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Inclusive Adaptation to AI: Adult Education, Digital Skills, and Older Workers' Employment in the EU

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ABSTRACT

This study examines how artificial intelligence adoption, adult education participation, digital skills, and tertiary educational attainment are associated with older workers' employment in the European Union. Driven by population aging and technological change, the analysis examines whether national labor-market systems across 27 EU member states provide conditions associated with stronger aggregate employment among people aged 55–64. The study evaluates employment in relation to combined technological, educational, digital, and human-capital conditions rather than artificial intelligence adoption alone. Using the employment rate of individuals aged 55–64 as the main outcome, fuzzy-set Qualitative Comparative Analysis (fsQCA) identifies configurations associated with high and low employment. Calibration sensitivity and a temporal comparison with 2023 assess the robustness of the employment-based findings. No single condition is necessary for high or low employment. No configuration meets the predefined criteria for high employment in 2025, whereas four pathways are associated with low employment. The findings identify three descriptive patterns: weak foundations, a technology–learning mismatch, and strong worker-side resources combined with limited AI diffusion. They suggest considering technological diffusion, learning opportunities, and digital inclusion together.

KEYWORDS AI adoption, fuzzy-set Qualitative Comparative Analysis, adult education participation, digital inclusion, active aging

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Introduction

Artificial intelligence is changing European labor markets by affecting tasks, work organization, and skill requirements. Although AI adoption can support productivity growth and new forms of work organization, its effects are not equally distributed among workers and across countries [1]–[3]. This issue is particularly important in the context of population aging, because European economies increasingly need to extend working lives and support employment at older ages. Therefore, technological change should be considered not only as a source of productivity gains but also as a potential source of exclusion for workers with limited adaptive capacity.

Demographic trends, employment policy, and the inclusiveness of digital and educational systems shape older workers' employment. As AI adoption expands, remaining active and employed at older ages may depend on whether national systems provide the conditions needed for adaptation. Evidence on adult learning is context-dependent. Formal educational upgrading after age 40 was associated with subsequent labor-market participation in Norway [4], whereas a Swedish study found no effect of adult education on retirement timing [5]. Employer-side evidence from Poland

also indicates that computer skills and training requirements can reduce the recruitment prospects of workers aged 50 and over [6].

Existing research has examined the labor market effects of AI, the role of adult education in later working life, and the importance of digital skills for employability. However, these research areas are usually analyzed separately. This represents an important limitation because older workers' employment may depend on the joint presence or absence of several conditions, rather than on a single condition. Less attention has been paid to how technological adoption, adult education participation, digital skills, and human capital combine at the country level. For example, adult education may be less effective when digital skills are limited, and AI adoption may not support employment if older workers lack the foundational skills needed to adapt.

The paper addresses this gap by examining how AI adoption, adult education participation, digital skills, and tertiary educational attainment relate to older workers' employment in the European Union. The empirical analysis uses country-level data for the 27 EU member states. The employment rate of individuals aged 55–64 operationalizes aggregate employment attachment at the country level; it does not measure individual job retention or employment transitions. The AI adoption indicator is interpreted as a country-level measure of the technological environment rather than as direct AI exposure or use among older workers. The applied methodology is fuzzy-set Qualitative Comparative Analysis (fsQCA), which identifies configurations of conditions associated with stronger or weaker outcomes.

The paper's scientific contribution lies in examining older workers' employment in relation to combined national adaptation conditions rather than AI adoption alone. By identifying multiple pathways to low employment, the analysis shows how similar employment outcomes can be associated with different combinations of adult learning, digital inclusion, and accumulated human capital.

Background and Conceptual Framework

The literature on AI and labor markets shows that the labor-market effects of technological change depend not only on adoption, but on how new technologies interact with task structures, skill requirements, and work organization [1], [3]. However, these effects are not equally distributed across workers and countries [2]. This is particularly relevant for older workers because population aging increases the need for longer working lives, while technological change can increase the risk of skill obsolescence.

