“National AI development and adult lifelong-learning participation: Evidence for knowledge-transfer policy in European countries”

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NATIONAL AI DEVELOPMENT AND ADULT LIFELONG-LEARNING PARTICIPATION: EVIDENCE FOR KNOWLEDGE-TRANSFER POLICY IN EUROPEAN COUNTRIES

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Abstract

Artificial intelligence has become a driver of knowledge transformation, skills renewal, and institutional change, making lifelong learning increasingly important for adapting to AI-driven labor markets and societies. This study aims to examine whether national AI development indicators are associated with realized participation in education and training across different adult age groups in European countries, and to discuss what these associations may imply for lifelong learning and knowledge transfer policies. The analysis is based on a panel of 18 European countries for 2017–2024 and applies two-way fixed-effects models with country and year effects, contemporaneous, one-year, and two-year lag specifications, and Driscoll–Kraay robustness checks. The results show that the total AI Vibrancy Score is not a statistically significant predictor of participation in education and training: the contemporaneous coefficients are 0.4822 for adults aged 18-74, 0.1054 for those aged 45-54, and 0.5006 for those aged 50-74. Descriptive statistics indicate that average lifelong-learning participation declines with age, from 20.09% among adults aged 18-74 to 14.82% among those aged 45-54, and 9.34% among those aged 50-74. The lagged structural models show that AI-related R&D is negatively associated with subsequent participation, with one-year lag coefficients of –1.2310, –0.9392, and –0.8911 for the three age groups, respectively. In contrast, AI-related Policy and Government activity has a positive two-year lagged association for adults aged 18-74 and 45-54, with coefficients of 0.6064 and 0.7346. This suggests that policy-related AI development, rather than national AI development alone, may be more relevant for observed adult participation in education and training.

Keywords national AI development, lifelong learning, adult education, education and training participation, human capital, knowledge transfer, panel data

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INTRODUCTION

Artificial Intelligence (AI) is no longer only a technological issue; it has become a driver of knowledge transformation, skills renewal, and institutional change. The European Commission (2025) explicitly links AI competitiveness with human capital development, emphasizing the need to train and attract AI specialists while also improving AI skills and AI literacy among workers and the general population. The EU AI Act has strengthened this agenda by introducing an AI literacy requirement for providers and deployers of AI systems, while recent EU initiatives, including the AI Skills Academy and European Digital Innovation Hubs, place upskilling and reskilling at the center of AI adoption (European Parliament & Council of the European Union, 2024). This underscores the importance of investigating whether national AI development is reflected in actual adult participation in education and training, rather than only in policy declarations or technological indicators.

The topic is also relevant because European and international reports show that digital and adaptive skills remain unevenly distributed across the adult population. The European Commission's Joint Research Centre notes that only 55.6% of the EU adult population had at least basic digital skills, compared with the Digital Decade target of 80% by 2030; without further measures, this share may reach only 60% by 2030 (Bertoni et al., 2025). The same report stresses that older people, adults with lower levels of education, manual workers, and people with limited digital exposure require particular policy attention (Bertoni et al., 2025). Similarly, the OECD's Survey of Adult Skills shows that, on average across OECD countries, 18% of adults do not reach the most basic proficiency levels in literacy, numeracy, or adaptive problem solving, despite the growing importance of such skills for employment, social inclusion, and technological adaptation (OECD, 2024a).

This research is particularly timely for universities because international organizations increasingly frame lifelong learning as a key response to AI-driven labor market and knowledge changes. The OECD (2024b) argues that adult learning systems are being called upon to respond to major labor-market transitions, including the diffusion of AI in workplaces, and that upskilling and reskilling the existing workforce are essential because initial education alone is insufficient. UNESCO also stresses the need to integrate AI learning objectives into education systems and highlights AI competencies such as a human-centered mindset, AI ethics, AI techniques and applications, and AI system design (Miao et al., 2024). Therefore, analyzing adult participation in education and training provides empirical evidence on whether national AI development is accompanied by realized lifelong learning engagement, while any implications for universities should be interpreted as policy-oriented knowledge-transfer considerations rather than directly tested effects. At the same time, macro-level evidence on adult participation in education and training can provide strategic information for universities and other knowledge-transfer institutions, as the analysis of broader market, labor, and social trends is an important element of planning educational services, lifelong-learning provision, and institutional development.

1. LITERATURE REVIEW

National AI development is increasingly viewed as part of the knowledge-economy architecture because it affects how knowledge is generated, codified, transferred, and absorbed by organizations, labor markets, and public institutions. AI-related technological capacity, digital infrastructure, talent concentration, economic application, and policy activity are, therefore, not only innovation indicators but also signals of broader knowledge-system transformation (Abdullayev et al., 2026; Meidute-Kavaliauskiene et al., 2026; Yarovenko et al., 2025). However, the relationship between AI development and socio-economic performance is not automatic, as productivity effects, creative-economy opportunities, and knowledge-economy gains depend on organizational absorption capacity, institutional readiness, and the ability to translate technological progress into usable knowledge (Škare et al., 2025; Schinello, 2025; Olszewski & Krawczyk, 2026). This makes knowledge management a central condition for AI implementation, since AI adoption requires knowledge sharing, learning-oriented organizational cultures, an innovation climate, and mechanisms that reduce barriers such as knowledge hiding (Iaia et al., 2023; Jiraphanumes, 2026).

AI-driven change also reshapes labor markets and human-resource systems, which explains why adult participation in education and training becomes an important observable outcome. AI adoption transforms work tasks, skill profiles, and employment structures, but these effects differ across sectors, occupations, and education groups (Babashahi et al., 2024; Kuzior et al., 2025a; 2025b). Public administration, strategic human resource management, and broader technological disruption require employees to update both technical and non-technical competencies, while digital leadership, employee motivation, and digital self-

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efficacy influence how workers adapt to changing organizational environments (Androniceanu, 2025; Panasiuk & Kravchuk, 2025; Mamdouh et al., 2025). The same logic is visible in research on global HRM transformation, Industry 5.0, and managerial skill development, where sustainable leadership, soft and hard skills, and human-centered technological adaptation are treated as prerequisites for performance in digitally transformed organizations (Kozova et al., 2026; Melnyk et al., 2025; Podolchak et al., 2024). Talent management and innovative HR practices further show that organizational performance increasingly depends on how human capital is renewed and retained under technological change (Jeffers et al., 2025; Lipovka et al., 2025).

Higher education is relevant to this research not as a directly measured empirical unit, but as a knowledge-transfer actor that may help translate national AI development into lifelong-learning opportunities. Digital learning has long been associated with the development of skills needed for organizational digital transformation, and this role has expanded with AI-supported educational technologies (Sousa & Rocha, 2019; Zimosz & Ober, 2025). AI governance in higher education, institutional AI policies, and teachers' behavioral intention to adopt new technologies show that universities and educational institutions increasingly face the dual task of adopting AI internally and preparing learners for AI-mediated work and social environments (Abbas et al., 2025; Suchikova & Omelchuk, 2026; Akther et al., 2024). Personalized adaptive learning, generative AI, pedagogical agents, extended reality, metaverse-based learning, and multimodal precision education can support more flexible and accessible learning formats, including short courses and adult-learning modules, but they also require attention to quality assurance, assessment, inclusion, and institutional capacity (Apoki et al., 2022; Guettala et al., 2024; Jagatheesaperumal et al., 2024). These technologies create opportunities for knowledge transfer, but they may also introduce new challenges if learning systems are not designed to meet the needs of diverse adult groups (Qushem et al., 2021).

