

Article

Generative AI in the Labor Force: Multivariate Modeling and Cluster Typologies of Participation and Cost Dynamics

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Abstract

Generative artificial intelligence is gradually infiltrating contemporary socio-technical systems, affecting work practices, labor market participation, and the dynamics of labor-related costs. In this paper, we analyze cross-sectional relationships between generative AI use among active individuals and two macro-level labor-market indicators: the labor force participation rate and the evolution of nominal unit labor costs. The research is based on comparative European data. It analyses the use of AI in personal, professional, educational, and recent contexts as an expression of the interaction of human agency, technological infrastructure, and the institutional environment. The methodology combines multivariate modelling and regression with exploratory factor analysis and clustering to examine the statistical associations between AI use and labour-market indicators, as well as the emergent typologies of countries with diverse profiles. Results indicate stable links between the extent of generative AI use and employment, and unit labour cost disparities, suggesting that generative AI use is associated with broader socio-economic development patterns, without implying a causal relationship. The results highlight the need for an integrative view of AI adoption, linking human behaviors to organizational procedures and governance structures to ensure a responsible and fair transition.

Keywords: generative AI; labor force participation; persons in the labor force; nominal unit labor cost; multivariate general linear model; MANOVA-type model; exploratory factor analysis; cluster analysis; cross-country comparison; European Union



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1. Introduction

Generative AI is one of the most exciting forms of the ongoing digital transformation, extending the logic of automation from repetitive activities to language, analysis, innovation, reasoning, and decision support. The swift adoption and use of conversational models like ChatGPT have spurred interest in the effects of AI on work, as such technologies can perform complex cognitive tasks and have the potential to alter the nature of occupations and how people learn, create information, and participate in economic activity [1–3]. Recent studies associate AI with organizational change, productivity gains, process automation, the creation of new professional roles, and the re-configuration of the relationship between capital, labour, and skills [4,5]. Nevertheless, the labour-market effect

is questionable. Automation can replace some jobs, reduce the need for manual labor, and increase the risk of job polarization [6–8]. AI can also complement human work, boost productivity, create new jobs, and make it easier to participate in the economy in less rigid ways, especially if organizations and institutions use it to leverage digital skills [9–11]. This problem is especially relevant in the European context, where the development of AI is associated with regions' ability to generate innovation, levels of investment in research and development, digital infrastructure, and the persistence of inequalities between economies and regions [12].

The purpose of the article is to analyze the relationship between the use of generative artificial intelligence by active humans and two macro variables of the labour market: the labour force participation rate and the dynamics of nominal unit labour costs. The application of generative AI is a complex phenomenon that may be characterized by its current, personal, professional, and formal educational uses. The notion holds that generative AI may be related to labour-market differences not only through institutional mechanisms but also through individual processes of familiarization, learning, adaptation, and eventual integration into daily and professional activities.

The present literature on the relationship between AI, employment, productivity, and labour costs offers significant contributions but also fundamental limitations. First, many research studies examine AI in broad terms (sectoral or occupational), without linking the actual use of generative AI by active persons to macro-level labor market indicators. Second, economists usually consider employment and cost effects separately. Nevertheless, labor participation and unit labor costs may be correlated, reflecting a similar socio-technical revolution. Thirdly, there are few comparisons of generative AI across Europe, although research suggests that the repercussions of digitization vary across national, regional, and institutional contexts [12,13].

We address these shortcomings with a comparative, quantitative approach, grounded in harmonised European data and a combination of complementary statistical techniques. The multivariate modeling enables the exploration of direct relationships between the four types of generative AI use and labor market indicators, the exploratory factor analysis allows for the identification of the presence of a common latent factor of AI adoption, and the cluster analysis allows for the identification of typologies of countries with similar profiles of AI use, labor force participation, and unit labor cost. Thus, the research goes beyond a linear view of technology's impact and provides a systematic analysis of the embedding of generative AI within human, organizational, and institutional interactions.

The study contributes to the existing research in several ways. First, it shifts the focus from general discussions of artificial intelligence and automation to the actual use of generative AI among active individuals, distinguishing between recent, personal, professional, and educational use. This approach allows the analysis to capture how different forms of interaction with generative AI are associated with labour-market participation and nominal unit labour cost dynamics. Second, the paper connects labour economics with the socio-technical systems perspective. From a labour economics viewpoint, the study relates generative AI use to participation, productivity, cost adjustment, human capital formation, and the complementarity between technology and labour. From a socio-technical perspective, AI adoption is understood as part of a broader configuration that includes individual skills, organizational routines, digital infrastructure, and institutional contexts. Third, the empirical contribution lies in the use of harmonised European data to compare national patterns of generative AI adoption and labour-market outcomes across EU countries. Fourth, the methodological contribution derives from combining multivariate modelling, exploratory factor analysis, and cluster analysis. This approach enables examining direct statistical associations, identifying a latent dimension of generative AI use, and

distinguishing country typologies that reflect different AI–labour market configurations. Therefore, the paper not only tests whether generative AI use is related to labour-market indicators, but also shows how these relationships are embedded in broader socio-technical and institutional differences across European economies.

The paper is structured as follows: the introduction outlines the research topic, purpose, gaps, contribution and novelty; the Literature Review Section presents the background for the hypotheses concerning the use of generative AI, the latent adoption factor and the socio-technical differentiation across countries; the Materials and Methods Section describes the data, variables and statistical methods; the Results Section presents the results of the multivariate modeling, factor analysis and clustering; the Discussion Section interprets the results in the context of the specialized literature; the conclusions summarize the main findings, implications, limitations of the research and directions for future analysis.

2. Theoretical Framework, Literature Review, and Hypotheses Development

The theoretical framework of this study combines insights from labor economics with the socio-technical systems perspective. From the viewpoint of labor economics, generative AI use can be interpreted through the mechanisms of substitution and complementarity between technology and labor, skill-biased technological change, human capital accumulation, productivity adjustment, and unit labor cost dynamics. These mechanisms explain why the use of generative AI in professional, educational, personal, and recent contexts may be associated with labor force participation and cost pressures. At the same time, the socio-technical systems perspective allows AI adoption to be understood not as an isolated technological phenomenon, but as the outcome of interactions among individuals, digital skills, organizational routines, institutional environments, and national digital infrastructures. Therefore, the study interprets cross-country differences in generative AI use and labor-market indicators as socio-technical configurations shaped by both economic mechanisms and institutional contexts.

2.1. *The Use of Generative Artificial Intelligence and Macro-Level Labor Market Indicators*

The most obvious proof of the ongoing digital transition is generative artificial intelligence, which is not restricted to automating mundane tasks but is increasingly being used in areas such as language, analysis, creation, information synthesis, and decision support. Previous rounds of automation had mostly focused on standardized tasks. Generative AI is permeating professional, educational, and personal activities, changing how information is searched for, how people learn, how content is created, how problems are solved, and how economic activity is conducted. According to recent studies, AI is a set of technologies capable of providing qualities traditionally offered by human intelligence, such as language recognition, learning, reasoning, planning, and problem-solving [2,3]. A particular case of this paradigm is generative artificial intelligence, based on algorithms that can generate new material in the form of words, images, sounds, or data, and replicate some elements of human creativity [14,15]. It is this ability to do so that means the impact on the employment market cannot be reduced to a simple substitution of workers but must take into account the interaction among skills, organisation, participation, and costs.

Much of the study of AI and the employment market has focused on the trade-off between substitution and complementarity. Frey and Osborne [6] highlighted a substantial risk of automation for jobs with repetitive tasks, and De-Canio [16] showed that the effects of technology on wages and employment depend on the extent to which it substitutes for or complements human labor. Most recently, Acemoglu and Restrepo [9,17] argue that automation both displaces labour and creates new activities that are complementary to

technology. This argument is supported by Graetz and Michaels [18], Yang [19], and Borland and Coelli [20], who provide evidence that technical innovation can lead to additional employment through increased productivity, cost reductions, and higher production. However, the literature remains cautious, as empirical evidence is not yet fully converged and the influence of AI is dispersed across industries, skill levels, geographies, and institutional contexts [1,21].

Using its cognitive powers, generative AI is bringing the fight into areas experts once thought were less mechanized. Eisfeldt et al. [22] define generative AI as a technology that increases capital and crowds out labor by displacing jobs currently performed by people. On the other hand, Noy and Zhang [10] provide experimental evidence of the beneficial effects of generative AI on productivity, showing that it can improve workers' performance in writing and information-processing tasks. Frank et al. [8] observe that exposure to AI can predict the risk of unemployment in sensitive occupations. Still, Agrawal et al. [23] show that AI can also reduce inequality when people and organizations use it to reallocate production capacity. Thus, the use of generative AI for professional, personal, educational, and recent goals demonstrates not merely access to technology but also people's capacity to adapt to a new architecture of work.

Hence, the link between the adoption of generative AI and macro-level labor market indicators is theoretically meaningful. The labor force as a percentage of the population indicates how economically active the people are. It will be a question of whether AI users develop the right abilities for the digital economy [9]. The use of AI in formal contexts might suggest skill development that could lead to increased future labor-market participation. Still, professional use might mean direct integration of AI in work processes [17]. Personal use can facilitate informal development of digital skills and technical knowledge, even in the absence of a direct relationship to profitable employment. At the same time, AI could affect the nominal unit labour cost through increased efficiency, job reallocation, and changes in the link between pay costs and productivity. Effects of generative AI on productivity, employment, and demand for human capital [24–26]. Our analysis supports this association.

The literature on skill-biased technological progress also supports the difference in implications across kinds of AI applications. AI may enhance the industrial structure [27], increase the demand for advanced skilled personnel [28], and promote job polarization [29–32]. At the same time, Rivera-Hernaez et al. [33], Song et al. [34], Tomé et al. [35], and Zaldo-Santamaria et al. [36] show that AI can support professional competencies and create new opportunities rather than pose a threat of replacement. Thus, the relationship between the dimensions of generative AI applications and labor force participation and cost mechanisms may vary across several forms of technology adoption: recent experience, individual exposure, occupational application, and educational exposure.