The effects of AI, therefore, cannot be assessed only through the level of technological adoption. AI technologies include language and image processing, speech recognition, machine learning, and workflow automation. Their effects also depend on workers' and institutions' capacity to adapt to new skill requirements [1], [3], [7]. AI adoption may increase the demand for analytical, digital, and complementary skills, while reducing the value of routine tasks. For this reason, adaptation to AI requires upskilling, reskilling, and organizational support for learning. Countries with higher AI adoption are not necessarily better positioned to support older workers' employment, as technological change delivers such benefits only when accompanied by adequate learning opportunities and digital inclusion.

Adult education matters because it helps workers update their skills throughout their life course. Training participation was positively associated with retirement-eligible workers' decisions to remain employed in Dutch samples, particularly where organizational climates supported older-worker development [8]. However, participation and its effects are not uniform. Evidence indicates that age stereotypes, job skill requirements, time, organizational learning cultures, and workers' perceived growth needs shape recruitment and learning opportunities [6], [8], [9]. These findings suggest that continued learning depends on both individual motivation and supportive organizational conditions.

Digital skills are also important for older workers' employment in an AI-intensive labor market. They include the ability to find and evaluate information, communicate online, create digital content, protect personal data, and solve problems using digital tools. Even when workers do not directly use advanced AI tools, they may still need basic digital skills to adapt to changing work processes, access training, and remain employable. Digital inclusion can be understood as a foundation for broader adaptation to technological change. Tertiary educational attainment is also relevant because it reflects accumulated human capital and the capacity to adjust to more complex and changing work environments.

Based on these arguments, older workers' employment results from a combination of technological, educational, digital, and human capital conditions. The study, therefore, does not assume that any single condition is sufficient on its own. Instead, it assumes that different combinations of conditions may produce similar labor market outcomes. For example, adult education participation may support employment only when paired with adequate digital skills, whereas AI adoption may not strengthen employment if older workers lack the digital or educational foundations needed to adapt.

The four conditions capture distinct but complementary dimensions of national adaptation capacity, consistent with evidence that the labor-market implications of technological change depend on skills, learning opportunities, and organizational adaptation [1], [3], [7]–[9]. AI adoption represents firm-level technological diffusion; adult education participation captures continued learning opportunities at older ages; digital skills reflect the foundational capability required to participate in increasingly digital work and training; and tertiary educational attainment represents accumulated formal human capital. Together, these conditions allow the analysis to assess whether technological diffusion is accompanied by learning opportunities and workforce capabilities.

The framework is deliberately bounded and does not capture all determinants of older workers' employment. It excludes health, pension incentives, sectoral employment structures, and employer age-management practices, while the AI indicator does not measure direct exposure to or use of AI among older workers. These boundaries define the scope of the configurational analysis presented in the following section.

The four conditions also correspond to complementary elements of the current European policy architecture. The Digital Decade combines targets for digital skills and business digitalization, the European Pillar of Social Rights recognizes adult learning as a social and labor-market priority, and the Union of Skills places lifelong learning and workforce adaptability within the EU competitiveness agenda [10]–[12]. Together, these frameworks imply that technological diffusion, learning provision, and foundational capabilities should be treated as an integrated policy package rather than as separate interventions.

Recent evidence cautions against simple causal claims about skills development and extended working lives. A systematic review of prospective cohort studies reports mixed findings: several included studies associated skills development or opportunities for skills development with longer working lives, but the overall certainty of evidence was very low [13]. A systematic review of digital vocational education for older workers identifies flexible delivery and age-appropriate learning design as important for participation and engagement [14]. Together, these findings support examining training within its wider digital and organizational context.

Data and Method

The study uses a country-level dataset for the 27 European Union member states. All indicators are taken from Eurostat datasets to ensure cross-country comparability [15]. The main empirical analysis focuses on 2025, when all core indicators are available, while 2023 serves as a temporal robustness check. Employment among individuals aged 55–64 is the principal outcome; activity is retained only as a secondary outcome check.

