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ORIGINAL

The Concentration of AI Talent as an Industrial Strategy: A Cross-Country Panel Data Analysis Applied to Financial Services as an Industry

La concentración de talento en inteligencia artificial como estrategia industrial: un análisis de datos de panel entre países aplicado a los servicios financieros como industria

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ABSTRACT

Artificial intelligence is redrawing comparative advantages in financial services, while many studies remain descriptive or focused on a single country, without testing whether the observed gaps reflect distinct industrial strategies. In this context, our objective is to establish whether the concentration of AI talent in finance is due to a simple global trend or to differentiated national choices. Empirically, we conduct an observational, comparative, and longitudinal study on 10 OECD countries monitored annually between 2016 and 2025 (N = 100 country-years). The dependent variable is the share of professionals trained in AI in finance (AI_pct, harmonized definition). The dynamics is captured by a linear time trend, supplemented for robustness by annual dummies; heterogeneity is modeled via a random effects GLS with country intercepts, clustered standard errors, and the Hausman test does not reject the RE option. On the data side, we mobilize a single, harmonized public source (OECD.AI) and anchor the analysis in 18 scientific references. The results indicate an average increase of approximately +0,2263 percentage points per year (significant), an overall average of 2,86 %, and persistent gaps between countries (e.g., Israel ≈ 4,08 % vs. the United States ≈ 2,27 %), stable when the trend is replaced by time fixed effects. In sum, the rise in AI skills is general, but is part of national trajectories consistent with industrial strategy; hence implications for upskilling, data and model governance, and state-market coordination, subject to a limited scope and the absence of causal identification.

Keywords: AI Talent; Industrial Strategy; Financial Services; Panel Data; Geoeconomics.

RESUMEN

La inteligencia artificial está redefiniendo las ventajas comparativas en los servicios financieros, mientras que muchos estudios se mantienen descriptivos o se centran en un solo país, sin comprobar si las brechas observadas reflejan estrategias industriales diferenciadas. En este contexto, nuestro objetivo es determinar si la concentración de talento en IA en finanzas se debe a una simple tendencia global o a decisiones nacionales diferenciadas. Empíricamente, realizamos un estudio observacional, comparativo y longitudinal en 10 países de la OCDE, monitoreados anualmente entre 2016 y 2025 (N = 100 países-año). La variable dependiente es la proporción de profesionales con formación en IA en finanzas (AI_pct, definición armonizada). La dinámica se captura mediante una tendencia temporal lineal, complementada para mayor robustez con variables ficticias anuales; la heterogeneidad se modela mediante un GLS de efectos aleatorios con interceptos de país, errores estándar agrupados, y la prueba de Hausman no rechaza la opción de RE. En cuanto a los datos, movilizamos una única fuente pública armonizada (OECD.AI) y basamos el análisis en 18 referencias científicas. Los resultados indican un aumento promedio de aproximadamente +0,2263 puntos porcentuales anuales (significativo), un promedio general del 2,86 % y brechas persistentes entre países (p. ej., Israel ≈ 4,08 % frente a Estados Unidos ≈ 2,27 %), que se mantienen estables al sustituir la tendencia por efectos fijos temporales. En resumen, el aumento de las competencias en IA es general, pero forma parte de trayectorias nacionales coherentes con la estrategia industrial; por lo tanto, las implicaciones para la capacitación, la gobernanza de datos y modelos, y la coordinación entre el Estado y el mercado, están sujetas a un alcance limitado y a la ausencia de identificación causal.

Palabras clave: Talento en IA; Estrategia Industrial; Servicios Financieros; Datos de Panel; Geoeconomía.