From a labor economics perspective, these arguments suggest that generative AI use may be linked to labor force participation and nominal unit labor costs through the combined mechanisms of labor augmentation, task substitution, productivity improvement, and changes in the demand for digital skills. This literature justifies the following hypothesis:

Hypothesis H1. *Recent, personal, professional, and educational uses of generative AI show significant cross-sectional associations with labour force participation and nominal unit labour cost dynamics.*

2.2. The Latent Factor of Generative AI Use and the Aggregated Socio-Technical Pattern of the Labor Market

The various ways in which generative AI might be used can be evaluated independently. Still, the literature suggests that they also share a deeper common component in the overall degree to which technology is integrated into economic and social life. Recent

personal, professional, and educational uses of AI are not separate phenomena but various manifestations of the same socio-technical capacity to adapt to digital transition. In this sense, AI is not just a tool for isolated tasks, but a general-purpose technology with wide applications and strong complementarities with organizational change, skills development, and the re-configuration of economic processes. Agrawal et al. [37], Cockburn et al. [38], and Brynjolfsson et al. [39] suggest that AI should be viewed as a technology with diffuse impacts, in which the gains are contingent on complementary resources, organizational absorptive capacity, and institutional reforms.

This perspective leads to the identification of a common latent factor in the application of generative AI. If numerous observable forms of use are correlated with one another, they may reflect a broader technological inclination that a single indicator cannot capture. Professional use may reveal direct integration into productive activity; educational use may indicate skill accumulation; personal use may signal cultural familiarity with technology; and recent use may capture the overall intensity of contact with AI. These variables can together establish a hidden structure of AI adoption that matters for labor force participation and cost dynamics. The socio-technical systems view holds that technology and the human factor should be analyzed jointly, as the effects of AI depend on the interaction among digital infrastructure, organizational processes, user skills, and the institutional environment [40–42].

This body of literature is complemented by the Resource-Based View, which contends that AI becomes a strategic resource when firms combine it with competent human capital, digital infrastructure, and management competence. Technology itself does not create sustained competitive advantage but becomes effective when embedded in the organization's competencies and routines [43–45]. Similarly, Singh et al. [46] demonstrate that AI, Human Resource Management, and the circular economy are interrelated components of a socio-technical transition where the digital and human resources are conditionally connected. Continuous training, microcredentialing, adaptive leadership, and digital skills development are relevant to successful AI integration [47–53]. These contributions support the concept of a latent dimension that can synthesize AI use, because real technology adoption depends on a coherent collection of behaviours, abilities, and situations.

The literature on productivity and technical dilemmas suggests that the effects of AI do not always materialize immediately. Brynjolfsson [54], Gordon [55], and Brynjolfsson et al. [39] illustrate that technological advancement does not automatically translate into observable economic growth, as organizational changes, complementary investments, and time for skills-building remain necessary. This insight is important for interpreting the latent factor of generative AI use: a high aggregate score may reflect not only current use but also a transitional phase in which individuals and organizations experiment, learn, and modify their work methods. Damoli et al. [5] and Graetz and Michaels [18] indicate that AI and automation have favorable effects on productivity. Still, these effects vary and depend on the characteristics of enterprises, sectors, and economies.

In the context of the labor market, the latent factor of AI use is more efficient than separate indicators for controlling for the process by which technology concurrently affects worker participation and unit costs [17]. This effect can occur as people acquire the required abilities, as technology lowers barriers to entry for particular occupations, or as new professional roles are developed. When AI boosts productivity, reduces the time required to perform specific jobs, or enables better allocation of human resources, the nominal unit labor cost may decline [18]. The impacts are not due to a specific form of use but to a broader configuration of technological behaviors [24].

Institutional Theory supports this interpretation, as the adoption of AI is affected by conventions, rules, societal forces, and prevailing development models [56]. Organizations and society do not accept a technology in a vacuum but rather within institutional frame-

works that justify or limit certain actions [56–59]. The latent factor of generative AI use is perceived as both the frequency of use and the maturity of the socio-technical ecosystem, in which the technology is accepted and supported for learning and practical use [56,57]. This reasoning is consistent with other works [60–66], which define AI as a facilitator of organizational change, process improvement, and the move to sustainable models.

Therefore, generative AI use should be conceptualized not only in terms of distinct observable variables but also as a latent construct that captures the aggregated pattern underlying technological adoption. From the socio-technical systems perspective, the latent factor of generative AI use captures the joint embedding of technology, human capabilities, organizational practices, and institutional conditions. This literature justifies the following hypothesis:

Hypothesis H2. *The latent factor of generative AI use is significantly associated with labor force participation and nominal unit labor cost dynamics.*

2.3. Country Typologies, Socio-Technical Regimes, and the European Differentiation of Generative AI Use

When taking a comparative approach to assess the effects of generative AI on the labor market, one cannot overlook differences across countries. The global logic of expansion drives technology, but national contexts, economic arrangements, levels of digital skills, legislation, institutional infrastructure, and labour-market engagement patterns shape its adoption. These techniques are context-dependent and yield varied results across countries [67–69]. Schelkle et al. [70] note that the European Union is making progress with several types of integration. That will also mean there will be diverse techniques to execute digital transformation. These differences matter for generative AI because the technology's adoption is not just about having the tools but also about whether specific companies and institutions can translate them into productive behavior.

Studies of automation indicate that the effects of technology varied greatly across fields and economic systems. The impact of automation and AI on employment is heterogeneous across sectors, skill levels, geographies, and levels of institutional flexibility [71–76]. Sometimes technology can replace work, and people lose their jobs. Sometimes technology can create new jobs and boost employment through productivity and innovation. Autor et al. [77] emphasize that the shifting occupational content opens new vistas for labor. Bertulfo et al. [78] say that the impact of technology on employment is tied to global value chains. The results suggest that scholars should not treat countries as monolithic entities but as socio-technical systems with their own specificities.

One motivation for this is discussed in Shen and Zhang [11], which examines the effect of AI on employment in the context of virtual agglomeration. The authors conclude that AI might generate substantial employment gains if digital infrastructure facilitates economic coordination, productivity improvements, capital deepening, and shifts in the division of labor. However, the effects are not uniform among sub-groups, depending on the structural context (labour intensity, the centrality of the regional market). This lens is helpful for the European analysis, as countries with strong digital infrastructure, high human capital, and flexible institutions may use generative AI differently from those with more fragmented digitalization or where demographic, educational, or sectoral constraints drive labour force participation [12].

The socio-technical system paradigm allows the establishment of several adoption regimes. The study of technology and social organization should be considered [40,41]. Singh et al. [46] further extend this by connecting AI, HRM, and the circular economy. Institutional Theory [56–58] states that legislation, societal norms, and recognised industry standards influence the speed and nature of technological take-up. In one nation, AI can be

used professionally; in another, it can be used educationally, with a focus on integration into the job market [17].

Technological innovation is the engine of economic expansion, as stated by Solow [79], Romer [80], and Aghion and Howitt [81]. New research demonstrates that institutions and capacities mediate the effects. Technology has positive and negative implications for activities and skills [82]. Replacement and complementarity could provide similar effects [9]. At the county level, generative AI can be applied in various combinations of approaches, creating distinct clusters. Thus, the comparative European study has theoretical and empirical value, because it allows us to see systemic configurations of AI adoption, rather than linear interactions between elements. The clustering approach therefore connects labor economics, through participation and cost indicators, with the socio-technical systems perspective, through national differences in digital readiness, institutional capacity, and patterns of AI use. This literature justifies the following hypothesis:

Hypothesis H3. *European countries form distinct socio-technical clusters according to generative AI use, labor force participation, and nominal unit labor cost dynamics.*

3. Materials and Methods

3.1. Research Design

The paper uses a quantitative, cross-sectional, and comparative research design to investigate the systemic linkages between the deployment of generative artificial intelligence and macro-level labour market factors in a European context. Given the cross-sectional nature of the data, the analysis identifies statistical associations between generative AI use and labor-market indicators, but it does not establish causal relationships or temporal sequences. The perspective informs this approach of complex socio-technical systems, in which the use of AI is not seen as a separate event but as an integral part of the interaction among human agency, institutional frameworks, and economic performance.

The design examines cross-sectional associations between specific dimensions of AI use and labour-market indicators, as well as broader relational patterns emerging from their interaction. The research combines multivariate modelling, dimensionality reduction, and segmentation approaches to describe the relational dynamics and latent structure of the phenomenon under study. The resulting analysis provides an integrated description of how generative AI use is statistically linked to labour-market characteristics at the system level, without implying causal direction.

The sample consists of 27 European Union countries, corresponding to the availability of harmonised country-level data for the variables included in the analysis. This sample size is at the lower end of the range for multivariate modelling and exploratory factor analysis, and the results should therefore be interpreted with caution. The objective of the empirical strategy is not to provide definitive causal estimates, but to identify exploratory cross-sectional associations and broad socio-technical patterns across EU countries. The limited number of observations also justifies parsimonious specifications and a cautious interpretation of the factor-analytic results.

3.2. Selected Data

The study uses Eurostat, which provides harmonised European-level data that allow for consistent comparisons between the countries in the sample. Generative artificial intelligence usage data comes from the EU Survey on the Use of Information and Communication Technologies (ICT) in Households and by Individuals 2025. It is the share of the labor force that used generative AI tools in the last three months for personal purposes, work activities, and in formal education. These indicators capture tangible patterns of use at the

person level and give a granular perspective of the intensity and contexts of AI integration in everyday and professional life.

The micro image is supplemented by a macro interpretation using labour market data. The PLF variable refers to Eurostat's 'persons in the labour force' indicator, expressed as a percentage of the total population. The labour force includes both employed and unemployed persons, so the indicator captures economic activity rather than employment alone. Nominal unit labor cost per capita (NULCP) shows the development of payroll expenses relative to productivity, expressed as a percentage change from the same period of the previous year. Both variables are available for Q3 2025, which means they are temporally compatible with the AI use data. Table 1 lists the variables and their roles in the analysis.

Table 1. Variables and measures.