The ethical and inclusive dimensions of AI development are important because adult participation in education and training is shaped not only by technological change but also by trust, digital access, perceived risks, and social inequalities. Responsible AI, human-AI interaction, and dual-use technologies raise questions of accountability, fairness, privacy, professional responsibility, and the protection of human expertise (Mujtaba, 2025; Haley & Burrell, 2025; Springs, 2025). Public attitudes towards AI range from fear and hope to indifference, while digital platforms and algorithmic environments may generate gendered harms, ideological risks, and unequal exposure to digital opportunities (Yarovenko et al., 2024; Agyare, 2025). Digital inclusion research, therefore, helps explain why the relationship between national AI development and adult learning may differ across population groups: access, capability, trust, and socioeconomic position condition whether individuals can respond to technological change through education and training (Ruthvika & Hedau, 2025; Tan et al., 2025). Financial and digital literacy studies similarly show that knowledge-based adaptation in the digital age is uneven and depends on capability, perceived usefulness, institutional trust, and behavioral readiness to adopt digital services (Gupta et al., 2025; Rahayu et al., 2026; Parajuli et al., 2024).

Sectoral and crisis-related studies further confirm that training and lifelong learning are mechanisms through which AI and digital transformation can be converted into practical organizational and social resilience. AI-related training can support sustainable digital transformation in specific sectors such as energy, while healthcare and retail cases show that digital disruption requires workers and organizations to balance efficiency, ethics, service quality, and human judgment (Abou-Moghli, 2026; Hutchinson, 2025; Conley, 2025). In crisis conditions, retraining and lifelong learning become tools for preserving intellectual capital and maintaining adaptability when social and economic systems are under pressure (Yeremenko, 2026). These studies are not direct equivalents of national adult-learning participation, but they support the broader argument that training is one channel through which AI-related technological and institutional change may affect human capital renewal. At the same time, they also show why a positive relationship should not be assumed: training outcomes depend on policy support, organizational incentives, sectoral needs, and the accessibility of learning opportunities.

The literature shows that AI development affects knowledge production, labor-market transformation, organizational learning, higher education governance, digital inclusion, and human-capital renewal. However, most existing studies examine AI adoption, educational technologies, institutional strategies, labor-market restructuring, or sector-specific training, while paying less attention to whether national AI development indicators are associated with observed adult participation in education and training. This gap is important because participation in education and training captures realized lifelong-learning engagement, whereas motivation, willingness, AI literacy, and university-level program provision require different data and research designs. Therefore, this study contributes by linking national AI development indicators to adult participation in education and training across age groups, while treating university-related conclusions as policy-oriented knowledge-transfer implications rather than directly estimated effects.

This study aims to examine whether national AI development indicators are associated with realized participation in education and training across different adult age groups in European countries, and to discuss what these associations may imply for lifelong learning and knowledge transfer policy.

2. METHODOLOGY

This study investigates whether national AI development indicators are associated with participation in lifelong learning. The empirical design is based on the idea that the expansion of AI may increase the need for individuals to update their skills, adapt to digital transformation, and participate in additional education and training. However, the study does not directly measure subjective "willingness" or perceived "necessity" to undertake training. Instead, actual participation in education and training over the last four weeks is used as an indicator of realized lifelong learning participation. This approach is consistent with the university-oriented focus of the study, as universities may use such evidence to assess whether they should expand short professional courses, AI literacy programs, reskilling modules, and adult-learning opportunities for the wider population.

The analysis uses a country-year panel dataset covering 18 countries from 2017 to 2024. The countries included in the sample are Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and Turkey. The availability of the required dependent and explanatory variables in the selected databases determined the sample. The final core panel contains 144 observations, corresponding to 18 countries observed over eight years. Data on participation in education and training were collected from Eurostat (n.d.). In contrast, data on national AI development were obtained from the Global AI Vibrancy Tool (Stanford HCAI, n.d.), developed by the Institute for Human-Centered Artificial Intelligence at Stanford University. The current draft already documents that the core AI indicators are available for 2017–2024, while Responsible AI and Public Opinion are available only for shorter periods. The selection of these countries was guided by two criteria: simultaneous availability of Eurostat data on adult participation in education and training, and consistent coverage in the Stanford Global AI Vibrancy Tool for the core AI indicators during 2017–2024. Thus, the sample includes European countries for which comparable information on both lifelong-learning participation and national AI development could be matched across the full observation period. Countries with incomplete or non-comparable data for the core variables were excluded to preserve a balanced panel structure and ensure consistency of the econometric analysis.

The dependent variables measure participation rates in education and training during the last four weeks for three population groups. The first dependent variable captures the broad adult population aged 18-74 years. The second focuses on the mature working-age population aged 45-54 years. The third measures participation among older adults aged 50-74 years. This age-group structure allows the study to evaluate whether national AI development is associated with lifelong-learning participation only in the general adult population or also among mature and older adults, who may face stronger barriers to adapting to AI-driven technological change.

The main explanatory variable is the AI Vibrancy Score per capita, which reflects the overall level of national AI development. In addition, the study

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uses several AI development dimensions: R&D per capita, Economy per capita, Talent per capita, Policy and Government per capita, Infrastructure per capita, Responsible AI per capita, and Public Opinion per capita. The first five subindices are available for the full period from 2017 to 2024. Responsible AI per capita is available from 2019 to 2024, while Public Opinion per capita is available only from 2021 to 2024. For this reason, Responsible AI and Public Opinion are not forced into the full-period structural model. Instead, they are estimated separately as additional mechanism models.

Before estimation, AI indicators were transformed using the natural logarithm of one plus the original value, log(1 + x), because descriptive statistics indicate strong positive skewness in several AI variables. This transformation reduces the influence of extreme values while preserving observations with zero or near-zero values. After logarithmic transformation, the AI variables were standardized. Therefore, the estimated coefficients can be interpreted as the change in the participation rate in education and training, measured in percentage points, associated with a one-standard-deviation increase in the corresponding log-transformed AI indicator.

Missing values in Eurostat (n.d.) for Luxembourg in 2021–2022 for the indicator "Participation rate in education and training, from 50 to 74 years" were filled using country-specific linear interpolation between the nearest available observations for 2020 and 2023. Luxembourg is mentioned separately because it was the only country in the balanced core sample with missing internal values for this dependent variable. Therefore, this clarification is provided not to give Luxembourg special analytical status, but to ensure transparency regarding the only data adjustment made in the dataset. This approach was selected because the missing values represented internal gaps in a short annual time series. Linear interpolation preserves the country-specific temporal trend and avoids imposing assumptions based on other countries' experience. No broader cross-country imputation procedure was applied.

The dependent variables in this study measure actual participation in education and training over the last 4 weeks (Eurostat, n.d.). Therefore, they should be interpreted as indicators of realized lifelong learning participation rather than direct measures of willingness to learn, perceived necessity for reskilling, motivation, AI literacy, or subjective readiness for AI-driven change. The study also does not directly observe university programs, course provision, institutional strategies, or individual enrolment in AI-specific training. Consequently, the empirical results support conclusions about macro-level associations between national AI development indicators and adult participation in education and training, while university-related conclusions are formulated as policy and knowledge-transfer implications rather than directly tested effects.

The study, therefore, follows a macro-to-strategy interpretation logic. It does not estimate the direct effects of university programs, course provision, AI literacy modules, micro-credentials, or institutional strategies. Instead, it uses country-level AI development indicators and adult participation in education and training as macro-level signals of the external environment in which universities and other knowledge-transfer institutions operate. Such evidence is relevant for strategic and marketing-oriented decision-making because institutions often use aggregate market, demographic, and technological trends to assess whether new educational services, reskilling formats, or lifelong learning initiatives may be needed.