INTRODUCTION

Artificial intelligence is subtly reorganizing the map of comparative advantages in industry.[1,2] The increasing financialization of modern economies is accompanied by a strategic algorithmization of financial services, transforming this sector into a technological battlefield.[3] Yet, this transition reveals profound geoeconomic asymmetries: for example, in 2025, the concentration of AI talent in finance will vary by a factor of two between Israel (4,08 %) and Poland (2,27 %), creating new global hierarchies.[4]

Historically, industrial revolutions have reconfigured economic balances through comparative advantage shifts, a dynamic extensively analyzed since Rodrik's seminal work.[5] Today, AI transcends its role as a cross-functional tool to become a power infrastructure whose impact is contingent on absorptive capacity.[6] This dependency creates irreversible divides between nations, as technology's secondary role gives way to political, institutional, and human integration factors that inevitably diverge national trajectories.[7,8]

These disparities generate three critical operational risks. First, systemic instability emerges as AI's financial intrusion redefines stability mechanisms, introducing unprecedented vulnerabilities such as predictive model biases that may trigger novel crises.[9] Second, geopolitical fracture occurs as asymmetric talent concentration acts as a power multiplier, entrenching core-periphery divides in innovation ecosystems.[10] Third, regulatory arbitrage arises when conflicting governance models (state-driven, market-led, hybrid) transform ethical-legal differences into competitive distortions with poorly quantified global consequences.[11,12] These divergent paradigms fuel a competition where differences in ethical and legal frameworks are transformed into instruments of competitive distortion, with consequences for global economic balances that are still poorly understood.

The concentration of human capital in AI now constitutes a strategic lever redefining global industries. The competition for these talents embodies a determining mechanism of comparative advantage, where the acquisition of experts conditions the innovation capacity of States.[13] This phenomenon marks a major shift in public policies. The geography of AI skills thus emerges as a hybrid indicator, reflecting both technological maturity and a lever of geoeconomic influence.[14] This dynamic is played out in a normative framework where public decision-making guides the mapping of AI skills.[15]

Indeed, some countries are adopting very different strategies to attract artificial intelligence talent. While this analysis focuses on OECD economies for data standardization purposes,[3] the framework of strategic divergence extends globally. Israel and Singapore are investing in AI training and infrastructure, with strong state involvement.[16,17] In contrast, the United States leaves this issue to the private sector, which creates internal inequalities.[18,19] The European Union adopts an intermediate position, combining industrial ambition and an ethical regulatory framework. China is accelerating its dominance through the 'AI 2030' plan,[20,21] while Japan is prioritizing public-private partnerships as part of 'Society 5.0'.[22] Russia, despite facing sanctions, is developing import substitution programs.[23]

While AI is recognized as a major lever for industrial transformation, few studies analyze how national trajectories influence this dynamic in financial services. Many studies emphasize that human capital in AI constitutes a key geoeconomic resource, and several studies detail public policies "country by country." But two blind spots persist. First, the rise of AI is often treated as a homogeneous phenomenon, without consideration for the diversity of socio-industrial contexts that condition the appropriation of AI skills. Second, comparative empirical analyses that test, at the sectoral level, the hypothesis of a differentiated industrial strategy behind the concentration of talent are rare.

This gap appears even more clear in finance: while this sector was one of the first to massively integrate AI, no systematic study compares the dynamics of AI talent accumulation from one country to another. Current typologies of national AI strategies tend to favor idealized policy narratives rather than empirical validations based on robust sectoral indicators. This is the case for OECD economies. Our research aims to fill this gap: Is cross-country variation in AI talent concentration in financial services consistent with differentiated national industrial strategies rather than a uniform global trend? Our research fills this gap by examining, via a random effects model on panel data, the extent to which the gaps observed in 10 countries (2016-2025) reflect differentiated national industrial choices.

METHOD

We employ an observational, comparative, and longitudinal study using panel data (country x year),[24] without researcher intervention. The universe covers OECD economies with comparable sectoral indicators on AI; the sample deliberately selects 10 countries (Australia, Switzerland, Estonia, Israel, Ireland, Lithuania, Netherlands, Poland, United Kingdom, United States) observed annually from 2016 to 2025 (N = 100 country-years). The single inclusion criterion: the presence, in OECD.AI, of a continuous and strictly comparable series for the indicator "share of professionals trained in AI in financial services"; exclusion in the absence of a continuous/comparable series. This framing prioritizes construct comparability rather than maximum coverage.