Variable	Dataset	Measures	Source
UGAI_3M	Use of generative AI tools: in the last 3 months	Individuals in the labor force (employed and unemployed)—Percentage of individuals	[83]
UGAI_PP	Use of generative AI tools: for private purposes	Individuals in the labor force (employed and unemployed)—Percentage of individuals	[83]
UGAI_WP	Use of generative AI tools: for professional (work) purposes	Individuals in the labor force (employed and unemployed)—Percentage of individuals	[83]
UGAI_FE	Use of generative AI tools: for formal education	Individuals in the labor force (employed and unemployed)—Percentage of individuals	[83]
NULCP	Nominal unit labor cost based on persons	Percentage change compared to same period in previous year	[84]
PLF	Persons in the labor force	Percentage of total population	[85]

Source: authors' design based on [83–85].

3.3. Methods

The empirical analysis employs an integrated methodological strategy to investigate both the direct relationships between the use of generative artificial intelligence and labor market indicators and the latent structure and emerging patterns of the socio-technical system under study. The approach integrates multivariate modelling, dimensionality reduction, and unsupervised classification techniques, providing a cohesive explanation of the co-evolutionary processes of technology and work.

In the first stage, the association between each dimension of generative AI use and the two labour-market indicators was examined using four separate multivariate general linear models, estimated in a MANOVA-type framework. In each model, labour force participation and nominal unit labour cost were treated as correlated dependent variables, with one AI-use indicator serving as the explanatory variable. Thus, UGAI_3M, UGAI_PP, UGAI_WP, and UGAI_FE were not entered simultaneously in the same model. This specification was chosen because the four AI-use indicators are conceptually related and empirically correlated, and the limited cross-sectional sample of 27 countries does not support a stable model with several closely related predictors. Therefore, the models should be interpreted as parallel exploratory tests of simple associations, not as evidence of distinct partial effects (1):

$$(Y_{1i}, Y_{2i}) = \alpha + \beta X_{ki} + \varepsilon_i \quad (1)$$

Y_{1i} —labour force participation (PLF) and (NULCP);

Y_{2i} —nominal unit labour cost (NULCP);

X_{ki} —one AI-use indicator at a time: UGAI_3M, UGAI_PP, UGAI_WP or UGAI_FE;

α —intercept;

β —regression coefficient;

ε_i —errors.

The analysis evaluates the global significance of the models using multivariate statistics, namely Pillai's Trace and Wilks' Lambda, while examining individual associations using univariate tests and regression coefficients [86]. This approach captures the distinct association of each dimension of AI use with the two labor market indicators while accounting for correlations among the dependent variables.

Before interpreting the models, several diagnostic checks were performed. Residual normality was assessed using normal probability plots and Shapiro–Wilk tests, while standardized residuals, leverage values, and Cook's distance were inspected to identify influential observations. Because the four AI-use indicators were not included simultaneously in the same multivariate model, multicollinearity did not affect the single-predictor specifications. However, the correlations among the AI-use variables were taken into account when interpreting the results, and this was one reason for treating the four models as exploratory parallel associations and for extracting a common latent factor through exploratory factor analysis.

To capture the aggregate pattern of AI adoption, the study uses exploratory factor analysis on four variables measuring the use of generative AI. The factorial model can be expressed as follows (2):

$$X = LF + \varepsilon \quad (2)$$

X —observed variables;

L —matrix of factor loadings;

F —latent factors;

ε —errors.

Exploratory factor analysis was applied to the four indicators of generative AI use. Principal Axis Factoring was used as the extraction method, based on the correlation matrix [87]. A one-factor solution was retained to capture the common latent structure of recent AI use across personal, professional, and educational domains. Since only one factor was extracted, no rotation was applied. Factor scores were generated using regression and subsequently used as a synthetic indicator of generative AI adoption.

This latent factor then enters two simple linear regression models, estimated separately for each labor market indicator, according to the following form (3):

$$Y_i = \beta_0 + \beta_1 \text{FACT_UGAI}_i + \varepsilon \quad (3)$$

Y_i —dependent variables (PLF and NULCP);

FACT_UGAI_i —independent variable;

β_0 —intercept;

β_1 —regression coefficient;

ε —error.

Such models enable the evaluation of the overall association of AI deployment with labor participation and cost structure, providing a synthetic perspective on the correlation between technological adoption and labor market performance.

Finally, cluster analysis is applied to identify emergent national-level trends based on variables indicating AI use and labor market factors. The initial data structure and the ideal number of groups are determined by hierarchical clustering with Pearson correlation and the Average Linkage agglomeration method [88,89]. This is an exploratory step, and

the study uses the k-means algorithm to stabilize the clusters by minimizing the sum of squared distances between cluster centres. Differences between clusters were described using analysis of variance (ANOVA). Since the clusters were constructed from the same variables used in the ANOVA, these results are interpreted descriptively rather than as independent statistical confirmation of cluster separation.

This combination of methods allows the study to capture direct linear relationships, the latent structure, and the system's emergent typologies. This combination provides an integrated reading of the relationship among the use of generative artificial intelligence, labor participation, and cost dynamics within a complex adaptive socio-technical systems framework.

4. Results

4.1. Cross-Sectional Relationships Between Generative AI Adoption, Labor Force Participation, and Unit Labor Cost

The first multivariate model analyzed the association between recent use of generative artificial intelligence (UGAI_3M) and the labor force participation rate (PLF) and nominal unit labor cost (NULCP). The multivariate tests indicate a significant global association with a large effect size (Pillai's Trace = 0.487, Wilks' Lambda = 0.513, $F = 11.370$, $p < 0.001$), suggesting that recent use of generative AI is associated with both labor market indicators. At the univariate level, UGAI_3M is associated with approximately 31% of the cross-sectional variance in PLF and 21% of the variation in NULCP. Recent increases in AI use are associated with a significant rise in the share of active persons and, at the same time, with a reduction in unit labor costs, suggesting a possible relationship among technological adoption, labor participation, and cost pressure (Table 2).

Table 2. Parameter estimates for the relationship between recent use of generative artificial intelligence and labor market indicators.

Dependent Variable	Parameter	B	Std. Error	t	Sig.	95% CI Lower	95% CI Upper	Partial Eta Squared
PLF	Intercept	72.389	3.045	23.7690	0.000	66.116	78.661	0.958
	UGAI_3M	0.248	0.074	3.371	0.002	0.096	0.399	0.313
NULCP	Intercept	8.969	2.086	4.301	0.000	4.674	13.265	0.425
	UGAI_3M	−0.131	0.050	−2.595	0.016	−0.234	−0.027	0.212

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA). Note: N = 27. CI = confidence interval.

The curve-fit analysis suggests a linear relationship between UGAI_3M and PLF. At the same time, Figure 1 illustrates divergent trajectories for the two dependent variables: PLF shows an upward trend, whereas NULCP exhibits a downward slope as AI use increases.

The second model evaluated the use of generative AI for personal purposes (UGAI_PP). The multivariate effect remains significant, although less pronounced (Pillai's Trace = 0.258, Wilks' Lambda = 0.742, $F = 4.174$, $p = 0.028$), suggesting a weaker systemic influence than with recent or professional use. At the individual level, UGAI_PP is positively associated with PLF, but this association does not reach the conventional 5% significance threshold ($p = 0.098$). It can only be interpreted as marginal at the 10% level and is therefore treated cautiously. By contrast, the association with NULCP is statistically significant at the 5% level ($p = 0.031$). Still, it exerts a significant negative effect on NULCP, indicating that personal use of AI correlates more strongly with cost dynamics than with effective labor participation (Table 3).

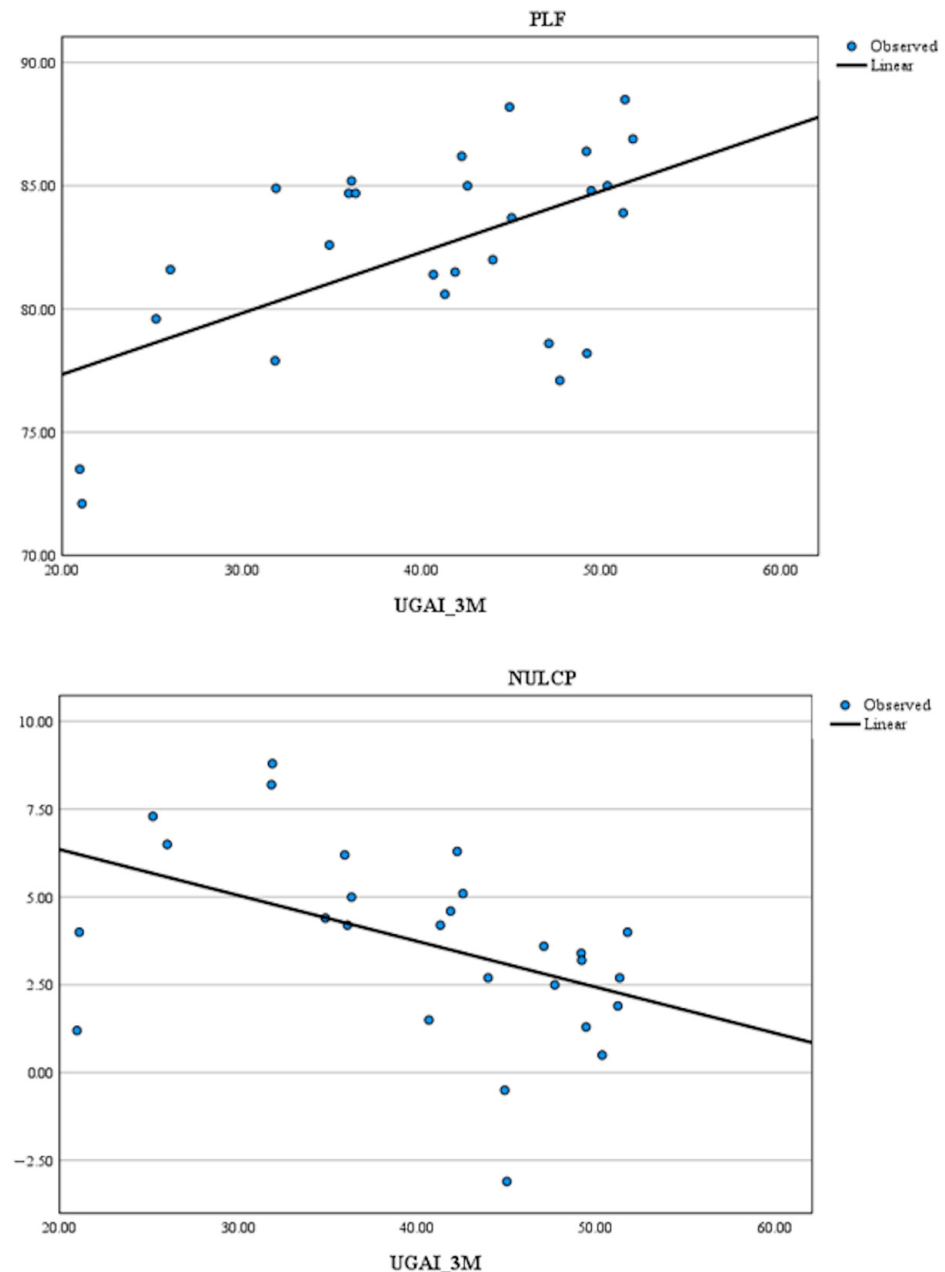


Figure 1. Evolution of labor force participation and unit labor cost according to the recent use of generative artificial intelligence.