The empirical analysis is based on two-way fixed-effects panel models. Country fixed effects control for time-invariant national characteristics, such as institutional structures, education systems, cultural attitudes towards lifelong learning, labor-market arrangements, and long-standing differences in digital development. Year-fixed effects control for common shocks affecting all countries in a given year, including the post-pandemic recovery period, general European digitalization dynamics, and common macroeconomic or institutional changes. The baseline specification can be written as:

$$Training_{it}^{g} = \alpha^{g} + \beta^{g} \cdot AI_{it} + \mu_{i} + \lambda_{t} + \varepsilon_{it}^{g}, \quad (1)$$

where $Training_{it}^{g}$ is the participation rate in education and training for the age group g in country i and year t, AI_{it} is the relevant AI indicator, is the constant/intercept of the model, μi denotes country fixed effects, λ_t denotes year fixed effects, and ε_{it} is the error term. his equation presents the general structure of the baseline model; in the structural specifications, AI_{it} is replaced by the corresponding set of AI subindices, while in the lagged models the AI indicator is included as AI_{it-1} or AI_{it-2}. Therefore, the formula is intended as a general econometric representation of the estimation strategy rather than as a separate model for only one variable. Since the models are estimated separately for each age group, the subscript (g) indicates that the coefficients may differ across the three age-specific specifications.

Three groups of models were estimated. Block A estimates the association between the total AI Vibrancy Score per capita and participation in education and training. Block B replaces the total score with the subindices of the structural AI development dimensions: R&D, Economy, Talent, Policy and Government, and Infrastructure. The total AI Vibrancy Score and its subindices are not included in the same model because the total score is constructed from underlying components, and simultaneous inclusion could create multicollinearity and unstable coefficient estimates. Block C estimates additional mechanism models for Responsible AI and Public Opinion separately, due to their shorter time coverage.

To examine delayed associations, the study estimates contemporaneous, one-year lag, and two-year lag models. The contemporaneous models capture whether national AI development and training participation move together within the same year. The one-year and two-year lag specifications test whether AI development is associated with subsequent changes in lifelong-learning participation. This is important because individuals, universities, employers, and public institutions may need time to respond to technological change, policy initiatives, or labor-market signals. However, the lagged models reduce the number of observations, especially for Responsible AI and Public Opinion. Therefore, lagged mechanism models should be interpreted with caution.

The main inference is based on country-level clustered standard errors. As a robustness check, all models were re-estimated using Driscoll-Kraay standard errors with a lag length of 1. This correction is appropriate for macro-panel data because it is robust to heteroskedasticity, serial correlation, and cross-sectional dependence. The Driscoll-Kraay models do not change the estimated coefficients, but they provide an alternative basis for statistical inference. This robustness check is particularly relevant because European countries may be affected by common technological, economic, and policy shocks.

All calculations were performed in RStudio using R version 4.4.0. Data preparation, variable transformation, lag construction, and model estimation were carried out using standard R packages for data manipulation and fixed-effects panel modelling. The results are reported in appendices as follows: descriptive statistics in Appendix A, baseline two-way fixed-effects estimates with clustered standard errors in Appendix B, and Driscoll-Kraay robustness estimates in Appendix C.

3. RESULTS

The descriptive statistics reported in Table A1, Appendix A, show that the dataset contains 144 country-year observations for the balanced core panel, corresponding to 18 countries observed over eight years, from 2017 to 2024. The term "core panel" refers to the variables available for the full period, while Responsible AI per capita and Public Opinion per capita are reported separately because they have shorter time coverage. The main AI development indicators (R&D, Economy, Talent, Policy and Government, Infrastructure, and the overall AI Vibrancy Score per capita) are available for all 144 observations. However, the availability of the two subindices is more limited: Responsible AI per capita has 108 observations, reflecting availability from 2019 onwards, while Public Opinion per capita has only 72 observations, reflecting availability from 2021 onwards. This confirms that these two indicators should be analyzed separately or used only in additional robustness/mechanism models, rather than being included in the full-period baseline specification. The AI-related variables also demonstrate substantial heterogeneity across countries and years. For example, the overall AI Vibrancy Score per capita has a mean of 12.56, but ranges from 1.14 to 62.18,

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with a high standard deviation of 10.60. Most AI subindices are positively skewed, especially Talent, Responsible AI, Public Opinion, Infrastructure, and the total Vibrancy Score, indicating that a small number of country-year observations have much higher AI development values than the rest of the sample. This supports the use of standardization and, where appropriate, logarithmic transformation before econometric modelling.

The dependent variables also show meaningful variation across population groups. The average participation rate in education and training is highest for the broad adult population aged 18-74 years, at 20.09%, followed by the 45-54 age group at 14.82% and the 50-74 age group at 9.34%. This pattern suggests that participation in lifelong learning declines with age, which is directly relevant to the university-oriented research question. If AI development is found to increase participation in education and training, universities may have stronger grounds to expand not only general AI literacy and digital-skills programs, but also targeted reskilling and upskilling courses for mature and older adults. The participation variables are less skewed than the AI indicators. However, the 50-74 group still shows relatively stronger positive skewness, meaning that high adult-learning participation among older adults is concentrated in a smaller set of observations. The descriptive statistics indicate that the dataset is suitable for panel analysis. Still, the uneven availability and non-normal distribution of several AI subindices must be considered in the empirical strategy.

The main empirical result is cautious and predominantly negative. Across all three age groups and across contemporaneous, one-year lag, and two-year lag specifications, the total AI Vibrancy Score is not a statistically significant predictor of participation in education and training. This means that national AI development, measured as an aggregate indicator, does not automatically translate into observed adult training participation. The subsequent models should therefore be interpreted not as evidence that AI development generally increases lifelong learning, but as an exploration of whether specific AI development dimensions, particularly R&D and Policy and Government, show more differentiated associations with realized participation in education and training.

Table 1 summarizes the main findings across the three age groups and confirms that the relationship between national AI development and adult participation in education and training is not automatic. The total AI Vibrancy Score is not statistically significant in any contemporaneous, one-year lag, or two-year lag specification, which indicates that aggregate national AI development does not by itself translate into observed lifelong-learning participation. More differentiated results appear only for selected AI development dimensions. AI-related R&D shows negative lagged associa-

Table 1. Summary of main findings across age groups

AI development indicator	18-74 years	45-54 years	50-74 years	Interpretation
AI Vibrancy Score	Not significant in current, t − 1, and t − 2 models	Not significant in current, t − 1, and t − 2 models	Not significant in current, t − 1 and t − 2 models	National AI development does not automatically translate into observed adult training participation
R&D per capita	Negative and significant in lagged models	Negative in lagged models, with weaker robustness	Negative in the one-year lag model, weaker in robustness checks	AI-related research capacity may remain concentrated in specialized environments
Policy and Government per capita	Positive and significant in the two-year lag model	Positive and significant in the two-year lag model	Positive but not statistically significant	Policy-related AI development may matter more than aggregate AI development, especially with a delay
Responsible AI per capita	Negative in the two-year lag model, but not robust under Driscoll-Kraay SE	Negative in the two-year lag model, but not robust under Driscoll-Kraay SE	Negative in the two-year lag model, but not robust under Driscoll-Kraay SE	Responsible AI results are exploratory because of shorter data coverage
Public Opinion per capita	No reliable substantive evidence	No reliable substantive evidence	No reliable substantive evidence	Public Opinion models are based on a short period and should be interpreted cautiously

Note: The table summarizes the main two-way fixed-effects results and Driscoll-Kraay robustness checks. Detailed estimates are reported in Appendices B and C.