The dependent variable (AI_pct) is the share (%) of AI-trained professionals in the financial services workforce (OECD.AI harmonized definition; bound [0,100]). The main explanatory variable is Year (2016…2025), coded continuously to capture the trend; no other covariates are included in the base, to preserve cross-country comparability given the limited harmonized coverage. Data are extracted from the OECD.AI platform (access 2025), at the country-year level and at an annual frequency; we harmonize country codes (ISO-3), check for duplicates and completeness to build a balanced panel, detect potential outliers (leverage/residuals), and inspect the distribution. No imputation or re-weighting is performed; the values are kept in levels (natural limit [0,100]) and the percentages are reported to two decimal places for consistency of presentation, without impact on the estimate.

Country-level heterogeneity is modeled via random intercepts (RE). We estimate a random-effects (RE) panel model with country-level random intercepts, i.e., $yit = \alpha + \beta Yearit + ui + \varepsilon it$, assuming ui is uncorrelated with the regressors. This specification retains between-country variation and allows inclusion of time-invariant factors; standard errors are cluster-robust at the country level. No additional covariates are included in the baseline to preserve cross-country comparability, given the harmonized but limited indicator coverage.

We focus on the AI talent concentration indicator, which measures the proportion of professionals specializing in AI within the finance sector. This choice was made to capture the degree of algorithmic specialization in a sector susceptible to technological transformations. The 2016–2025 timeframe was determined by the OECD.AI data standardization from 2016, which covered the pivotal integration phase of AI-finance, and the optimal trade-offs between temporal scope and metric reliability. The panel approach not only allows for the identification of these trends, but also to consider the structural specificities of each country, something that a cross-sectional model would not allow. It also improves the robustness of our results by strengthening statistical precision and distinguishing lasting trends from one-off events.

In the panel specification, the dependent variable is AI talent concentration in finance (AI_pct), defined as the percentage of AI-trained professionals within each country's financial-services workforce (OECD.AI). Given its natural [0,100] bound and distributional diagnostics (outlier/leverage checks, skewness), we keep the variable in levels. The regressor Year (2016–2025) is entered as a continuous trend so that β reads as the average annual change in AI_pct. We estimate a random-effects GLS model with country random intercepts, justified by a Hausman test (Appendix Table A1) indicating no systematic correlation between ui and the regressors; FE estimates are reported as a robustness check. We diagnose serial correlation (Wooldridge) and cross-sectional dependence (Pesaran CD); standard errors are clustered by country. Model fit and variance components are summarized via within/between/overall $R2$, σu, $\sigma\varepsilon$, and ρ. Sensitivity analyses replace the linear trend with year dummies and perform leave-one-country-out re-estimations; the magnitude and sign of β remain stable across specifications.

Data is public, aggregated, and non-personal; no human/animal experiments. The study is exempt from formal ethics approval and complies with OECD.AI terms of use.

RESULTS

We summarized AI_pct by country over 2016–2025 (mean, SD, min, max) to document coverage and dispersion. The overall mean is 2,86 % (N=100), with country means ranging from 2,27 % (United States) to 4,08 % (Israel); observed values span 1,01 %–5,78 %. For transparency, we also report the stacked correlation between Year and AI_pct as a descriptive indication of a monotonic time association; no inference is drawn from this statistic in Methods (table 1).

Across pooled OLS, fixed-effects, and random-effects specifications, the coefficient on Year is positive and statistically significant (table 2). The Pooled OLS model does not detect any significant time effects because it wrongly assumes that all countries follow an identical trajectory.

