equation modeling, and qualitative process analysis provides a more comprehensive understanding of learning mechanisms than approaches based on single-method designs.

6.4. Theoretical Propositions

On the basis of the obtained results and their interpretation, the study proposes several theoretical statements that reflect its main contributions. These statements are grounded in both quantitative and qualitative evidence and are intended to support further theoretical development in this field.

Table 10 summarizes the key propositions together with their empirical support and conceptual background.

Table 10.
Theoretical Propositions and Empirical Support

Proposition	Statement	Empirical Basis	Theoretical Link
P1	AI effects are mediated by engagement and self-regulation	β = 0,41, p < 0,001; SEM paths	Self-regulated learning
P2	Governance structures shape learning outcomes	Qualitative themes	Socio-technical theory
P3	Integrated ecosystems outperform isolated tools	Effect size, retention rates	Systems theory
P4	Learning analytics function as regulatory instruments	Regression and SEM results	Learning analytics

The propositions presented in Table 10 show that the effectiveness of educational technologies largely depends on how learners actually use them and on how learning processes are organized and regulated within institutions. The results suggest that artificial intelligence does not replace teaching practices, but rather strengthens existing learning processes when it is introduced in a supportive and well-structured organizational environment.

In this way, the proposed propositions broaden current theoretical models by highlighting the importance of governance and system integration as key factors shaping learning outcomes.

6.5. Refinement of the Conceptual–Analytical Model

The results of the study showed that the original conceptual model required certain adjustments. Although the initial framework assumed that pedagogical, technological, and analytical components played relatively equal roles, the empirical evidence points to a more central role of learner engagement and self-regulation.

In addition, governance mechanisms appeared to influence learning outcomes indirectly, mainly by shaping levels of trust, participation, and patterns of platform use. These factors proved to be important for sustaining learner involvement over time.

Taking these observations into account, the original model was revised to place greater emphasis on behavioral mediation and institutional regulation. The updated conceptual – analytical framework, developed on the basis of empirical validation, is presented in Figure 6.

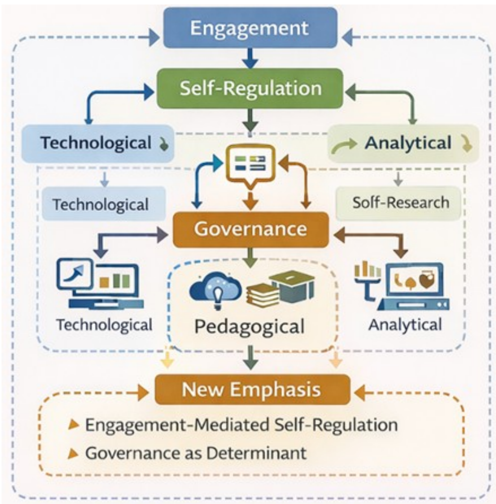

Figure 6: Refined Conceptual–Analytical Model of AI-Supported Digital Competence Development

Figure 6 illustrates the strengthened links between AI tools, learner engagement, self-regulation, and competence development, while also showing the active role of governance in shaping these processes.

The revised model points to three important changes in how learning processes should be understood. First, engagement appears as the main link between technological support and actual learning activities. In other words, technology influences learning primarily through the way it involves learners in the process. Second, self-regulation plays a central role in helping learners internalize new skills and apply them independently. Third, governance is no longer treated as a secondary control mechanism, but as an active factor that influences how learning systems function in practice.

Overall, this updated framework reflects more accurately how AI-supported lifelong learning systems operate in real institutional settings and offers a clearer picture of the processes that shape learning outcomes.

6.6. Theoretical and Practical Implications

The findings of this study are relevant both for theoretical discussions and for practical work in the field of education.

From a theoretical point of view, the results confirm that successful AI-supported learning cannot be explained by technology alone. Learning outcomes depend on how instructional design, learner self-regulation, technological tools, and institutional arrangements work together in practice. The study shows that artificial intelligence influences learning mainly by supporting engagement, reflection, and self-management, rather than by replacing traditional teaching processes. In this way, the proposed framework helps to better understand how digital competence develops over time and how it can be assessed as a dynamic and evolving ability.

At the practical level, the results provide several useful insights for educators and trainers. They indicate that AI tools should be carefully integrated into teaching strategies and learner support systems. Simply introducing new technologies without reconsidering pedagogical approaches is unlikely to lead to lasting improvements. In this context, developing staff competencies in learning analytics and data-informed decision-making appears to be especially important.

For institutional leaders, the findings emphasize the need to build strong governance structures that support responsible and transparent use of artificial intelligence. Such structures are essential not only for ethical compliance, but also for maintaining learner trust and long-term engagement.

From a policy perspective, the study supports a shift away from rigid digital standards toward flexible, evidence-based strategies for competence development. Approaches grounded in learning analytics and continuous evaluation are better suited to the changing needs of lifelong learning systems. The proposed model may therefore serve as a practical reference for designing and expanding digital upskilling initiatives at regional and national levels.

Overall, the results suggest that meaningful and sustainable use of artificial intelligence in lifelong learning depends on coordinated progress in theory, institutional capacity, and public policy, rather than on technological innovation alone.