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tions in several models, suggesting that research-intensive AI development may remain concentrated in specialized innovation environments rather than spreading immediately into broader adult training participation. By contrast, Policy and Government per capita has a positive two-year lagged association for the 18–74 and 45–54 groups, indicating that policy-related AI development may be more relevant for observed adult learning participation than aggregate AI development alone. The results for Responsible AI and Public Opinion should be treated as exploratory because these indicators are available for shorter periods, and their lagged specifications are based on smaller samples.

3.1. Participation in education and training among the population aged 18-74

The TWFE estimates for the population aged 18-74, reported in Table B1 of Appendix B, show that national AI development is not automatically associated with higher participation in education and training. Since the dependent variable measures actual participation over the previous four weeks, the results should be interpreted as evidence of realized lifelong learning participation rather than willingness, motivation, perceived necessity, or subjective readiness to reskill. The total AI Vibrancy Score is positive but statistically insignificant in the contemporaneous model and remains insignificant in the one-year and two-year lag specifications. This means that stronger national AI development, as measured by the aggregate AI Vibrancy Score, does not necessarily lead to a within-country increase in adult participation in education and training. The contemporaneous structural models support the same conclusion: R&D, Economy, Talent, Policy and Government, and Infrastructure are not statistically significant in the same-year specification.

The lagged models in Table B1, Appendix B, provide more differentiated evidence. R&D per capita becomes negative and statistically significant in the lagged specifications, suggesting that AI-related research intensity may remain concentrated in specialized scientific, technological, or corporate environments rather than immediately spreading into broad adult learning participation. By contrast, Policy and Government per capita is positive and statistically significant in the two-year lag model. This suggests that policy-oriented AI development may take time to become visible in educational and training behavior. Therefore, the evidence points less to a spontaneous increase in training participation driven by AI advancement itself and more to the possible importance of institutional and policy-related channels.

The additional models for Responsible AI and Public Opinion, also presented in Table B1 of Appendix B, should be interpreted cautiously, as these indicators are available for shorter periods. In the contemporaneous models, neither Responsible AI nor Public Opinion is significantly associated with participation in education and training among adults aged 18-74. The negative two-year lagged result for Responsible AI should be treated as exploratory rather than definitive because of the smaller effective sample. The results suggest that national AI development and lifelong-learning participation are connected in a more complex way than a simple “more AI means more training” assumption would imply. The findings do not provide strong evidence that overall AI development automatically increases participation in education and training among the general adult population. Instead, they show that specific institutional and policy-related components of AI development may be more relevant, especially with a time delay. These findings have policy-oriented implications for universities, but they should not be interpreted as direct evidence of university-level effects. Rather, the results provide macro-level signals that may help universities, public institutions, and employers assess whether accessible, practice-oriented, and socially inclusive lifelong-learning programs are needed, especially when supported by public policy.

From a policy and institutional perspective, the findings may inform a more proactive role for universities in lifelong-learning provision, especially when such provision is supported by public policy and employer cooperation. However, this implication is derived from macro-level evidence and does not directly measure university programs, enrolment in university courses, or institutional strategies. The insignificant effect of the total AI Vibrancy Score suggests that national AI development alone is insufficient to explain observed adult

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participation in education and training. What matters is whether AI development is translated into educational opportunities, public awareness, and institutional pathways for reskilling through coordinated action by governments, employers, universities, and regional institutions.

3.2. Participation in education and training among the population aged 45-54

For the mature working-age population aged 45-54, the TWFE estimates reported in Table B2 of Appendix B show that national AI development does not automatically translate into higher participation in education and training. The total AI Vibrancy Score is positive but statistically insignificant in the contemporaneous, one-year lag, and two-year lag models. This means that stronger national AI development is not systematically associated with higher observed training participation among mature working-age adults. The contemporaneous structural model confirms this conclusion, as none of the AI development dimensions (R&D, Economy, Talent, Policy and Government, or Infrastructure) is statistically significant. The additional contemporaneous models for Responsible AI and Public Opinion are also insignificant.

The lagged models provide more differentiated evidence. R&D per capita becomes negative and statistically significant in the one-year lag model, suggesting that AI-related research capacity may remain concentrated in specialized innovation environments rather than generating broad training participation among mature adults. In contrast, Policy and Government per capita is positive and statistically significant in the two-year lag model, with a coefficient of 0.7346, indicating that policy-oriented AI development may influence participation with a delay. The Responsible AI result in the two-year lag model is negative and significant, but it should be treated cautiously because this indicator is available only from 2019 onwards, and the effective sample is smaller. Public Opinion remains statistically insignificant, including in the two-year lag model, which is based on only 36 observations. Overall, the findings suggest that participation among people aged 45-54 is not driven by aggregate AI development itself, but rather by policy-related and institutional channels.

The results for the 45-54 age group reinforce the conclusion that national AI development does not automatically stimulate participation in education and training. The most consistent message is that broad AI development, as measured by the total AI Vibrancy Score, has no statistically significant effect in contemporaneous, one-year-lag, or two-year-lag models. Instead, the evidence points to selected delayed mechanisms. R&D appears negatively associated with training participation in the one-year lag model, while Policy and Government has a positive delayed association in the two-year lag model. The findings may inform university lifelong-learning policy by showing that technological progress or AI research intensity alone should not be assumed to generate mature-adult training participation. From a macro-to-strategy perspective, cooperation between universities, public institutions, and employers may be one possible pathway for translating AI-related policy activity into adult-learning opportunities, although this mechanism is not directly estimated in the model.

3.3. Participation in education and training among the population aged 50-74

For the older adult population aged 50-74, the TWFE estimations reported in Table B3, Appendix B, show that national AI development has only a limited and non-uniform association with participation in education and training. Since the dependent variable measures actual participation during the last four weeks, the results should be interpreted as realized lifelong-learning participation, not as willingness, motivation, or perceived necessity to reskill. The total AI Vibrancy Score is positive but statistically insignificant in the contemporaneous model and remains insignificant in the lagged specifications. The same pattern appears in the structural models: R&D, Economy, Talent, Policy and Government, and Infrastructure are not statistically significant in the contemporaneous specification. This means that stronger national AI development does not automatically translate into higher training participation among older adults.

The lagged models provide only partial evidence for selected mechanisms. R&D per capita becomes negative and statistically significant in the one-year lag model, suggesting that AI-related research activity may remain concentrated in specialized innovation environments and may not immediately create broader learning participation among people aged 50-74. In the two-year lag model, Policy and Government has a positive but statistically insignificant coefficient, indicating that the policy channel is weaker for older adults than for younger adult groups. Responsible AI becomes negative and statistically significant in the two-year lag model, but this result should be interpreted cautiously because the indicator is available only from 2019 onwards, and the effective sample is smaller. Public Opinion remains statistically insignificant.

The findings for the 50-74 age group suggest that national AI development does not automatically increase older adults' participation in education and training. The most consistent result is the absence of a statistically significant relationship for the total AI Vibrancy Score across contemporaneous, one-year lag, and two-year lag specifications. The significant negative associations for lagged R&D and two-year lagged Responsible AI indicate that advanced AI development may remain concentrated in specialized institutional environments unless it is deliberately translated into accessible learning pathways. From the university's perspective, these findings may inform strategic planning rather than directly demonstrate the effectiveness of the university's intervention. They suggest that universities and other knowledge-transfer institutions should consider how AI-related research and innovation capacity can be linked to accessible learning pathways for older adults, especially given this age group's lower participation in education and training.