Table 1. Descriptive statistics of our data				
Country	**Mean**	**SD**	**Min**	**Max**
All	2,86	1,03	1,01	5,78
Australia	2,54	0,764	1,48	3,65
Switzerland	2,44	0,576	1,68	3,31
Estonia	2,65	1,14	1,01	4,21
United Kingdom	3,07	0,814	2,00	4,36
Ireland	3,17	0,938	1,84	4,60
Israel	4,08	1,37	2,05	5,78
Lithuania	2,96	1,02	1,52	4,41
Netherlands	3,10	1,02	1,68	4,56
Poland	2,36	0,786	1,16	3,51
United States	2,27	0,701	1,32	3,38
Correlation coefficient		0,84		

Table 2. Panel Model Estimates for AI Talent Concentration Time Trend								
Models	**Estimate (Year)**	**Std. Error**	**t/z-value**	**p-value**	**R^2 overall**	**R^2 within**	**R^2 between**	**θ**
Pooled OLS	0,22630	0,26254	0,8620	0,3910	0,7066	-	-	-
Fixed Effects	0,22630	0,10955	2,0657*	0,0421 *	-	0,9389	-	-
Random Effects	0,22630	0,10955	2,0657*	0,0389 *	0,9326	0,9258	0,9310	0,8563

The Hausman test does not reject the random-effects specification; we therefore retain RE as the reporting model for the remainder of the analysis.We therefore resolutely opt for this model, especially since it displays superior efficiency; its lower variances attest to more precise estimates and clarify the analysis by combining the effects of time and inter-country variability in one go, without compromising the robustness of our inferences. Breusch–Pagan indicates no heteroskedasticity, while Wooldridge detects serial correlation, and Pesaran CD points to mild cross-sectional dependence. Accordingly, all reported estimates use RE-GLS with standard errors clustered by country; inference and substantive conclusions are unchanged (table 3).

Table 3. Panel Model Diagnostic Test Results				
Test	**Statistic**	**df**	**p-value**	**Interpretation**
Breusch–Pagan (heteroscedasticity)	8,1952	9	0,5146	No heteroscedasticity
Wooldridge's pbgtest (autocorrelation)	62,291	10	< 0,001	Detected autocorrelation
Pesaran CD (cross dependency)	–1,9647	-	0,0495	Slight cross-dependence

The specification with year indicators confirms a monotonic increase relative to the 2016 baseline: all year coefficients are positive and statistically significant. This pattern corroborates the linear-trend result retained for reporting and indicates a steady rise in the share of AI-trained professionals in finance (table 4).

Table 4. AI Talent Growth Estimates by Year				
Variable	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	1,5741	0,108965	14,446	< 2,2e-16***
Year2017	0,2263	0,027969	8,0911	2,646e-12***
Year2018	0,5027	0,05434	9,2511	1,033e-14***
Year2019	0,8179	0,083529	9,7918	7,738e-16***
Year2020	1,1022	0,106169	10,3816	< 2,2e-16***
Year2021	1,4221	0,145257	9,7903	7,794e-16***
Year2022	1,7504	0,183172	9,556	2,394e-15***
Year2023	2,07	0,195729	10,5758	< 2,2e-16***
Year2024	2,4019	0,195616	12,2787	< 2,2e-16***
Year2025	2,6018	0,193821	13,4237	< 2,2e-16***
Note: Signif. codes: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1				

All year indicators are positive and statistically significant relative to the 2016 baseline, confirming a monotonic increase in AI_pct (Concentration of AI talent) over 2017–2025. Coefficients represent level differences vs. 2016 (not cumulative effects) and corroborate the linear-trend specification.