Table 3. Parameter estimates for the relationship between the use of generative artificial intelligence for personal purposes and labor market indicators.

Dependent Variable	Parameter	B	Std. Error	t	Sig.	95% CI Lower	95% CI Upper	Partial Eta Squared
PLF	Intercept	77.922	2.714	28.710	0.000	72.332	83.511	0.971
	UGAI_PP	0.140	0.081	1.721	0.098	−0.027	0.307	0.106
NULCP	Intercept	7.345	1.671	4.397	0.000	3.905	10.786	0.436
	UGAI_PP	−0.114	0.050	−2.280	0.031	−0.217	−0.011	0.172

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA). Note: N = 27. CI = confidence interval.

The linear curve fit shows reduced explanatory power for PLF. In contrast, Figure 2 shows a more diffuse relationship between personal AI use and labor participation, whereas the NULCP declines more clearly as UGAI_PP increases.

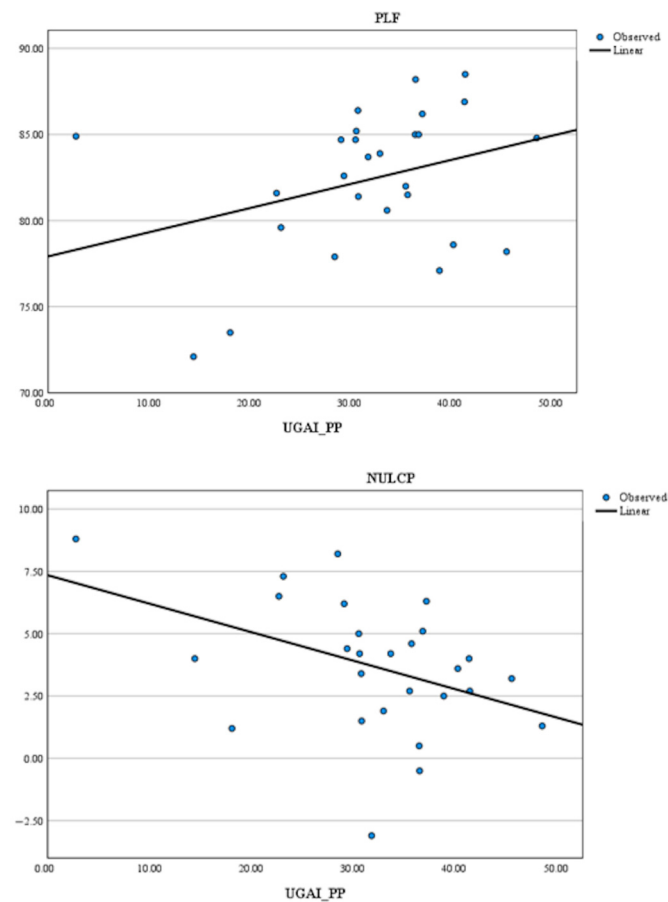


Figure 2. Relationship between the use of generative artificial intelligence for personal purposes, labor force participation, and unit labor cost. Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The third model, centered on the professional use of generative AI (UGAI_WP), points to one of the most robust systemic associations (Pillai's Trace = 0.474, $F = 10.801$, Wilks' Lambda = 0.526, $p < 0.001$). UGAI_WP explains approximately 19% of the variation in PLF and more than 31% of the variation in NULCP. An increase in AI use in professional activity is associated simultaneously with broader labour force participation and a consistent decrease in unit labour costs, suggesting that professional AI use is more clearly associated with aggregate labour-market differences than other forms of use (Table 4).

Table 4. Parameter estimates for the relationship between the use of generative artificial intelligence in professional activity and labor market indicators.

Dependent Variable	Parameter	B	Std. Error	t	Sig.	95% CI Lower	95% CI Upper	Partial Eta Squared
PLF	Intercept	77.808	2.010	38.705	0.000	73.668	81.948	0.984
	UGAI_WP	0.196	0.080	2.453	0.021	0.031	0.360	0.194
NULCP	Intercept	7.445	1.184	6.287	0.000	5.006	9.884	0.613
	UGAI_WP	−0.160	0.047	−3.402	0.002	−0.257	−0.063	0.316

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA). Note: N = 27. CI = confidence interval.

The curve-fitting analysis suggests a linear relationship, while Figure 3 shows the clearest visual separation between the trajectories of PLF and NULCP, further supporting the interpretation of professional AI use as an important socio-technical marker of labour-market differences.

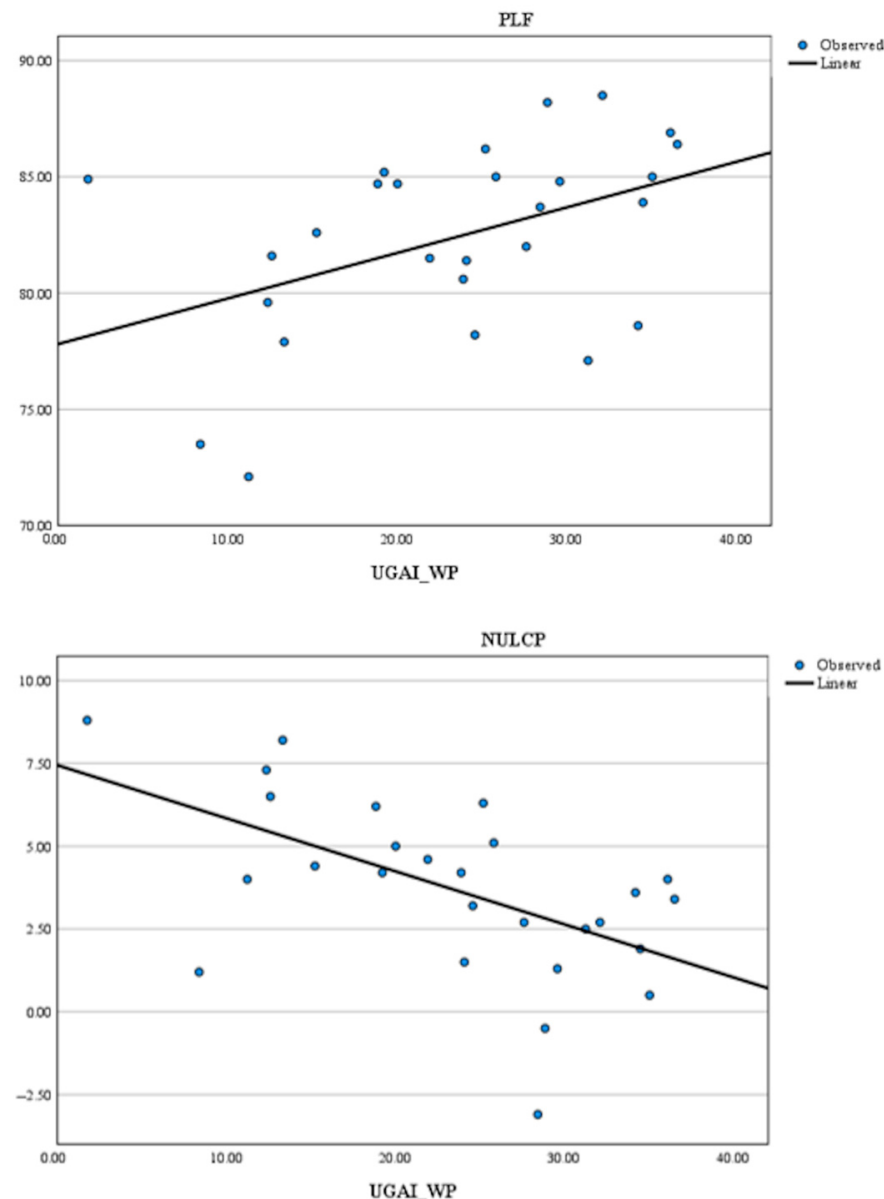


Figure 3. Dynamics of labor force participation and unit labor cost in relation to the use of generative artificial intelligence in professional activity. Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