3.4. The Driscoll-Kraay robustness estimates

The Driscoll-Kraay robustness estimates (Table C1, Appendix C) mainly confirm the central conclusion of the baseline TWFE models: overall national AI development does not automatically increase actual participation in education and training. This is important because the dependent variables measure observed participation in education and training during the last four weeks, not subjective willingness or perceived necessity to study. Therefore, the results should be interpreted as evidence of realized lifelong-learning participation, rather than as direct evidence of motivation or intention. This interpretation is consistent with the current paper structure, which treats Responsible AI and Public Opinion separately due to limited data availability.

After correcting for standard errors using the Driscoll-Kraay estimator, the AI Vibrancy Score remains statistically insignificant across all three age groups and lag structures. This means that the general level of national AI development, by itself, is not a robust predictor of participation in education and training among the broad adult population aged 18-74, mature working-age adults aged 45-54, or older adults aged 50-74. From a university perspective, this is a key finding: stronger national AI development dimensions do not automatically create visible demand for lifelong learning. The findings may inform university lifelong-learning policy by showing that the expansion of AI research, infrastructure, or AI-related economic activity does not automatically lead adults to participate in training.

The most robust substantive result appears in the two-year lag structural models. For the population aged 18-74 and 45-54, the coefficient for R&D per capita, $t-2$, is negative and statistically significant, while the coefficient for Policy and Government per capita, $t-2$, is positive and statistically significant. This suggests that AI-related R&D may remain concentrated in specialized scientific, technological, and corporate environments and may not easily spill over into broad public participation in training. By contrast, AI-related policy and government activity seem more likely to support lifelong learning participation, but only with a delay. This delayed effect is theoretically plausible because public strategies, regulatory frameworks, digitalization programs, and institutional initiatives require time before they influence universities, employers, and individuals.

For the older population aged 50-74, the Driscoll-Kraay estimates are weaker. The total AI Vibrancy Score remains insignificant, and the two-year lagged Policy and Government coefficient is positive but not statistically significant. This suggests that the policy channel is less clearly transmitted

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to older adults within the observed period. The implication is that older adults may face stronger barriers to participation in AI-related or digital training, even when national AI development dimensions and policy frameworks are in place. The findings suggest that policy-supported university lifelong-learning strategies may need to pay particular attention to older adults, who may face stronger barriers to participation in education and training.

The Responsible AI results also become weaker after using Driscoll-Kraay standard errors. Unlike the baseline clustered-SE models, the negative two-year lagged Responsible AI coefficients are no longer statistically significant. This means that the earlier negative Responsible AI result should not be treated as robust. The Public Opinion $t-2$ coefficients appear statistically significant due to extremely small Driscoll-Kraay standard errors, but these models are based on only 36 observations, corresponding to a very short effective period after applying the two-year lag. These results should therefore be treated as unstable and not used as substantive evidence. The safest interpretation is that Public Opinion does not provide reliable evidence of a systematic relationship with actual lifelong-learning participation in this dataset.

4. DISCUSSION

The central contribution of this study is not evidence of a direct positive effect of national AI development on adult lifelong-learning participation, but rather evidence that such a relationship cannot be assumed. The total AI Vibrancy Score remains statistically insignificant across all analyzed age groups and lag structures, indicating that national AI development alone does not automatically generate observed participation in education and training. This finding is important because much of the policy and academic debate assumes that AI-driven transformation will naturally increase reskilling and lifelong-learning engagement. The results suggest instead that the translation of AI development into adult learning is likely to depend on institutional, policy, and knowledge-transfer mechanisms that are not captured by the aggregate AI Vibrancy Score alone.

The findings refine the dominant expectation in the literature that AI-driven transformation should automatically increase the need for reskilling and lifelong learning. This negative result is substantively important because it challenges the assumption that AI advancement alone produces measurable adult-learning engagement. Previous studies emphasize that AI changes work tasks, skill requirements, human resource systems, and labor market structures, thereby creating pressure for continuous learning rather than one-time education (Babashahi et al., 2024; Kuzior et al., 2025a; Kuzior et al., 2025b). However, the results of this study show that this pressure is not directly reflected in realized participation in education and training. The total AI Vibrancy Score is statistically insignificant across all three age groups and all lag structures, with contemporaneous coefficients of 0.4822 for adults aged 18-74, 0.1054 for those aged 45-54, and 0.5006 for those aged 50-74. This means that AI-driven knowledge transformation, measured at the national level, does not automatically translate into actual adult participation in lifelong learning. This result is consistent with the view that the effects of AI are uneven and depend on absorption capacity, organizational learning and knowledge-management mechanisms, rather than on technological development alone (Iaia et al., 2023; Jiraphanumes, 2026; Škare et al., 2025). Therefore, the empirical evidence supports a more cautious interpretation: adult participation in education and training should be understood as a realized behavioral outcome, not as a direct measure of willingness, perceived necessity, or subjective readiness to learn.

The negative association between AI-related R&D and later participation in education and training is one of the most important findings because it partly contrasts with the assumption that innovation intensity naturally stimulates broad knowledge renewal. In the one-year lag models, R&D per capita is negatively associated with participation in all three age groups, with coefficients of −1.2310 for adults aged 18-74, −0.9392 for those aged 45-54, and −0.8911 for those aged 50-74. This result may indicate that AI-related R&D is concentrated in specialized scientific, technological, and corporate environments, where knowledge circulates mainly among highly skilled groups rather than being transferred to the broader adult population. Such an interpretation aligns with studies showing that AI adoption reshapes skills and employment structures unevenly across sec-

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tors, educational groups, and labor-market segments (Kuzior et al., 2025b; Androniceanu, 2025; Panasiuk & Kravchuk, 2025). It also aligns with research arguing that digital transformation can produce uneven economic and social outcomes unless it is supported by inclusive access, digital capability, and institutional support (Meidute-Kavaliauskiene et al., 2026; Ruthvika & Hedau, 2025; Tan et al., 2025). From this perspective, AI-related R&D may advance the frontier of technological knowledge without necessarily expanding lifelong learning participation unless universities, employers, and public institutions translate this knowledge into accessible training formats.

The positive delayed effect of Policy and Government per capita provides a more constructive interpretation and is especially relevant to universities. In the two-year lag models, Policy and Government per capita are positively associated with participation in education and training among adults aged 18-74 and 45-54, with coefficients of 0.6064 and 0.7346, respectively. This suggests that AI-related policy initiatives, institutional frameworks, and public-sector strategies may need time before they influence realized learning behavior. The finding is consistent with the literature, which emphasizes that AI governance in higher education, institutional AI policies, and technology adoption strategies are necessary for transforming AI development into practical learning opportunities (Abbas et al., 2025; Suchikova & Omelchuk, 2026; Akther et al., 2024). It also supports research on digital learning, personalized education, and AI-supported learning environments, demonstrating that universities can provide flexible, adaptive, and accessible formats for reskilling and knowledge transfer (Sousa & Rocha, 2019; Guettala et al., 2024; Zimosz & Ober, 2025). At the same time, the weaker results for the 50-74 group suggest that older adults may require more targeted interventions, as general AI policy does not automatically reach this population. Therefore, the findings support a cautious policy implication: higher education institutions may be important knowledge-transfer actors, but their role is inferred from macro-level patterns rather than directly estimated. The results suggest that universities, together with governments, employers, and regional institutions, may help translate AI-related policy and technological change into lifelong-learning opportunities, including AI literacy, micro-credentials, professional reskilling, and digital inclusion programs.