The explanatory conditions describe four dimensions of national adaptation capacity. Artificial intelligence adoption is measured by the share of enterprises with 10 or more employees using at least one AI technology. These technologies include text mining, natural language generation, speech and image recognition, machine learning for data analysis, and AI-based workflow automation or decision support [15]. The indicator is interpreted as a country-level measure of the technological environment and does not capture direct AI exposure or use among older workers.

Adult education participation is measured by the participation rate in education and training among individuals aged 55–64. Digital inclusion is measured by the share of individuals aged 55–64 with basic or above-basic overall digital skills. The digital-skills indicator covers information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving [15]. Human capital is measured by the share of individuals aged 55–64 with tertiary educational attainment.

The model therefore combines an enterprise-level AI indicator with individual-level indicators aggregated to the country level; it does not link the same workers to the enterprises reporting AI use. Table 1 reports descriptive statistics. Eurostat dataset codes are lfsa_ergan (EMP), isoc_eb_ai (AI), trng_lfse_01 (AET), isoc_sk_dskl_i21 (DIG), and edat_lfse_03 (TER).

Table 1. Descriptive Statistics

Variable	Mean	Median	Min	Max
EMP	66.8	69.4	49.5	78.3
ACT	69.9	71.8	51.9	83.7
AI	20.7	19.6	5.2	42.0
AET	10.3	8.5	2.1	31.2
DIG	49.2	46.6	18.0	80.0
TER	28.7	29.8	11.4	43.4

Note: EMP = employment 55–64; ACT = activity 55–64; AI = enterprises using at least one AI technology; AET = adult education/training 55–64; DIG = basic or above-basic digital skills 55–64; TER = tertiary attainment 55–64. All variables are expressed as percentages. N = 27 EU member states.

Descriptive statistics show clear cross-country variation in older workers' employment and adaptation conditions. Employment among individuals aged 55–64 ranges from 49.5% to 78.3%, while AI adoption ranges from 5.2% to 42.0%. Variation is also visible in adult education participation, digital skills, and tertiary attainment. This supports a configurational approach because EU member states differ not only in individual indicators but also in combinations of conditions.

The variables are calibrated into fuzzy-set membership scores using direct calibration, with the 10th percentile representing full non-membership, the median representing the crossover point, and the 90th percentile representing full membership (Table 2) [16], [17]. Because externally validated substantive thresholds are not available consistently across all indicators, these distribution-based anchors provide a transparent comparative calibration for the full population of 27 EU member states. They distinguish relatively low, intermediate, and high positions within the EU distribution rather than compliance with absolute substantive benchmarks.

Because the 10th and 90th percentiles are located near the distribution tails in a small sample, an additional check uses the 20th percentile, median, and 80th percentile to assess sensitivity to the placement of the outer anchors. Exact crossover memberships are assigned to 0.501 in the main analysis, while a 0.499 specification evaluates sensitivity to the opposite assignment. The 2023 sets are recalibrated using their own annual distributions.

The empirical strategy relies on fuzzy-set Qualitative Comparative Analysis (fsQCA), which identifies configurations associated with an outcome rather than isolated net effects [16], [17]. The analysis uses QCA version 3.25 and conservative minimization. Consistency assesses how closely the observed set memberships conform to the tested necessity or sufficiency relation. Proportional reduction in inconsistency (PRI) assesses whether a sufficient configuration is associated with the outcome rather than also with its negation. Coverage indicates the empirical relevance of a sufficient solution by showing how much of the outcome membership it covers. Necessity is evaluated at a consistency threshold of 0.90.