The estimated equation, structured around a constant intercept (1,5741) and a series of dummy time variables, allows us to model the incremental evolution of the concentration of AI talent in the financial sector. At first glance, it offers a detailed and empirical reading of the phenomenon over the period 2017–2025. However, this structure raises three major analytical limitations, which a rigorous academic approach cannot ignore. So the equation takes the following form:

$$AI\_pct_{it} = 1{,}5741 + 0{,}2263 \cdot Year_{2017} + 0{,}5027 \cdot Year_{2018} + 0{,}8179 \cdot Year_{2019} + 1{,}1022 \cdot Year_{2020} + 1{,}4221 \cdot Year_{2021} + 1{,}7504 \cdot Year_{2022} + 2{,}0700 \cdot Year_{2023} + 2{,}4019 \cdot Year_{2024} + 2{,}6018 \cdot Year_{2025} + \alpha i + u_{it}$$

The graph illustrates an overall rise in AI talent in finance between 2016 and 2025, but not all countries are following the same pace. Ireland, for example, shows rapid and sustained growth, while the United States stands out for its much more moderate, almost lagging, momentum.

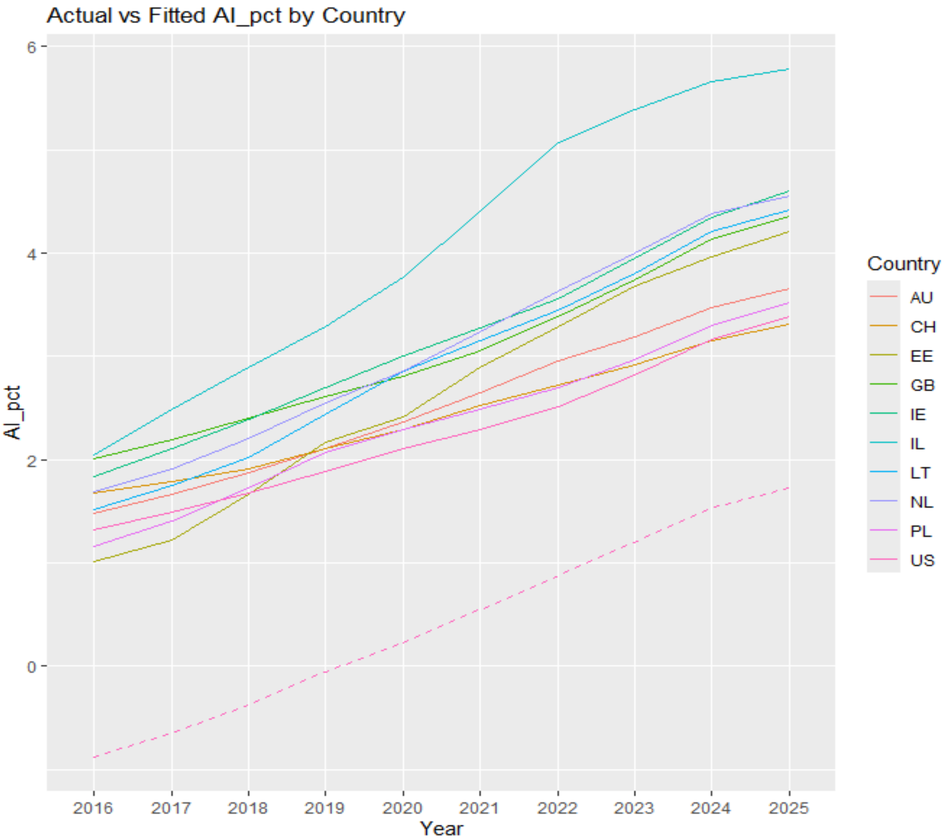

Figure 1. Temporal Dynamics of AI Talent in Finance: Model Fit Across 10 Countries

DISCUSSION

The results show a steady increase in the share of AI talent in finance over the period 2016–2025. This trend is not merely an impression, as it is supported by the positive coefficient associated with the year in all models, as well as by the year fixed effects (all dummies > 0 and significant). The stacked correlation with the year (r≈0,84) points in the same direction. However, it remains descriptive. In essence, we observe that, on average, the proportion of professionals trained in AI in financial services increases steadily each year across the entire sample.