This study has several limitations that should be considered when interpreting the findings and designing future research. First, participation in education and training is used as a proxy for realized participation in lifelong learning and readiness. However, it does not directly measure individual willingness, perceived necessity, motivation, or attitudes towards AI-related reskilling. Second, the panel covers only 18 countries during 2017–2024, which limits the time dimension of the analysis and makes the lagged specifications, especially for Responsible AI and Public Opinion, exploratory rather than definitive. Third, although two-way fixed-effects models control for country-specific and year-specific factors, the results should be interpreted mainly as associations rather than strict causal effects because broader institutional, economic, and educational conditions may jointly shape AI development and lifelong-learning participation. Fourth, the AI indicators are measured at the national level, whereas education and training decisions are made by individuals, universities, employers, and regional institutions, which may create aggregation bias. Future research should extend the dataset as new AI indicators become available, include more countries and longer time periods, and combine macro-panel analysis with micro-level survey data on individual motivation, perceived AI risks, digital skills, and training barriers. Further studies could also examine university-level and regional data to identify which types of AI literacy courses, micro-credentials, reskilling programs, and adult-learning formats are most effective for different age groups.

CONCLUSION

This study examined whether AI-driven knowledge transformation, measured through national AI development indicators, is associated with actual participation in lifelong learning across different adult age groups. It also assessed which dimensions of AI development are most relevant to universities in their role as knowledge-transfer institutions responsible for supporting reskilling, AI literacy, and adult learning.

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The empirical analysis was based on a country–year panel of 18 countries observed over 2017–2024, producing 144 core observations. The study applied two-way fixed-effects models with country and year effects, estimated contemporaneous, one-year lag, and two-year lag specifications. It used Driscoll-Kraay standard errors as a robustness check.

The results show that the total AI Vibrancy Score is not a statistically significant predictor of participation in education and training across age groups: the contemporaneous coefficients are 0.4822 for adults aged 18-74, 0.1054 for adults aged 45-54, and 0.5006 for adults aged 50-74. The average participation rate in lifelong learning declines with age, from 20.09% among the population aged 18-74 to 14.82% among those aged 45-54 and 9.34% among those aged 50-74. The lagged structural models reveal that AI-related R&D is negatively associated with later participation in education and training, with one-year lag coefficients of −1.2310 for the 18-74 group, −0.9392 for the 45-54 group, and −0.8911 for the 50-74 group. By contrast, AI-related Policy and Government activity shows a positive delayed association in the two-year lag models for adults aged 18-74 and 45-54, with coefficients of 0.6064 and 0.7346, respectively. The additional models for Responsible AI and Public Opinion should be interpreted cautiously, as Responsible AI is available for only 108 observations and Public Opinion for only 72. In comparison, two-year-lagged Public Opinion models are based on only 36 observations.

Since university programs, individual motivation, and enrolment in AI-specific courses are not directly analyzed, the practical implications of this study should be interpreted as policy-oriented recommendations rather than directly estimated university-level effects. The findings suggest that national AI development does not automatically generate broader participation in lifelong learning. Since university programs, individual motivation, and enrolment in AI-specific courses are not directly analyzed, the practical implications should be interpreted as policy-oriented recommendations rather than directly estimated university-level effects. Nevertheless, macro-level evidence on adult participation in education and training may serve as a strategic signal for universities, governments, and employers when planning accessible lifelong-learning opportunities. Particular attention should be paid to mature and older adults, whose participation rates are lower and who may face stronger barriers to adaptation in AI-driven labor markets and digital societies. The results, therefore, highlight the need to strengthen cooperation between governments, employers, universities, and regional institutions if AI development is to become not only a source of technological progress but also a driver of inclusive knowledge renewal.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Table A1. Descriptive statistics of the variables

Variable	N	Mean	SD	Median	Min	Max	Skewness	Kurtosis
R&D per capita	144	4.08	2.58	3.64	0.36	13.66	1.04	1.15
Responsible AI per capita	108	0.68	0.99	0.41	0.00	4.98	2.65	6.87
Economy per capita	144	3.02	3.00	2.00	0.01	15.56	1.92	4.16
Talent per capita	144	1.66	4.01	0.44	0.01	18.75	3.42	10.56
Policy and Government per capita	144	0.73	0.97	0.27	0.00	4.06	1.66	1.99
Public Opinion per capita	72	0.85	0.92	0.68	0.05	4.57	2.89	8.40
Infrastructure per capita	144	2.14	2.52	1.25	0.08	12.35	2.46	5.80
AI Vibrancy Score per capita	144	12.56	10.60	9.46	1.14	62.18	2.19	5.80
Participation rate in education and training, 18-74 years, %	144	20.09	7.26	18.90	8.50	39.00	0.49	−0.64
Participation rate in education and training, 45-54 years, %	144	14.82	8.54	13.60	1.70	38.40	0.62	−0.39
Participation rate in education and training, 50-74 years, %	144	9.34	6.35	7.80	0.60	28.30	0.96	0.32

Note: Responsible AI per capita and Public Opinion per capita have fewer observations because these indicators are available only for shorter periods.

APPENDIX B

Table B1. Fixed-effects estimates for AI development and participation in education and training among the population aged 18-74

Variable	Model A: AI Vibrancy	Model B: AI subindices	Model C1: Responsible AI	Model C2: Public Opinion
Panel A. Contemporaneous models				
AI Vibrancy Score	0.4822 (0.6129)			
R&D per capita		−0.1793 (0.5021)		
Economy per capita		0.1184 (0.2890)		
Talent per capita		−0.6085 (1.7710)		
Policy and Government per capita		−0.2287 (0.3907)		
Infrastructure per capita		0.1098 (0.4170)		
Responsible AI per capita			0.3215 (0.5386)	
Public Opinion per capita				0.3833 (0.9108)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Country	Country	Country	Country
Observations	144	144	108	72
R^2	0.9426	0.9430	0.9504	0.9738
Within R^2	0.0043	0.0119	0.0107	0.0039
Panel B. One-year lag models				
Variable	**Model A: AI Vibrancy, t − 1**	**Model B: AI subindices, t − 1**	**Model C1: Responsible AI, t − 1**	**Model C2: Public Opinion**
AI Vibrancy Score, t − 1	0.2926 (0.7239)			
R&D per capita, t − 1		−1.2310* (0.4904)		

Table B1 (cont.). Fixed-effects estimates for AI development and participation in education and training among the population aged 18-74

Variable	Model A: AI Vibrancy, t − 1	Model B: AI subindices, t − 1	Model C1: Responsible AI, t − 1	Model C2: Public Opinion
Economy per capita, t − 1		0.0299		
		(0.3133)		
Talent per capita, t − 1		1.2580		
		(1.6300)		
Policy and Government per capita, t − 1		0.0255		
		(0.3054)		
Infrastructure per capita, t − 1		0.4260		
		(0.4301)		
Responsible AI per capita, t − 1			−0.4098	
			(0.5600)	
Public Opinion per capita				0.3833
				(0.9108)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Country	Country	Country	Country
Observations	126	126	90	72
R^2	0.9456	0.9480	0.9604	0.9738
Within R^2	0.0015	0.0467	0.0173	0.0039
Panel C. Two-year lag models				
Variable	Model A: AI Vibrancy, t − 2	Model B: AI subindices, t − 2	Model C1: Responsible AI, t − 2	Model C2: Public Opinion, t − 2
AI Vibrancy Score, t − 2	−0.3099			
	(0.8095)			
R&D per capita, t − 2		−1.3040*		
		(0.6178)		
Economy per capita, t − 2		−0.0329		
		(0.3537)		
Talent per capita, t − 2		−0.6959		
		(1.6440)		
Policy and Government per capita, t − 2		0.6064**		
		(0.1805)		
Infrastructure per capita, t − 2		0.2722		
		(0.6482)		
Responsible AI per capita, t − 2			−1.0210***	
			(0.1038)	
Public Opinion per capita, t − 2				−1.1120
				(0.9049)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Country	Country	Country	Country
Observations	108	108	72	36
R^2	0.9499	0.9542	0.9785	0.9947
Within R^2	0.0018	0.0872	0.1836	0.1009

Note: The dependent variable is the participation rate in education and training during the last four weeks among the population aged 18-74. All AI variables are log-transformed using log(1+x) and standardized. Standard errors clustered by country are reported in parentheses. Country and year fixed effects are included in all specifications. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. In Panel B, the Public Opinion specification is reported in contemporaneous form, as provided in the output, due to the short availability of this indicator.