Table 2. Variables and Calibration Anchors

Set	Calibration Anchors		
	Out	Cross	In
EMP	57.4	69.4	76.3
ACT	59.3	71.8	79.5
AI	8.78	19.6	34.7
AET	3.6	8.5	19.1
DIG	31.4	46.6	72.8
TER	19.6	29.8	38.9

Note: EMP = employment 55–64; ACT = activity 55–64; AI = enterprises using at least one AI technology; AET = adult education/training 55–64; DIG = basic or above-basic digital skills 55–64; TER = tertiary attainment 55–64. Out/Cross/In are the p10/p50/p90 empirical calibration anchors and represent relatively low, intermediate, and high positions within the annual EU distribution. Values are percentages.

For the sufficiency analysis, each truth-table row represents a combination of the presence or absence of the four conditions. A row is included in the minimization when it contains at least one case and meets the consistency threshold of 0.80 and the PRI threshold of 0.50. Limited diversity occurs when not all logically possible combinations are observed. Conservative minimization uses only observed truth-table rows and does not use unobserved logical remainders to simplify the solution. Prime implicants and complete solutions must also reach 0.80 consistency.

The configurational model is expressed as:

$$Y_i = f(AI_i, AET_i, DIG_i, TER_i) \quad (1)$$

where *i* denotes an EU member state, and *Y* denotes the calibrated outcome set. Older workers' employment is evaluated as EMP and its complement LOW_EMP. This notation preserves set-theoretic asymmetry: configurations associated with low employment need not be the inverse of configurations associated with high employment.

The analysis is conducted in two steps. First, a necessity analysis evaluates whether any condition, or its absence, is required for the outcome. Second, truth tables and Boolean minimization identify sufficient configurations [16], [17]. In fsQCA, sufficiency means that membership in a configuration is consistently associated with membership in the outcome set; it does not establish causation.

Robustness is assessed through the alternative 0.499 crossover assignment, the recalibrated 2023 model, and a secondary activity-outcome check. Three additional checks examine the sensitivity of the 2025 LOW_EMP solution to alternative p20/p50/p80 calibration anchors, a stricter PRI threshold of 0.60, and a frequency threshold of two cases. The stricter PRI threshold requires a clearer distinction between the outcome and its negation, while the higher frequency threshold tests whether the solution depends on truth-table rows represented by a single country.

Results and Discussion

The necessity analysis shows that no individual condition, or its absence, meets the conventional consistency threshold of 0.90 for high or low employment. The conclusion is virtually unchanged under the 0.501 and 0.499 crossover assignments. Older-worker labor-market disadvantage therefore cannot be reduced to a single technological, educational, or digital condition.

At the predefined thresholds, no sufficient configuration was identified for high employment in 2025. This finding is consistent with set-theoretic asymmetry because the conditions associated with low employment need not be the inverse of those associated with high employment. However, it may also reflect the limited diversity of the 27-country sample, the predefined consistency and PRI thresholds, and conservative minimization. It should therefore not be interpreted as proof of causal asymmetry or as evidence that pathways to high employment do not exist. By contrast, LOW_EMP produces four conservative pathways (Table 3), with a solution consistency of 0.821, a PRI of 0.734, and a coverage of 0.699. The four pathways are obtained by conservatively minimizing truth-table rows that meet the predefined frequency, consistency, and PRI thresholds. They are interpreted below as alternative patterns associated with LOW_EMP.

Table 3. Final fsQCA Solution for Low Employment

Condition	Pathway			
	P1	P2	P3	P4
AI	⊗	●		⊗
AET		⊗	●	●
DIG	⊗		⊗	●
TER	⊗	●	⊗	●
Cons.	0.833	0.852	0.887	0.888
PRI	0.741	0.697	0.763	0.679
Raw cov.	0.510	0.261	0.330	0.199
Uniq. cov.	0.224	0.075	0.046	0.019