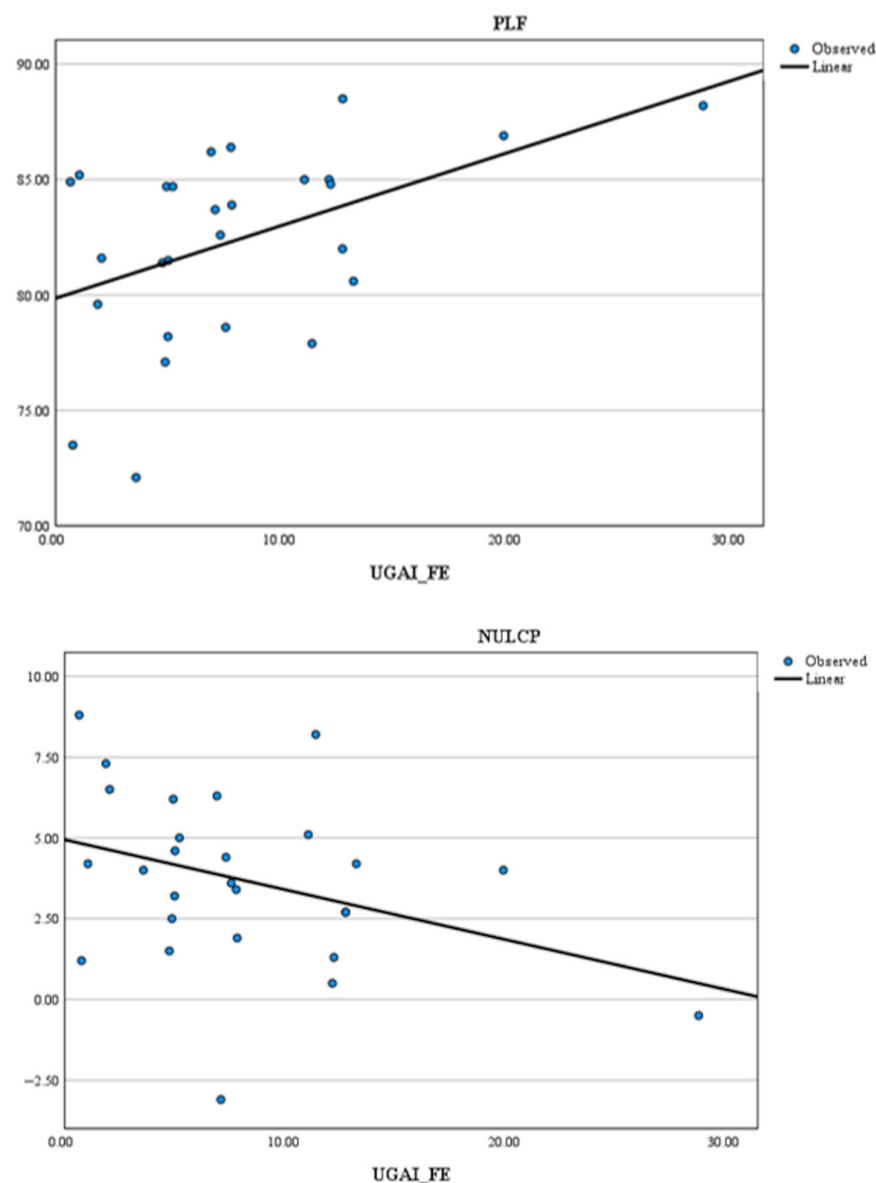
The final model investigated the use of generative AI in formal education (UGAI_FE). The multivariate effect remains significant (Pillai's Trace = 0.327, $F = 5.829$, Wilks' Lambda = 0.673, $p = 0.009$). UGAI_FE shows a statistically significant positive association with PLF at the 5% level. However, its association with NULCP is only marginal and does not meet the conventional 5% significance threshold ($p = 0.064$). Therefore, this result should not be interpreted as evidence of a significant relationship between educational use of generative AI and nominal unit labour cost. Rather, it suggests a possible but weak association that requires cautious interpretation (Table 5).

Table 5. Parameter estimates for the relationship between the use of generative artificial intelligence in formal education and labor market indicators.

Dependent Variable	Parameter	B	Std. Error	t	Sig.	95% CI Lower	95% CI Upper	Partial Eta Squared
PLF	Intercept	79.859	1.195	66.852	0.000	77.399	82.319	0.994
	UGAI_FE	0.313	0.117	2.665	0.013	0.071	0.554	0.221
NULCP	Intercept	4.943	0.807	6.123	0.000	3.280	6.606	0.600
	UGAI_FE	−0.154	0.079	−1.940	0.064	−0.317	0.009	0.131

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA). Note: N = 27. CI = confidence interval.

The curve-fit results show a moderate linear relationship between UGAI_FE and PLF. In contrast, Figure 4 shows an upward trend in labor participation as AI use in education intensifies, while NULCP remains relatively stable.

**Figure 4.** Dynamics of labor force participation and unit labor cost in relation to the use of generative artificial intelligence in formal education. Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

Overall, the four models suggest differentiated rather than uniform associations. Recent and professional uses of generative AI are significantly associated with both labour-market indicators. Personal use is significantly associated with nominal unit labour cost, but not with labour force participation at the 5% significance level. Educational use is significantly associated with labour force participation, while its association with nominal unit labour cost remains marginal and non-significant at the conventional 5% threshold. Therefore, H1 is only partially supported.

Given the unusually low values recorded for Hungary across personal, professional, and formal-education uses of generative AI, an additional robustness check was conducted by excluding Hungary from the sample. The direction of the associations remained unchanged across the models. However, the statistical significance of some associations changed. In particular, the association between personal use of generative AI and labour force participation became significant, while the association between personal use and nominal unit labour cost became non-significant. These results suggest that Hungary is an influential case, especially in models of personal AI use. Therefore, the results should be interpreted as exploratory cross-sectional associations that may be sensitive to country-level outliers.

To address the possible role of broader structural country characteristics, a supplementary bivariate correlation analysis was conducted. The four generative AI-use indicators were correlated with contextual variables available in the dataset, namely the share of population with lower education, upper-secondary and post-secondary non-tertiary education, tertiary education, and real labour productivity per person (Table 6). This analysis was not intended to replace a controlled regression model, but rather to provide a robustness check on whether generative AI use covaries with broader educational and productivity-related country characteristics.

Table 6. Supplementary bivariate correlations with structural contextual variables.

Structural Contextual Variable	UGAI_3M	UGAI_PP	UGAI_WP	UGAI_FE
Lower education share (PLP)	0.083 ($p = 0.682$)	0.044 ($p = 0.826$)	0.192 ($p = 0.338$)	0.227 ($p = 0.255$)
Upper-secondary/post-secondary non-tertiary education (PUSPS)	−0.603 ($p = 0.001$)	−0.496 ($p = 0.009$)	−0.692 ($p < 0.001$)	−0.497 ($p = 0.008$)
Tertiary education share (PTE)	0.684 ($p < 0.001$)	0.583 ($p = 0.001$)	0.697 ($p < 0.001$)	0.422 ($p = 0.028$)
Real labour productivity per person (RLPP)	−0.508 ($p = 0.007$)	−0.225 ($p = 0.259$)	−0.531 ($p = 0.004$)	−0.275 ($p = 0.165$)

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA) based on [83,84,90]. Note: N = 27. CI = confidence interval. Note: Pearson correlation coefficients are reported, with p -values in parentheses. N = 27. PLP—population with less than primary, primary, and lower secondary education; PUSPS = population with upper-secondary and post-secondary non-tertiary education; PTE—population with tertiary education; RLPP—real labour productivity per person.

The supplementary correlations indicate that generative AI use is not independent of broader structural country characteristics. The strongest and most consistent positive associations are observed between AI-use indicators and tertiary education attainment, especially for recent, personal, and professional use. Conversely, the correlations with upper-secondary and post-secondary non-tertiary education are negative and statistically significant across all four AI-use indicators. The associations with real labour productivity are more mixed, being significant for recent and professional AI use but not for personal or formal-education use. These results suggest that the observed relationships between generative AI use and labour-market indicators may partly overlap with broader differences in educational structure and productivity across countries. Therefore, the main regression results should continue to be interpreted as exploratory cross-sectional associations rather than as estimates of the independent effect of AI use.

4.2. The Latent Dimension of Generative Artificial Intelligence Use and Its Systemic Associations with the Labor Market

The exploratory factor analysis aimed to reduce the four observable variables to a common factor structure, capturing the aggregate process by which multiple kinds of generative artificial intelligence use can be articulated into a cohesive socio-technical dynamic. The KMO value of 0.805, the significance of Bartlett's test, and significant correlations among the variables indicate that the data are suitable for extracting a common latent construct (Table 7). The factorial solution converges to a single factor that accounts for over 71% of the overall variance, indicating a unified dimension of generative AI adoption across active persons.

The communalities indicate that the common latent factor effectively represents recent, personal, and professional uses of generative AI. By contrast, UGAI_FE has a considerably lower extracted communality (0.346), suggesting that formal-education use shares less variance with the other AI-use indicators. This finding does not justify excluding the variable, since its factor loading remains positive and meaningful, but it indicates that educational use captures a more specific dimension of generative AI adoption. Therefore, the latent factor mainly reflects recent, personal, and especially professional AI use, while the educational dimension should be interpreted more cautiously.

Table 7. Exploratory factor analysis of generative AI use indicators.

Indicator/Statistic	Value		
Kaiser–Meyer–Olkin measure	0.805		
Bartlett's test of sphericity	$\chi^2 = 78.676$; $df = 6$; $p < 0.001$		
Extraction method	Principal Axis Factoring		
Number of factors extracted	1		
Initial eigenvalue, Factor 1	3.098		
Initial variance explained	77.455%		
Extraction sum of squared loadings	2.876		
Variance explained after extraction	71.892%		
Rotation	No rotation		
	Communalities		Factor
	Initial	Extraction	1
UGAI_3M	0.842	0.884	0.940
UGAI_PP	0.682	0.730	0.854
UGAI_WP	0.851	0.916	0.957
UGAI_FE	0.329	0.346	0.588

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

This latent factor, labelled FACT_UGAI, reflects an emerging construct of the socio-technical system of work, in which individual patterns of AI use aggregate into a coherent macro-level signal.

The first regression analyzed the relationship between the latent factor of generative artificial intelligence use (FACT_UGAI) and the labor force participation rate, offering a synthetic view of how aggregate AI adoption relates to labor force participation. The model indicates a positive and statistically significant relationship, with a correlation coefficient of 0.491 and an explanatory capacity of approximately 24% of the variation in the share of active persons ($R^2 = 0.241$; adjusted $R^2 = 0.211$). The F test indicates that the model is statistically significant ($F = 7.933$, $p = 0.009$). Given the cross-sectional structure of the data and the absence of a meaningful ordering of countries, no autocorrelation interpretation is reported (Table 8).

Table 8. Regression results for the relationship between the latent factor of generative AI use and labor force participation.