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Table B2. Fixed-effects estimates for AI development and participation in education and training among the population aged 45-54

Panel A. Contemporaneous models				
Variable	**Model A: AI Vibrancy**	**Model B: AI subindices**	**Model C1: Responsible AI**	**Model C2: Public Opinion**
AI Vibrancy Score	0.1054 (0.8169)			
R&D per capita		−0.1375 (0.4905)		
Economy per capita		0.3322 (0.3316)		
Talent per capita		−0.8323 (1.8110)		
Policy and Government per capita		−0.0299 (0.3315)		
Infrastructure per capita		−0.2680 (0.5366)		
Responsible AI per capita			0.4732 (0.6229)	
Public Opinion per capita				−0.2480 (0.8133)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Country	Country	Country	Country
Observations	144	144	108	72
R^2	0.9418	0.9426	0.9494	0.9754
Within R^2	0.0002	0.0141	0.0164	0.0012
Panel B. One-year lag models				
Variable	**Model A: AI Vibrancy, t − 1**	**Model B: AI subindices, t − 1**	**Model C1: Responsible AI, t − 1**	**Model C2: Public Opinion, t − 1**
AI Vibrancy Score, t − 1	0.1600 (0.8659)			
R&D per capita, t − 1		−0.9392* (0.4423)		
Economy per capita, t − 1		0.1592 (0.3385)		
Talent per capita, t − 1		0.6311 (1.9450)		
Policy and Government per capita, t − 1		0.2451 (0.2731)		
Infrastructure per capita, t − 1		0.1258 (0.5753)		
Responsible AI per capita, t − 1			0.0499 (0.4538)	
Public Opinion per capita, t − 1				−0.4275 (0.5161)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Country	Country	Country	Country
Observations	126	126	90	54
R^2	0.9450	0.9462	0.9587	0.9905
Within R^2	0.0003	0.0232	0.0002	0.0078

Table B2 (cont.). Fixed-effects estimates for AI development and participation in education and training among the population aged 45-54

Panel C. Two-year lag models				
Variable	**Model A: AI Vibrancy, t – 2**	**Model B: AI subindices, t – 2**	**Model C1: Responsible AI, t – 2**	**Model C2: Public Opinion, t – 2**
AI Vibrancy Score, t – 2	0.0558 (0.8747)			
R&D per capita, t – 2		−1.2300 (0.6884)		
Economy per capita, t – 2		−0.0533 (0.3775)		
Talent per capita, t – 2		−1.0080 (2.4920)		
Policy and Government per capita, t – 2		0.7346** (0.2151)		
Infrastructure per capita, t – 2		0.3930 (0.5937)		
Responsible AI per capita, t – 2			−0.8045* (0.3537)	
Public Opinion per capita, t – 2				−1.9000 (1.3900)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Country	Country	Country	Country
Observations	108	108	72	36
R^2	0.9485	0.9524	0.9775	0.9935
Within R^2	0.0000	0.0742	0.0877	0.1641

Note: The dependent variable is the participation rate in education and training during the last four weeks among the population aged 45–54. All AI variables are log-transformed using log(1+x) and standardized. Standard errors clustered by country are reported in parentheses. Country and year fixed effects are included in all specifications. Significance levels: ** $p < 0.01$, * $p < 0.05$. The Public Opinion models should be interpreted cautiously because this indicator is available only from 2021 onwards, which substantially reduces the number of observations in lagged specifications.

Table B3. Fixed-effects estimates for AI development and participation in education and training among the population aged 50-74

Panel A. Contemporaneous models				
Variable	**Model A: AI Vibrancy**	**Model B: AI subindices**	**Model C1: Responsible AI**	**Model C2: Public Opinion**
AI Vibrancy Score	0.5006 (0.7151)			
R&D per capita		−0.1309 (0.3608)		
Economy per capita		0.3082 (0.3051)		
Talent per capita		−0.0912 (1.6500)		
Policy and Government per capita		−0.0872 (0.2903)		
Infrastructure per capita		−0.0274 (0.4114)		
Responsible AI per capita			0.2385 (0.5212)	
Public Opinion per capita				0.3441 (1.1250)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

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Table B3 (cont.). Fixed-effects estimates for AI development and participation in education and training among the population aged 50-74

Variable	Model A: AI Vibrancy	Model B: AI subindices	Model C1: Responsible AI	Model C2: Public Opinion
Clustered SE	Country	Country	Country	Country
Observations	144	144	108	72
R^2	0.9309	0.9312	0.9400	0.9698
Within R^2	0.0050	0.0102	0.0064	0.0034
Panel B. One-year lag models				
Variable	**Model A: AI Vibrancy, t − 1**	**Model B: AI subindices, t − 1**	**Model C1: Responsible AI, t − 1**	**Model C2: Public Opinion, t − 1**
AI Vibrancy Score, t − 1	0.3247 (0.5946)			
R&D per capita, t − 1		−0.8911* (0.3777)		
Economy per capita, t − 1		0.2459 (0.2473)		
Talent per capita, t − 1		1.1700 (1.6520)		
Policy and Government per capita, t − 1		0.0364 (0.2582)		
Infrastructure per capita, t − 1		0.2261 (0.4794)		
Responsible AI per capita, t − 1			-0.0333 (0.4129)	
Public Opinion per capita, t − 1				0.3444 (0.7532)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Country	Country	Country	Country
Observations	126	126	90	54
R^2	0.9330	0.9350	0.9497	0.9896
Within R^2	0.0020	0.0317	0.0001	0.0076
Panel C. Two-year lag models				
Variable	**Model A: AI Vibrancy, t − 2**	**Model B: AI subindices, t − 2**	**Model C1: Responsible AI, t − 2**	**Model C2: Public Opinion, t − 2**
AI Vibrancy Score, t − 2	−0.2855 (0.6830)			
R&D per capita, t − 2		−1.1170 (0.5978)		
Economy per capita, t − 2		−0.2091 (0.3435)		
Talent per capita, t − 2		−0.3572 (1.5510)		
Policy and Government per capita, t − 2		0.3651 (0.1980)		
Infrastructure per capita, t − 2		0.3998 (0.5216)		
Responsible AI per capita, t − 2			−0.6338*** (0.1592)	
Public Opinion per capita, t − 2				−0.6259 (0.4497)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Country	Country	Country	Country
Observations	108	108	72	36
R^2	0.9397	0.9433	0.9721	0.9970
Within R^2	0.0016	0.0611	0.0773	0.0668

Notes: The dependent variable is the participation rate in education and training during the last four weeks among the population aged 50–74. All AI variables are log-transformed using log(1+x) and standardized. Standard errors clustered by country are reported in parentheses. Country and year fixed effects are included in all specifications. Significance levels: *** $p < 0.001$, * $p < 0.05$. Responsible AI per capita and Public Opinion per capita are available only for shorter periods; therefore, especially the lagged mechanism models should be interpreted cautiously.