This increase is not uniform. The overall average (≈2,86 %) masks substantial differences between countries (e.g., ≈4,08 % in Israel versus ≈2,27 % in the United States), differences that persist once time is controlled for in the selected model. In other words, a common trend is emerging, but the levels remain persistently differentiated depending on the national context. This heterogeneity is compatible with misaligned public and private strategies—policies for training and attracting skills, data and model governance, the degree of digital transformation of institutions, and state-market coordination arrangements. The annual effects also absorb shared shocks (e.g., the COVID period) without erasing the specificities of each country.

To clarify the analysis and situate the results, we interpret the evolution of the concentration of AI talent in three stages. Initiation (2017–2019): relative to 2016, the annual effects increase by approximately +0,23 % to +0,82 %, indicating a generalized takeoff. Acceleration (2020–2022): The increments reach +1,10 % to +1,75 %, a

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sign of a rapid strengthening of algorithmic adoption in finance. Consolidation (2023–2025): coefficients stabilize around +2,07 % to +2,60 %, confirming a monotonous and solid progression. This common dynamic coexists with cross-country comparisons revealing persistently distinct levels: the high pole (e.g., Israel 4,08 %) stands out from the low poles (United States 2,27 %, Poland 2,36 %), while intermediate European economies (Ireland 3,17 %, Netherlands 3,10 %, United Kingdom 3,07 %) occupy a median position. Higher standard deviations (e.g., Israel, Estonia) suggest more bumpy trajectories or occasional accelerations, while others (e.g., Switzerland) remain smoother.

Taken together, these elements show a shared but not uniform sectoral trend, compatible with differentiated national strategies (training/attraction of skills, governance of data and models, state-market coordination). As a precaution, we do not infer causality: the results reflect stable associations between 2016 and 2025, robust to variations (RE retained, year dummies), and frame the evolution of the AI talent cluster in terms of both its pace and its levels.

The diagnostics support reliable inference: no detectable heteroscedasticity (Breusch–Pagan), intra-country autocorrelation (Wooldridge), and moderate cross-dependence (Pesaran). Consequently, the estimates are presented with standard errors clustered by country, which secures the tests and confidence intervals; the conclusions remain unchanged when annual dummies are introduced, which strengthens the robustness of the central result.

Finally, caution should be exercised regarding causality: the time slope alone is not sufficient to identify the policies at work, and the sectoral indicator (share of AI talent) remains a proxy. The empirical scope is limited to OECD countries for which a harmonized series is available. Extensions could incorporate policy covariates (R&D intensity, tax incentives, training schemes) and mobilize identification plans (e.g., reforms, exogenous shocks) to shed light on why some countries progress faster than others.

The observed differences in levels, despite a common temporal gradient, can be interpreted coherently as the product of a differentiated institutional activation of AI uses in finance. More specifically, three registers compose a plausible analytical framework: first, talent policies (training, international attraction, public procurement of innovation) that guide the supply and density of skills; second, data and model governance that conditions the effective use of algorithms;[15] and finally, modes of coordination between the state and the market that modulate the pace and extent of specialization.[10] These dimensions are not measured in this exercise, but they offer a framework that links our results to concrete risks: on the one hand, stability issues, with increased exposure to model risk during acceleration phases; on the other, a possible geoeconomic divide, if skill stratification becomes entrenched; and, in parallel, regulatory arbitrage phenomena when regimes create differential incentives.

This interpretation extends Rodrik's intuition: technological revolutions reconfigure comparative advantages through the prism of political and human trade-offs.[5] It corroborates the idea that the density of AI skills constitutes a strategic resource, a factor of comparative advantage in its own right, and is consistent with studies that link technological maturity, normative frameworks, and the geography of skills. In short, it is not only technology that "pushes"; it is institutional architectures that "activate" it and guide its impacts.

Our contribution is threefold. Empirically, at both the sectoral (finance) and transnational levels, we simultaneously document a common trend and persistently distinct levels of talent concentration, producing a harmonized comparative map where primarily descriptive or strictly national approaches previously dominated.