Note: ● indicates the presence of a condition, ⊗ indicates the absence of a condition, and blank cells indicate that the condition is not part of the minimized pathway. AI = enterprise AI adoption; AET = adult education and training participation among people aged 55–64; DIG = basic or above-basic digital skills among people aged 55–64; TER = tertiary attainment among people aged 55–64. Cons. = consistency; PRI = proportional reduction in inconsistency; Raw cov. = raw coverage; Uniq. cov. = unique coverage. Solution consistency = 0.821; PRI = 0.734; solution coverage = 0.699. Cases: P1 = BG, EL, HU, IT, PL, RO, SK; PT; P2 = LT; DE; P3 = PT; MT, SI; P4 = FR. Semicolons separate distinct observed truth-table configurations covered by the same minimized expression. The main analysis assigns exact crossover memberships to 0.501.

Figure 1 shows the sufficiency relation between membership in the combined 2025 LOW_EMP solution and membership in the LOW_EMP outcome.

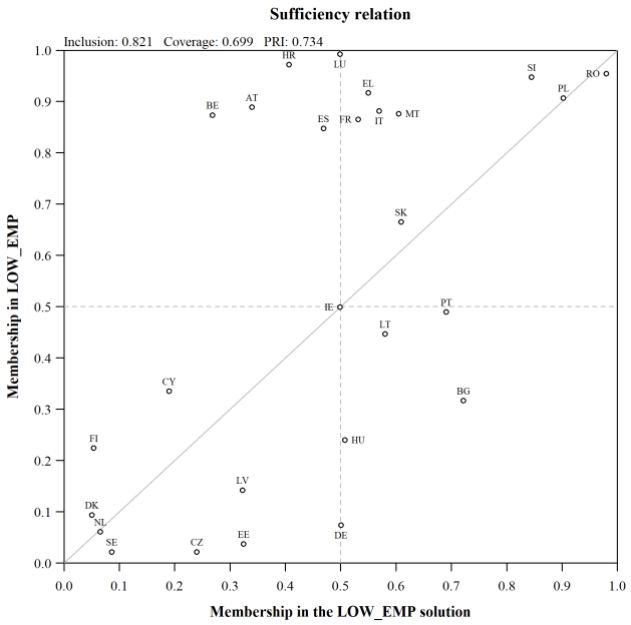


Fig. 1. Sufficiency plot for the 2025 LOW_EMP solution

To make the country distribution of the verified main solution transparent, Table 4 reports the cases covered by each 2025 LOW_EMP pathway. Semicolons separate cases that belong to distinct observed truth-table configurations covered by the same minimized expression.

Table 4. Country Membership in the Low-Employment Solution

Outcome	Pathway	Country membership	Main pattern
LOW_EMP	P1	BG, EL, HU, IT, PL, RO, SK; PT	Low AI, low DIG, and low TER
LOW_EMP	P2	LT; DE	High AI, low AET, and high TER
LOW_EMP	P3	PT; MT, SI	High AET, low DIG, and low TER
LOW_EMP	P4	FR	Low AI, high AET, high DIG, and high TER

Note: The table reports cases covered by the four pathways in the main 2025 LOW_EMP solution; membership is not exclusive. LOW_EMP = low employment among people aged 55–64; AI = enterprise AI adoption; AET = adult education and training participation among people aged 55–64; DIG = basic or above-basic digital skills among people aged 55–64; TER = tertiary attainment among people aged 55–64. "Low" and "high" denote calibrated fuzzy-set membership. BG = Bulgaria; DE = Germany; EL = Greece; FR = France; HU = Hungary; IT = Italy; LT = Lithuania; MT = Malta; PL = Poland; PT = Portugal; RO = Romania; SI = Slovenia; SK = Slovakia. Additional country codes shown in Figure 1 are: AT = Austria; BE = Belgium; HR = Croatia; CY = Cyprus; CZ = Czechia; DK = Denmark; EE = Estonia; FI = Finland; IE = Ireland; LV = Latvia; LU = Luxembourg; NL = Netherlands; ES = Spain; and SE = Sweden. Semicolons separate distinct observed truth-table configurations covered by the same minimized expression.