APPENDIX C

Table C1. Driscoll-Kraay robustness estimates for AI development and participation in education and training

Age group	Specification	Model	Coefficient(s), Driscoll–Kraay SE in parentheses	N	R^2	Within R^2
18-74	Current	AI Vibrancy	AI Vibrancy: 0.4822 (0.2828)	144	0.9426	0.0043
18-74	Current	AI subindices	R&D: –0.1793 (0.4379); Economy: 0.1184 (0.2955); Talent: –0.6085 (0.8268); Policy and Government: –0.2287 (0.3150); Infrastructure: 0.1098 (0.2421)	144	0.9430	0.0119
18-74	Current	Responsible AI	Responsible AI: 0.3215 (0.3924)	108	0.9504	0.0107
18-74	Current	Public Opinion	Public Opinion: 0.3833 (0.4339)	72	0.9738	0.0039
18-74	t – 1	AI Vibrancy	AI Vibrancy, t – 1: 0.2926 (0.3325)	126	0.9456	0.0015
18-74	t – 1	AI subindices	R&D, t – 1: –1.2310 (0.6687); Economy, t – 1: 0.0299 (0.1784); Talent, t – 1: 1.2580 (1.0090); Policy and Government, t – 1: 0.0255 (0.2711); Infrastructure, t – 1: 0.4260 (0.2431)	126	0.9480	0.0467
18-74	t – 1	Responsible AI	Responsible AI, t – 1: –0.4098 (0.3309)	90	0.9604	0.0173
18-74	t – 1	Public Opinion	Public Opinion, t – 1: 0.0999 (0.1860)	54	0.9864	0.0004
18-74	t – 2	AI Vibrancy	AI Vibrancy, t – 2: –0.3099 (0.3047)	108	0.9499	0.0018
18-74	t – 2	AI subindices	R&D, t – 2: –1.3040* (0.4705); Economy, t – 2: –0.0329 (0.4874); Talent, t – 2: –0.6959 (1.0110); Policy and Government, t – 2: 0.6064* (0.1650); Infrastructure, t – 2: 0.2722 (0.4225)	108	0.9542	0.0872
18-74	t – 2	Responsible AI	Responsible AI, t – 2: –1.0210 (0.3900)	72	0.9785	0.1836
18-74	t – 2	Public Opinion	Public Opinion, t – 2: –1.1120*** (<0.001)	36	0.9947	0.1009
45-54	Current	AI Vibrancy	AI Vibrancy: 0.1054 (0.3815)	144	0.9418	0.0002
45-54	Current	AI subindices	R&D: –0.1375 (0.4368); Economy: 0.3322 (0.2806); Talent: –0.8323 (0.9840); Policy and Government: –0.0299 (0.2696); Infrastructure: –0.2680 (0.2113)	144	0.9426	0.0141
45-54	Current	Responsible AI	Responsible AI: 0.4732 (0.2672)	108	0.9494	0.0164
45-54	Current	Public Opinion	Public Opinion: –0.2480 (0.9383)	72	0.9754	0.0012
45-54	t – 1	AI Vibrancy	AI Vibrancy, t – 1: 0.1600 (0.4707)	126	0.9450	0.0003
45-54	t – 1	AI subindices	R&D, t – 1: –0.9392 (0.5787); Economy, t – 1: 0.1592 (0.1525); Talent, t – 1: 0.6311 (1.0070); Policy and Government, t – 1: 0.2451 (0.1889); Infrastructure, t – 1: 0.1258 (0.1588)	126	0.9462	0.0232
45-54	t – 1	Responsible AI	Responsible AI, t – 1: 0.0499 (0.3570)	90	0.9587	0.0002
45-54	t – 1	Public Opinion	Public Opinion, t – 1: –0.4275 (0.5832)	54	0.9905	0.0078
45-54	t – 2	AI Vibrancy	AI Vibrancy, t – 2: 0.0558 (0.4215)	108	0.9485	0.0000
45-54	t – 2	AI subindices	R&D, t – 2: –1.2300* (0.3698); Economy, t – 2: –0.0533 (0.4782); Talent, t – 2: –1.0080 (1.1780); Policy and Government, t – 2: 0.7346* (0.2145); Infrastructure, t – 2: 0.3930 (0.3073)	108	0.9524	0.0742
45-54	t – 2	Responsible AI	Responsible AI, t – 2: –0.8045 (0.5226)	72	0.9775	0.0877
45-54	t – 2	Public Opinion	Public Opinion, t – 2: –1.9000*** (< 0.001)	36	0.9935	0.1641
50-74	Current	AI Vibrancy	AI Vibrancy: 0.5006 (0.4111)	144	0.9309	0.0050
50-74	Current	AI subindices	R&D: –0.1309 (0.3917); Economy: 0.3082 (0.3738); Talent: –0.0912 (0.8021); Policy and Government: –0.0872 (0.2217); Infrastructure: –0.0274 (0.1702)	144	0.9312	0.0102
50-74	Current	Responsible AI	Responsible AI: 0.2385 (0.2715)	108	0.9400	0.0064
50-74	Current	Public Opinion	Public Opinion: 0.3441 (0.7566)	72	0.9698	0.0034
50-74	t – 1	AI Vibrancy	AI Vibrancy, t – 1: 0.3247 (0.3503)	126	0.9330	0.0020
50-74	t – 1	AI subindices	R&D, t – 1: –0.8911 (0.5611); Economy, t – 1: 0.2459 (0.1329); Talent, t – 1: 1.1700 (0.6697); Policy and Government, t – 1: 0.0364 (0.2115); Infrastructure, t – 1: 0.2261 (0.1508)	126	0.9350	0.0317
50-74	t – 1	Responsible AI	Responsible AI, t – 1: –0.0333 (0.3206)	90	0.9497	0.0001

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Table C1 (cont.). Driscoll-Kraay robustness estimates for AI development and participation in education and training

Age group	Specification	Model	Coefficient(s), Driscoll–Kraay SE in parentheses	N	R^2	Within R^2
50-74	t − 1	Public Opinion	Public Opinion, t − 1: 0.3444 (0.1927)	54	0.9896	0.0076
50-74	t − 2	AI Vibrancy	AI Vibrancy, t − 2: –0.2855 (0.3391)	108	0.9397	0.0016
50-74	t − 2	AI subindices	R&D, t − 2: –1.1170 (0.5119); Economy, t − 2: –0.2091 (0.3741); Talent, t − 2: –0.3572 (0.7189); Policy and Government, t − 2: 0.3651 (0.1910); Infrastructure, t − 2: 0.3998 (0.3156)	108	0.9433	0.0611
50-74	t − 2	Responsible AI	Responsible AI, t − 2: –0.6338 (0.3793)	72	0.9721	0.0773
50-74	t − 2	Public Opinion	Public Opinion, t − 2: –0.6259*** (<0.001)	36	0.9970	0.0668

Note: The dependent variables are participation rates in education and training during the last four weeks for the age groups 18–74, 45–54 and 50–74. All AI indicators are transformed using log(1 + x) and standardized. All models include country and year fixed effects. Standard errors are Driscoll–Kraay standard errors with lag length L = 1 and are reported in parentheses. Significance levels: *** $p < 0.001$, * $p < 0.05$. Responsible AI per capita and Public Opinion per capita are available only for shorter periods; therefore, their lagged estimates should be interpreted cautiously. The two-year lagged Public Opinion models are based on only 36 observations and should be treated as exploratory rather than substantive evidence.