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate		
1	0.491	0.241	0.211	3.69192		
Model	Sum of Squares	df	Mean Square	F		
1	Regression	108.123	1	108.123	7.933	0.009
	Residual	340.757	25	13.630		
	Total	448.880	26			
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	82.400	0.711		115.973	0.000
	FACT_UGAI	2.088	0.741	0.491	2.816	0.009

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The regression coefficient indicates that, on average, a one-unit rise in the factor score is associated with an increase of about 2.09 percentage points in the labor force participation rate ($B = 2.088$, $p = 0.009$). The standardized coefficient ($\beta = 0.491$) indicates a moderate association, suggesting that the latent dimension of generative AI use is significantly associated with workforce participation.

In socio-technical terms, these results suggest that the latent factor of generative AI use may be interpreted as a broader indicator of digital engagement among active individuals. Its positive association with labour force participation is consistent with the idea that AI use, digital skills, and labour-market involvement co-occur in more digitally prepared national contexts. However, this interpretation remains exploratory and should not be taken as evidence that generative AI adoption increases labour force participation.

The second regression examines the association between the latent factor for generative artificial intelligence use and nominal unit labor cost, providing a further perspective on the relationship between aggregate AI adoption and labor cost dynamics. The model shows a substantial negative association ($r = -0.529$) and explains around 28% of the variation in unit cost ($R^2 = 0.280$; Adj. $R^2 = 0.251$). The F test indicates that the model is statistically significant ($F = 9.727$, $p = 0.005$). As the observations are unordered countries in a cross-sectional sample, autocorrelation diagnostics are not interpreted (Table 9).

Table 9. Regression results for the relationship between the latent factor of generative AI use and nominal unit labor cost.

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate		
1	0.529	0.280	0.251	2.29996		
Model	Sum of Squares	df	Mean Square	F		
1	Regression	51.453	1	51.453	9.727	0.005
	Residual	132.246	25	5.290		
	Total	183.699	26			
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.693	0.443		8.342	0.000
	FACT_UGAI	−1.440	0.462	−0.529	−3.119	0.005

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The regression coefficient indicates that, on average, a one-unit increase in the factor score is associated with a decrease of around 1.44 percentage points in nominal unit labor cost ($B = -1.440$, $p = 0.005$). The standardized coefficient ($\beta = -0.529$) indicates a moderate-to-strong relationship, implying that the latent dimension of generative AI use is consistently associated with cost dynamics.

From a socio-technical perspective, the negative association between FACT_UGAI and nominal unit labour cost suggests that countries with higher aggregate generative AI use also tend to report lower unit labour cost growth. This pattern may reflect broader differences in productivity, digital readiness, organizational adaptation, or economic structure, but the cross-sectional data do not allow these mechanisms to be tested directly. Therefore, the latent factor should be interpreted as an exploratory indicator of AI-use intensity rather than as evidence of a causal socio-technical transformation.

These results provide exploratory support for H2 by showing that the latent factor of generative AI use is statistically associated with both labour-market indicators.

4.3. Emerging Socio-Technical Typologies: National Profiles of Generative AI Use and Labour-Market Dynamics

To explore the latent structure of the relationships between the use of generative artificial intelligence and labor market indicators, the analysis began with hierarchical clustering, using the average method and the Pearson correlation coefficient to measure proximity between countries. The dendrogram presented in Figure 5 suggests a possible two-group structure in the sample.

The dendrogram presented in Figure 5 suggests a possible two-group structure in the sample. Following this exploratory indication, the k-means algorithm was applied to describe two country profiles. The resulting two-cluster solution should be interpreted as an exploratory and descriptive typology, not as a definitive classification of European countries. The distance between the final cluster centres indicates that the two groups differ on the variables included in the clustering procedure, but it does not provide independent confirmation of distinct socio-technical regimes.

The cluster centers provide a synthetic view of the two exploratory typologies. In the first cluster, the average levels are 44.92% for recent use, 36.31% for personal use, and 27.92% for AI incorporated into professional activity. In formal education, the average is 9.58%. These adoption rates are associated with an average labour force participation rate of 83.63% and a nominal unit labour cost of 2.97%. This profile corresponds to an environment with relatively strong AI penetration and positive labor market dynamics, with higher participation and mild cost pressures.

Conversely, the second cluster has substantially lower levels across all dimensions of generative AI applications. Recent use drops to 27.43%, personal use to 19.90%, and professional use to a mere 10.72%. In formal education, the average is 3.96%. This technological profile is marked by a lower labor force participation rate of 78.89% and a substantially higher nominal unit labor cost of 5.77%. The resulting typology suggests a less advanced socio-technical system, in which lower AI integration is associated with more severe labor market rigidities.

As a minimal validation metric, the average silhouette coefficient was computed for the final two-cluster solution using the six variables included in the clustering procedure. The average silhouette coefficient is 0.473, indicating a moderate degree of separation between the two exploratory clusters. The mean silhouette value is 0.486 for Cluster 1 and 0.436 for Cluster 2. These positive values suggest that the two-cluster solution has acceptable internal coherence for exploratory purposes, although the level of separation should not be interpreted as strong. Therefore, the silhouette results support the descriptive

usefulness of the two-cluster typology and confirm that the classification should remain exploratory rather than definitive.

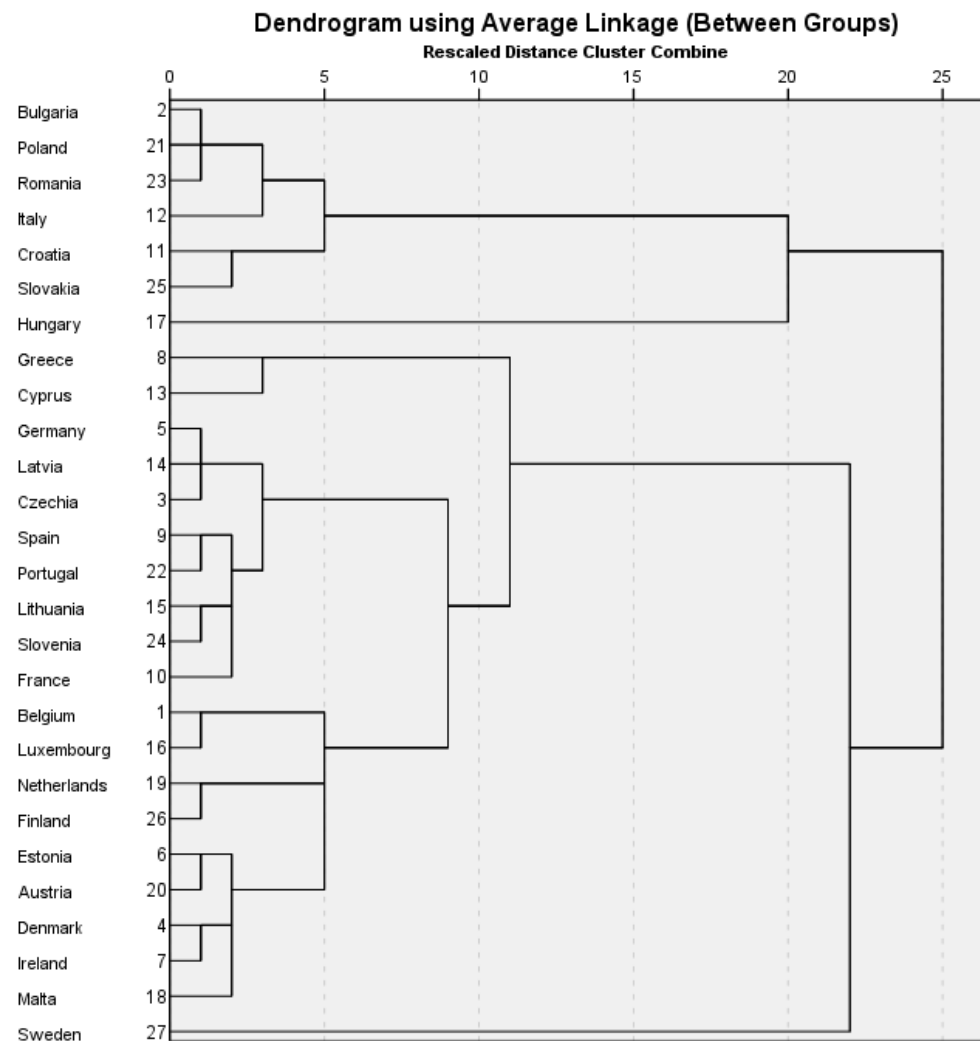


Figure 5. Dendrogram of the hierarchical clustering of European countries based on generative artificial intelligence use and labor market indicators. Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The ANOVA results provide a descriptive characterization of the differences between the two clusters (Table 10).

Table 10. Differences between clusters for generative artificial intelligence use and labor market indicators (ANOVA).

Variable	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
UGAI_3M	1586.498	1	27.865	25	56.935	0.000
UGAI_PP	1395.494	1	41.624	25	33.526	0.000
UGAI_WP	1534.418	1	29.529	25	51.963	0.000
UGAI_FE	163.663	1	34.062	25	4.805	0.038
PLF	116.709	1	13.287	25	8.784	0.007
NULCP	40.839	1	5.714	25	7.147	0.013

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The high F values for recent and professional AI use indicate that these variables strongly influence cluster separation and are the primary markers of socio-technical divergence. The observed disparities in PLF and NULCP indicate that the two exploratory profiles differ not only in generative AI use but also in labour-market characteristics.

These ANOVA results should be interpreted with caution. Because the clusters were formed using the same variables that are subsequently compared, the F values are descriptive and should not be treated as independent hypothesis tests. Therefore, the cluster solution is used to explore socio-technical profiles across countries, not to provide a definitive validation of country groupings.

Table A1 in Appendix A shows the composition of each country across the two clusters, with a strong concentration of Nordic and Western European economies in the high-adoption category. The second cluster, however, is primarily composed of Central and South-eastern European countries, suggesting that structural gaps remain in the digital transformation process.

From the perspective of complex adaptive systems, these studies show how interactions among technology, human capital, and institutional frameworks produce persistent, emerging patterns. The discovered clusters are socio-technical regimes in which the co-evolution of generative AI adoption, labor engagement, and cost dynamics produces distinct paths of economic adaptability.