6.7. Implications for AI Governance and Regulation

The results of this study indicate that responsible governance of artificial intelligence plays a practical and indispensable role in ensuring the effectiveness of educational systems. Clear rules for data use, transparent algorithmic processes, and meaningful human involvement in decision-making were closely associated with higher levels of learner trust and long-term engagement.

For this reason, regulatory approaches should focus not only on technical compliance, but also on strengthening institutional capacities for ethical supervision, regular monitoring, and pedagogical guidance. Such organizational mechanisms appear to be essential for maintaining both educational quality and social legitimacy.

The multi-level governance framework proposed in this study may therefore serve as a useful reference for developing sector-specific regulatory models in lifelong learning and adult education.

The extended discussion moves beyond a simple description of results and develops broader theoretical and practical insights. By linking empirical evidence with clearly formulated propositions and a revised conceptual framework, the study contributes to a more mature understanding of AI-supported lifelong learning systems.

In this context, the use of Table 10 and Figure 6 plays an important role in clarifying analytical relationships and strengthening the cumulative value of the proposed model.

7. Limitations and Future Research

Although the study offers solid theoretical arguments and empirical evidence, its results should be interpreted with certain limitations in mind.

To begin with, the research was carried out in a relatively small number of educational institutions, each with its own organizational structures, financial resources, and technological infrastructure. For this reason, similar results may not necessarily be obtained in other institutional settings, particularly in systems with weaker governance mechanisms or limited digital capacity. Moreover, large-scale implementations may encounter coordination and data management difficulties that were beyond the scope of the present study.

In addition, the participants came from specific social, cultural, and economic backgrounds. Attitudes toward technology, privacy, and independent learning vary across regions and communities, and these differences may influence how AI-supported systems are adopted and used. Language barriers and unequal access to digital resources may further affect learning outcomes, especially in disadvantaged areas.

The study also relied on technological platforms and analytical tools that were available at the time of data collection. Given the rapid development of generative AI and intelligent agents, learning environments may change in ways that require new theoretical models and evaluation approaches. Some of the assumptions underlying the current analytical framework may therefore need to be reconsidered in future research.

From a methodological perspective, several key variables, including motivation and perceived cognitive load, were measured mainly through self-report questionnaires. Although these data were complemented by behavioral indicators, they may still reflect subjective bias. Furthermore, the quasi-experimental design limits strong causal claims, and unobserved external factors, such as informal learning activities or workplace experiences, may have influenced the results. The follow-up period was also too short to capture long-term learning and career trajectories.

Future research should seek to address these limitations through longitudinal studies, cross-regional comparisons, and experimental designs that examine different governance and implementation models. Special attention should be given to the integration of emerging technologies, such as generative systems and immersive learning environments, within transparent and ethically grounded institutional frameworks. Interdisciplinary collaboration among educators, data scientists, and policymakers will be particularly valuable in this process.

In conclusion, while the present study provides strong evidence for the potential of integrated AI-supported competence development, its findings remain influenced by contextual, technological, and methodological factors. Continued research will be essential for building sustainable, responsible, and inclusive lifelong learning systems.

8. Conclusions

This study aimed to design, test, and validate an integrated model for supporting digital competence development in lifelong learning through the use of artificial intelligence. By combining conceptual analysis, mathematical modeling, experimental evaluation, and qualitative research methods, the study offers a coherent approach to understanding how AI can be meaningfully integrated into adult education systems.

The results show that digital competence develops most effectively when artificial intelligence supports and guides the learning process rather than replaces it. In the experimental group, learning progress was mainly linked to higher levels of engagement and improved self-regulation. These processes were reinforced through personalized learning paths, learning analytics, and appropriate institutional support.

From a conceptual point of view, the study proposes an ecosystem-based model that connects pedagogical design, technological infrastructure, analytical tools, and governance mechanisms within a single framework. Empirical evidence confirms that such coordinated systems lead to more stable and long-lasting learning outcomes than isolated technological solutions.

The analytical framework developed in this research also contributes to a clearer understanding of digital competence as a dynamic and measurable process. By combining competence indicators, progression models, and causal relationships, the study provides a solid basis for designing and evaluating data-informed learning systems.

In methodological terms, the research demonstrates the benefits of integrating quasi-experimental methods with learning analytics and qualitative analysis. This combination makes it possible not only to measure learning outcomes accurately, but also to understand how and why these outcomes emerge in real educational settings.

In addition to its scientific contribution, the study offers practical guidance for educational institutions, policymakers, and technology developers. The findings underline the importance of linking AI implementation with pedagogical planning, staff training, and effective governance structures. Sustainable digital skills development requires organizational learning and regulatory readiness alongside technological investment.

The results also highlight the crucial role of responsible AI governance in education. Transparent data management, meaningful human oversight, and institutional accountability proved essential for building learner trust and maintaining long-term engagement. These insights support the development of targeted regulatory approaches for AI-supported lifelong learning.

Overall, the study shows that artificial intelligence can significantly strengthen digital competence development when it is embedded in well-coordinated, human-centered educational ecosystems. By bringing together theory, analytical modeling, and empirical evidence, the proposed framework contributes to the further development of research in this field and provides a practical foundation for future innovation.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT-5.2 in order to: Grammar, spelling check and Generate images (for figures 2-6). After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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