The pathway labels used below are descriptive and do not imply causal relationships. The first and broadest pathway combines low AI adoption, weak digital skills, and low tertiary attainment (~AI*~DIG*~TER). It accounts for the largest share of LOW_EMP and describes a configuration in which low employment coexists with limited technological diffusion, basic digital capability, and accumulated human capital. The same combination of weak digital skills and low tertiary attainment also appears in the 2023 comparison. Poland clearly illustrates P1: low AI adoption, weak digital skills, and low tertiary attainment coexist with high membership in LOW_EMP.

The second pathway combines high AI adoption, low adult education participation, and high tertiary attainment (AI*~AET*TER). In this configuration, accumulated education and technological diffusion coexist with limited continued learning and weak employment. P2 covers Lithuania and Germany and should therefore be interpreted as a case-specific pattern rather than a general EU pattern. The third pathway (AET*~DIG*~TER) describes a configuration in which high adult learning coexists with low employment and weak digital and educational foundations. P3 is calibration-sensitive because its exact form changes under the alternative crossover assignment and should therefore be interpreted with caution.

The fourth pathway combines low AI adoption with high adult learning, digital skills, and tertiary attainment (~AI*AET*DIG*TER). In this configuration, favorable worker-side resources coexist with weak employment, while firm-level AI diffusion remains limited. P4 is represented only by France and should therefore be interpreted cautiously. It remains stable across the two 2025 crossover assignments but does not recur in 2023 and is therefore treated as period-specific rather than as a general EU pattern.

Table 5 summarizes the robustness checks. In addition to the alternative crossover assignment, the 2023 comparison, and the secondary activity outcome, the additional checks vary the outer calibration anchors, the PRI threshold, and the minimum number of cases required for a truth-table row.

Table 5. Analytical Robustness Checks

Check	Solution consistency	PRI	Coverage
2025, crossover 0.501	0.821	0.734	0.699
2025, crossover 0.499	0.805	0.710	0.686
2025, alternative anchors	0.805	0.739	0.661
2025, PRI threshold 0.60	0.821	0.734	0.699
2025, frequency threshold 2	0.854	0.777	0.524
2023 LOW_EMP	0.818	0.741	0.767
2025 LOW_ACT	No solution ≥ 0.80	-	-

Note: The main 2025 model uses p10/p50/p90 calibration anchors, a 0.501 crossover assignment, a consistency threshold of 0.80, a PRI threshold of 0.50, and a frequency threshold of one case. Each additional 2025 check changes only the stated specification. The alternative-anchor check uses p20/p50/p80. The 2023 model is recalibrated using its annual distribution. LOW_ACT produced no conservative solution at the predefined solution-consistency threshold of 0.80.

The p20/p50/p80 calibration retains the same four pathways, with a solution consistency of 0.805, a PRI of 0.739, and a coverage of 0.661. Raising the PRI threshold to 0.60 reproduces the main solution and its parameters. When the frequency threshold is raised to two cases, the solution narrows to two more specific configurations nested within P1 and P3. Consistency increases to 0.854 and PRI to 0.777,

while coverage decreases to 0.524. This result shows that the multi-case configurations are more consistent but cover a smaller share of LOW_EMP. It also supports the cautious interpretation of P2 and P4, which depend on truth-table rows represented by single countries. Across the remaining checks, weak digital and human-capital foundations and the technology–learning mismatch remain the most relevant recurring patterns.

Overall, inclusive adaptation to AI cannot be reduced to technological adoption alone. The results identify different combinations of technological diffusion, learning participation, digital inclusion, and accumulated human capital. These patterns point to different policy priorities.

Rather than providing a single ranking of national performance, Table 6 links each policy priority to the conditions present or absent in the corresponding 2025 LOW_EMP pathway. These implications are diagnostic and configuration-sensitive; they do not estimate causal treatment effects or support universal prescriptions.