Overall, the cluster analysis supports Hypothesis H3, that European countries can be grouped into meaningful typologies based on the usage profiles of generative artificial intelligence and labor market indicators. The typologies compare socio-technical regimes with varying use of AI, workforce engagement, and unit labor costs, thus presenting a full picture of the heterogeneity of digital transformation in Europe.

5. Discussion

The data suggest a differentiated pattern of associations between generative AI use, labour force participation, and nominal unit labour cost across European countries. Rather than implying a causal process, these findings point to cross-sectional co-occurrences that may reflect broader socio-technical and economic conditions. This interpretation is consistent with the literature, which characterizes AI as a technology with pervasive effects on work, productivity, and economic organization. Still, it emphasizes that these effects depend on the adoption context and on the complementarities between technology and the human factor [37–39].

The four models should not be interpreted as comparing the independent or partial contribution of each AI-use dimension. Since the AI-use variables are conceptually related and highly correlated, each single-predictor model may partly reflect the same broader underlying pattern of generative AI adoption. For this reason, the results are interpreted as simple cross-sectional associations, while the exploratory factor analysis provides a complementary means of summarizing their common latent structure.

The observed associations should also be interpreted in relation to broader national development conditions, since countries with higher income levels, stronger digital infrastructure, higher educational attainment, greater R&D intensity, and different sectoral structures may be more likely to adopt generative AI earlier and more intensively.

The results of the multivariate models provide partial support for H1. Recent and professional uses of generative AI are significantly associated with both labour-market indicators, while personal and educational uses show more limited and mixed associations. Higher worker engagement and lower cost constraints are associated with current AI use and intensity. This finding is consistent with research that argues AI can be an augmenting technology, increasing worker productivity and efficiency, but not necessarily replacing

workers [1,10]. This result is also consistent with Shen and Zhang [11], who found that AI can lead to substantial employment growth when paired with efficiency gains, capital deepening, and digital infrastructure.

Professional use appears to be the AI-use dimension most consistently associated with labour-market indicators. This pattern is consistent with the idea that work-related AI use may be closer to productive and organizational contexts than personal or educational use. However, the analysis does not show that professional AI use directly improves labour-market outcomes. This result is consistent with Damioli et al. [5], who find a positive effect of AI technologies on labor productivity at the firm level, and with Huang [4], who shows how firms and industries that adopt AI can mobilize resources, improve efficiency, and change the relationship between labor and capital. However, the results are not to be seen as naive technical optimism. The consequences of AI can be confusing because the same technology can be both a substitute and a complement, depending on the type of occupation and the occupational structure [9,16,17], necessitating research on automation.

For personal use, the association of generative AI is more limited and relates solely to the growth of the nominal unit labour cost, rather than, in an equally important way, to the evolution of labour force participation. This research demonstrates that informal familiarity with AI may help build more distributed digital capabilities, but this does not translate directly into economic participation. Alternatively, it might be the mark of a very advanced digital culture, which, in turn, makes us more efficient and enables us to adapt to new technology. The study highlights the need for lifelong learning, micro-credentials, and reskilling digital skills to prepare the workforce for intelligent systems [48,51,52]. The use of AI in formal education has a substantial positive effect on labour force participation but a weaker effect on unit labour cost. Currently, the educational aspect of AI is not about efficiency but about developing and activating human capital. This result aligns with the literature on skill-biased technological change, which finds that digital technologies benefit people who can learn and employ high-level skills [29,30,82].

In addition, the second hypothesis is supported by the latent factor of generative AI, derived from factor analysis and regression models. The KMO score, the significance of Bartlett's test, and the presence of a single component explaining more than 71% of the total variance suggest that the four types of AI use are not independent occurrences but rather represent a shared dimension of socio-technical integration. The latent factor is strongly associated with labour force participation and negatively correlated with the nominal unit labour cost. This outcome aligns with the notion of generative AI application as an aggregate process, the fusion of familiarity with the technology, professional use, formal learning, and current use into a general profile of adaptability to the digital economy. This finding theoretically supports the socio-technical systems perspective, which posits that technology does not produce effects solely through its technical availability, but rather in conjunction with organizational processes, human skills, and institutional frameworks [40–42]. This finding is supported by studies on the acceptance of digital transformation and on the ethical implications of AI solutions, showing that the impact of intelligent technologies on performance is not only dependent on the extent of use, but also on user trust, the quality of organizational integration, and the way ethical risks are handled in decision-making and management processes [91,92].

The positive relationship between the latent component and workforce involvement suggests that the more intensive and diverse the use of AI in a country, the greater the potential to engage its population in the labor force. This result is consistent with Acemoglu and Restrepo's [9] view that technology creates not only substitution but also new tasks that could raise labor demand. At the same time, the negative connection with NULCP can be seen as an efficiency signal, as the growing use of AI helps alleviate cost pressures by

boosting productivity, redesigning tasks, and improving resource allocation. This interpretation is consistent with the findings of Graetz and Michaels [18] and Damolioli et al. [5], who find positive effects of automation and AI on productivity, but is also still nuanced by the literature on the productivity paradox, which warns that the benefits of digital technologies may appear unevenly and with delay [39,54,55].

These associations should not be interpreted as evidence that generative AI adoption causes higher labour force participation or lower unit labour costs. Reverse causality remains plausible, since countries with stronger labour markets, better digital infrastructure, higher educational attainment, and greater innovation capacity may be more likely to adopt generative AI earlier and more intensively.

The cluster analysis suggests the third hypothesis and points to two distinct socio-technical regimes. High application rates of generative AI characterise the first cluster (20 nations) across all forms analysed, with higher labour force participation and lower nominal unit labour costs. The second set of 7 countries has lower AI usage, less engagement, and more expensive units. These differences are studied using statistical testing (ANOVA). The cluster results should be read as descriptive and hypothesis-generating. They suggest that countries with higher AI-use indicators also tend to display more favourable labour-market profiles, but the analysis does not establish that AI use explains these differences. The observed profiles may also reflect broader structural conditions, including income levels, digital infrastructure, education, institutional capacity, and sectoral composition. This result aligns with studies on automation and regional development that suggest the impact of technology depends on economic structure, institutional capacity, and labor market resilience [71,73,76].

The difference between the two country groups points to a possible geographical and structural pattern in the uptake of generative AI across Europe. The higher-adoption cluster includes several Nordic and Western European economies, while the lower-adoption cluster includes several Central and South-Eastern European countries. This pattern may be related to differences in digital infrastructure, human capital, institutional capacity, innovation systems, and sectoral structure. However, because these contextual variables are not directly included in the cluster analysis, this interpretation should be treated as hypothesis-generating rather than confirmatory. Future research should test whether these broader structural conditions explain the observed country profiles. This cautious interpretation is consistent with research on differentiated European integration, which shows that common European processes may be filtered through national contexts and generate different trajectories [67–70].

The results are consistent with the idea that generative AI might be seen as an accelerator of the labor market shift, though not always or automatically. This finding goes with increased involvement and less cost pressure. Nevertheless, these consequences are context-dependent and vary across countries, depending on each country's socio-technical progress. This approach aligns with the literature analyzing AI as a factor in labor complementarity and augmentation, while considering concerns about polarization and substitution. Our key contribution is the claim that researchers need to study the use of generative AI at individual, aggregate, and comparative levels simultaneously, for only then can the links between usage patterns, worker engagement, and cost dynamics be revealed.

5.1. Theoretical Implications

Theoretically, the findings suggest that labor economics explains the patterns underlying the association between AI use, participation, and unit labor costs. In contrast, the socio-technical systems perspective explains why these associations differ across national contexts and depend on the interaction between technology, skills, organizations, and institutions.

The empirical results of this study contribute to the literature on generative artificial intelligence and the labor market by moving beyond simplistic interpretations of labor substitution or complementarity and offering a more comprehensive socio-technical understanding. The study demonstrates that the use of generative AI is not a unidimensional event but is manifested in several types of integration: recent, personal, professional, and educational. Each of these forms has its own relationship with labour force participation and with the dynamics of unit labour cost, which supports the idea that researchers cannot assess the association of AI with the labour market through only the presence of technology, but must also consider the concrete ways in which individuals use it.

One major theoretical contribution is the identification of a shared latent component for the use of generative AI. This element points to the fact that the diverse types of use are not fully independent but express an aggregate dimension of digital adaptation. Thus, the article endorses the view that generative AI operates within a socio-technical system in which technology, human capital, education, professional practices, and the institutional environment interact. This result enriches the literature on general-purpose technologies by revealing that AI yields benefits not only through productivity and automation but also through participation, skills, and social integration.

From a theoretical perspective, the identification of several country clusters also supports the thesis that digital transformation does not follow a uniform European trajectory. The examined economies are characterized by varied socio-technical regimes, in which generative AI use, labor participation, and unit costs interact in different combinations. Hence, the research's contribution to the comparative literature lies in its emphasis on the contextual nature of AI adoption and its contingent consequences for national structures, skills, and institutional capacity.

5.2. Practical Implications

The findings of this study offer several practical implications for public decision-makers, employers, educational institutions, social partners, and other actors involved in labour-market governance. Since generative AI use is positively associated with labour force participation and negatively associated with nominal unit labour cost dynamics, public policy should treat AI adoption not only as a technological issue, but also as a labour-market, education, and human-capital policy priority. The productive integration of generative AI depends on whether individuals, firms, and institutions can transform access to technology into usable skills, better work processes, and more inclusive forms of economic participation.

For policy-makers, the results suggest the need to connect AI strategies with active labour-market policies. Governments should support large-scale reskilling and upskilling programmes focused on practical AI use, especially for workers exposed to task restructuring, young people entering the labour market, older workers, and unemployed or inactive persons who may benefit from new forms of digital participation. These programmes should not remain limited to general digital literacy but should include applied training in the use of generative AI for information processing, communication, administrative tasks, data interpretation, problem-solving, and decision support. Public employment services could also integrate AI-related training into job-matching schemes, career counselling, and lifelong learning programmes.