Methodologically, we operationalize AI specialization using a harmonized indicator (OECD.AI) and a panel that dissociates shared time pressure from unobserved heterogeneity between countries (RE specification used, error diagnostics, annual effects). Conceptually, we propose interpreting the concentration of AI talent not as a simple technical by-product, but as a politically "activated" industrial mechanism, the product of national trade-offs (acceleration vs. regulatory prudence, international openness of talent vs. data sovereignty) that are reconfiguring the map of advantages in financial services.

The scope of inference is limited: the results apply to the OECD economies included in the sample (10 countries), for which OECD.AI provides a continuous and comparable series for 2016–2025 in finance. They therefore shed light on aggregated sectoral dynamics—share of professionals trained in AI in financial services—in countries with harmonized statistical infrastructures. However, they do not automatically transpose to uncovered economies (e.g., outside the OECD or without comparable series), nor to other sectors (industry, health, etc.), nor micro (companies, individuals) or sub-national (regions, cities) dynamics. Since the indicator is a share and not a workforce, it does not provide information on the absolute volume of AI talent: large financial systems may show a lower share for a high workforce. Finally, the estimate identifies associations compatible with differentiated national strategies without establishing political causality; any extrapolation beyond 2016–2025 therefore calls for caution.

The selection of the ten OECD countries is based on strict comparability criteria: the standardized data from the OECD.AI platform offer harmonized metrics on the concentration of AI talent, which do not exist for non-member economies (including China, Russia, and Japan). This methodological constraint guarantees the reliability of longitudinal comparisons but excludes major players. Our analytical framework nevertheless remains relevant for deciphering industrial strategies in advanced economies, where the observed dynamics (e.g., Israel-Poland divergence) shed light on mechanisms that can be transposed to non-OECD ecosystems. Future research integrating UNESCO-AI data or Chinese/Russian national reports could extend this approach.

To go further, it would be appropriate to broaden the information base with truly comparable public indicators: R&D effort, initial and continuing training in science/computer science, skills attraction schemes (scholarships, dedicated courses, skilled visas) and, above all, rules for accessing and sharing data. In terms of method, dynamic panel models would make it possible to capture the inertia of trajectories (countries that start high do not evolve like those that start low) while allowing for speeds specific to each economy (random coefficients, heterogeneous slopes, growth curves). To better identify policy effects, quasi-experimental frameworks anchored in dated reforms (event study, differences-in-differences, or even synthetic control) would be used to contrast "exposed" countries with credible witnesses. Regional interdependencies also deserve examination: spatial models (SAR/SDM) or proximity matrices (borders, professional flows, linguistic links) to test possible neighborhood and diffusion effects. Finally, the extension to other sectors and, where possible, to company data would clarify the distinction between shares and absolute volumes of talent, offer cross-validations between sources, and open up the observation of more detailed mechanisms—internal reallocations, skills development, local externalities—over a broader time horizon.

CONCLUSIONS

Our study clearly shows that the concentration of AI talent in the financial sector does not follow a simple uniform global dynamic, but rather stems from country-specific industrial strategies.

Our objective was to test the hypothesis that the gaps between countries in the concentration of talent in AI applied to finance are the result of differentiated national industrial strategies rather than a uniform global trajectory. The evidence gathered generally points in this direction: beyond a common movement of adoption, the levels achieved and the pace of specialization vary systematically according to institutional architectures and public arbitrations.

This reading extends the central message of the article: financial competitiveness is reshaped less by the availability of technologies alone than by the training, attraction, and governance of skills, in other words, by national choices on human capital and data. For decision-makers, it calls for coherent policies for upskilling, openness and data security, and state-market coordination; for financial firms, for talent strategies and educational partnerships aligned with these frameworks.

The scope of the findings remains limited to OECD economies and the financial sector over 2016–2025, with no causal assumptions. Extensions will incorporate policy and investment variables, broaden the sectoral and temporal scope, and more precisely link mechanisms to economic performance.

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