Table 6. Configuration-Specific Policy Implications

Pathway	Policy bottleneck	Priority response
P1	Weak digital and educational foundations	Combine basic digital-skills provision with educational upgrading before or alongside AI diffusion.
P2	Technology-learning mismatch	Strengthen accessible mid- and late-career learning and employer-supported adaptation to AI-enabled work.
P3	Learning without foundation; calibration-sensitive	Integrate adult learning with foundational digital and educational support; avoid stand-alone training measures.
P4	Strong worker-side resources with limited AI diffusion	Support responsible AI adoption and work redesign so existing skills translate into age-inclusive employment.

Note: Implications are derived from the verified 2025 LOW_EMP pathways. Pathway labels are descriptive and do not imply causal effects. P3 is calibration sensitive.

For the weak-foundations pathway, digital-skills objectives and adult-learning systems need to operate together, consistent with the combined orientation of current EU skills and digital-policy frameworks [10]–[12]. For the technology–learning mismatch, policy should emphasize age-appropriate and flexible training design rather than access alone [14]. Because evidence on whether skills development extends working lives remains uncertain [13], these recommendations should be treated as pathway-specific priorities rather than universal causal prescriptions.

Croatia illustrates why this distinction matters. In 2025, its basic-or-above-basic digital-skills rate among people aged 55–64 was 50.0%, slightly above the EU-27 median of 46.6%, whereas adult education participation was 2.4% compared with 8.5%, tertiary attainment was 19.6% compared with 29.8%, and enterprise AI adoption was 15.2% compared with 19.6%. This profile therefore highlights not only digital access, but also continued learning, accumulated human capital, and organizational technology adoption. This descriptive profile does not, by itself, assign Croatia to a sufficient pathway.

Conclusion

This paper examined how AI adoption, adult education participation, digital skills, and tertiary educational attainment relate to older workers' employment in EU member states. No individual condition is necessary for high or low employment. In 2025, no sufficient configuration was identified for high employment, whereas four were identified for low employment. This difference is consistent with set-theoretic asymmetry, but it may also reflect the limited diversity of the 27-country sample, the predefined consistency and PRI thresholds, and conservative minimization. It does not demonstrate causal asymmetry.

The main contribution is to distinguish persistent and period-specific forms of adaptation disadvantage. The most stable cross-time pattern combines weak digital skills and low tertiary attainment. A second recurring pattern combines high AI adoption with limited continued learning despite stronger accumulated human capital. A third, 2025-specific configuration combines strong learning and skill resources with limited AI diffusion and weak employment.

The findings point to different policy priorities. For countries matching the weak-foundations pattern, these include integrated digital and educational capacity building. For those matching the technology–learning mismatch, they include access to relevant mid- and late-career training. These are configuration-specific priorities rather than universal prescriptions.

The pattern combining strong learning and skill resources with limited AI diffusion points to responsible AI diffusion, work redesign, and organizational support as possible priorities. Because only France represents this pathway and it does not recur in 2023, its interpretation remains case-specific and period-specific.

Pathway-based interpretation provides a configuration-sensitive approach to implementing EU and national policy instruments [10]–[12]. The four-path solution remains unchanged under the alternative calibration anchors and the stricter PRI threshold. Requiring at least two countries per truth-table row yields a narrower solution with lower coverage, reinforcing the need for caution when interpreting single-country configurations.

Limitations include the small number of national cases, reliance on empirical calibration, the cross-sectional design, use of aggregate indicators, and a mismatch

between enterprise-level AI adoption and individual-level skill measures. Configurations supported by only one or two countries are case-specific and should not be generalized without further evidence. In particular, the AI indicator does not capture older workers' direct exposure to or use of AI. Employment rates do not track individual job retention or transitions. Future research should use longitudinal microdata and sector-level AI exposure to test whether the identified configurations predict continued employment.

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Conflict of Interest

The authors declare no conflict of interest.

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