The professional use of generative AI appears particularly relevant for labour-market transformation. For this reason, employers should avoid treating AI as a simple cost-reduction tool and instead embed it in broader organisational change. Firms need to identify which tasks can be augmented by AI, redesign workflows, clarify responsibilities, and provide workers with clear guidelines for the safe, ethical, and effective use of AI. Practical

measures may include internal AI training sessions, sector-specific AI usage protocols, employee consultation before implementation, pilot projects in selected departments, and continuous assessment of how AI affects workload, productivity, job quality, and skill requirements. Such an approach may reduce resistance to technological change and increase the probability that AI complements human labour rather than being perceived only as a replacement threat.

Educational institutions also have an important role. The association between AI use in formal education and labour force participation suggests that schools, universities, and training providers should integrate generative AI into curricula in a responsible, applied manner. This does not mean replacing disciplinary knowledge with technological tools, but instead preparing students and adult learners to use AI critically, transparently, and productively. Universities and vocational training institutions should develop modules on AI-assisted learning, prompt formulation, data interpretation, ethical use, academic integrity, and sector-specific applications. Stronger cooperation between universities, employers, and public institutions could help align AI-related competences with actual labour-market needs.

The cluster analysis also shows that a differentiated policy approach is necessary across European countries. Countries with lower levels of generative AI adoption should prioritize basic digital infrastructure, affordable access to digital tools, digital skills programmes, and support for small and medium-sized enterprises that lack the resources to experiment with AI. In these contexts, public intervention should reduce barriers to adoption and prevent the widening of digital and labour-market inequalities. By contrast, countries with higher levels of AI adoption should place greater emphasis on governance, regulation, ethical standards, worker protection, transparency, and the quality of AI integration into work processes. In these economies, the main challenge is not only to increase adoption, but to ensure that AI use remains trustworthy, inclusive, and aligned with decent work principles.

Labour-market actors, including trade unions, employers' associations, professional bodies, and sectoral councils, should also be involved in shaping the transition. Social dialogue can help identify the occupations most affected by generative AI, define fair rules for AI-supported work, and negotiate training rights, transparency obligations, and safeguards against excessive work intensification. Sectoral partnerships may be especially useful in areas where AI is rapidly changing administrative, analytical, educational, creative, and managerial tasks. In this sense, the practical value of generative AI depends not only on technical adoption but also on negotiated forms of implementation that protect workers while allowing organisations to innovate.

Overall, the results indicate that generative AI can support labour-market participation and efficiency only when it is accompanied by investment in skills, organisational redesign, institutional coordination, and responsible governance. Policies focused exclusively on technological diffusion are unlikely to be sufficient. A more effective approach would combine digital infrastructure, human-capital development, firm-level innovation support, ethical regulation, and social dialogue. Such an integrated strategy may help ensure that generative AI contributes to more adaptive, inclusive, and productive labour markets.

5.3. Limitations and Further Research

The research provides a useful view of the relationship between the use of generative AI and labor market indices. However, the results need to be read alongside certain methodological and conceptual constraints. One restriction is the data's cross-sectional character. The analysis reflects relationships that exist at that instant in time but does not allow observation of AI effects over time. The adoption of digital technologies has frequently had lagging effects; hence, future studies should employ longitudinal data to

test whether the relationships shown here strengthen, weaken, or change as the use of generative AI grows.

A second limitation relates to the measurement of AI use. The study's metrics reflect the percentage of active users of generative artificial intelligence in different scenarios. Nevertheless, they do not have precise information on the intensity of their use, the types of tools used, the quality of their digital skills, or the depth of their integration into their professional activities. Thus, two countries may record equal amounts of use, yet rely on totally different practices. Further research should incorporate indicators of frequency of use, concrete purposes, users' qualification levels, and the types of occupations engaged in.

Another limitation is the macro-level character of the analysis. The study enables the detection of systemic tendencies by comparing countries, but it does not sufficiently capture distinctions among sectors, enterprises, jobs, or social groupings. The relationship between AI and work may vary by education, age, gender, and the nature of the occupation (cognitive vs. routine). In future studies, macroeconomic data and analyses at the firm-, occupational-, or individual-level should be included.

An important limitation of the study is its cross-sectional design and the limited sample of 27 European countries observed at a single point in time. Although the findings reveal significant associations between generative AI use, labour force participation, and nominal unit labour cost, they should not be interpreted as causal effects. The data do not allow the direction of influence to be established. Reverse causality is also possible, as countries with stronger labour-market performance, more advanced digital infrastructure, higher education levels, and greater R&D intensity may adopt generative AI earlier. The limited number of observations also affects the robustness of the exploratory factor analysis, which should be regarded as a preliminary identification of a common AI-use dimension rather than as a definitive measurement model. Future research should use longitudinal or panel data and include broader control variables to examine whether these associations persist over time and whether temporal ordering can be established.

Although the supplementary bivariate correlations provide additional information on the relationship between generative AI use, educational structure, and real labour productivity, the empirical models still do not include a full set of structural control variables. Generative AI use at the country level is likely to co-vary with broader national characteristics, including GDP per capita, tertiary education attainment, R&D intensity, digital infrastructure, DESI-related indicators, and sectoral composition. Therefore, the coefficients reported in the cross-sectional models should not be interpreted as estimates of the unique or independent role of generative AI use. Given the limited sample of 27 countries, adding several structural controls could reduce model stability and increase the risk of overfitting. Future research should address this issue by using panel data or larger cross-country samples and by estimating controlled models that include macroeconomic, educational, digital, innovation-related, and sectoral variables.

Future research should extend the empirical framework by incorporating macroeconomic, educational, digital, and innovation-related control variables, including GDP per capita, broadband connectivity or digital infrastructure indicators, tertiary education attainment, digital skills, and R&D intensity. A panel-data approach would be particularly useful, as it would allow researchers to examine whether the observed associations remain stable over time and whether generative AI adoption contributes to changes in labor force participation and unit labor cost dynamics after accounting for national development differences.

Cluster analysis is exploratory and depends on the selected variables, the distance measure, and the linkage method. The analysis may also be sensitive to country-level outliers. Hungary records particularly low values for personal, professional, and formal-education uses of generative AI compared with the rest of the sample. A robustness check

excluding Hungary showed that the direction of the associations remains unchanged, but some significance levels, especially those involving personal AI use, are affected. Future research should examine these patterns using larger samples, panel data, and additional robustness procedures for influential observations. Although the silhouette coefficient provides moderate support for the exploratory two-cluster solution, future research should further validate these typologies using additional criteria, such as gap statistics, external validation variables, or sensitivity assessments based on alternative clustering specifications. Also, future research could expand the model by including variables related to digital infrastructure, AI regulation, investments in research and development, quality of education, and digital inequalities. Such an expansion would contribute to a better understanding of the conditions that would make the deployment of generative AI a permanent economic and social benefit.

6. Conclusions

This study examined the cross-sectional associations between the use of generative artificial intelligence and two labour-market indicators in the European Union: labour force participation and nominal unit labour cost dynamics. By distinguishing between recent, personal, professional, and educational uses of generative AI, the analysis provides a differentiated view of how various forms of AI engagement are related to labour-market patterns across European countries. The findings should be interpreted as exploratory associations, not as evidence of causal effects.

The results show that the relationship between generative AI use and labour-market indicators is not uniform across all dimensions of use. Recent use of generative AI is significantly associated with both higher labour force participation and lower nominal unit labour cost growth. Professional use also shows significant associations with both indicators, suggesting that AI use in work-related contexts is more closely linked to labour-market differences than other forms of use. However, the results are more mixed for personal and educational use. Personal use of generative AI is significantly associated with nominal unit labour cost dynamics, but its association with labour force participation does not reach the conventional 5% significance threshold. Conversely, educational use is significantly associated with labour force participation, whereas its association with nominal unit labour cost is marginal and not statistically significant at the 5% level. These findings indicate that the labour-market relevance of generative AI depends on the context in which the technology is used.

The factor analysis further suggests that the four AI-use indicators share a common latent dimension of generative AI adoption. This latent factor is significantly associated with both labour force participation and nominal unit labour cost dynamics, supporting the interpretation that generative AI use may reflect a broader socio-technical pattern rather than isolated individual behaviour. At the same time, the factor-analytic results should be read cautiously, given the limited sample of 27 countries and the exploratory character of the analysis.

The cluster analysis indicates descriptive differences among European countries in AI use and labour-market profiles. The two-cluster solution should not be interpreted as a definitive classification, but as an exploratory typology that helps describe contrasting socio-technical profiles. Countries with higher levels of generative AI use tend to display higher labour force participation and lower nominal unit labour cost growth, while countries with lower AI-use levels tend to show less favourable labour-market indicators. These patterns suggest that AI adoption is embedded in broader national conditions, including digital readiness, institutional capacity, educational structure, and economic development,

although these structural explanations remain hypothesis-generating because they were not directly tested in the empirical models.

From a policy perspective, the findings do not justify strong claims that generative AI adoption directly improves labour-market outcomes. Rather, they suggest that the professional and recent use of generative AI may be meaningfully linked to labour-market participation and cost dynamics in countries better prepared to integrate digital technologies. Policy-makers should therefore approach generative AI as one element within broader labour-market and human-capital strategies, alongside education, digital infrastructure, organisational adaptation, social dialogue, and responsible governance. Policies focused only on technological diffusion are unlikely to be sufficient unless they are accompanied by measures that strengthen skills, institutional capacity, and inclusive access to digital tools.

Overall, the study contributes to research on AI and labour markets by linking different forms of generative AI use with macro-level labour indicators within a socio-technical comparative framework. Its findings highlight relevant associations, but it also cautions that the data are cross-sectional, the sample is small, some univariate relationships are not statistically significant, and broader structural factors may shape both AI adoption and labour-market outcomes. Future research should use longitudinal or panel data, include structural control variables, and examine sectoral, occupational, and individual-level differences to better understand how generative AI use is connected to labour-market change over time.

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Abbreviations

The following abbreviations are used in this manuscript:

UGAI_3M	Use of generative AI tools: in the last 3 months
UGAI_PP	Use of generative AI tools: for private purposes
UGAI_WP	Use of generative AI tools: for professional (work) purposes

UGAI_FE Use of generative AI tools: for formal education
 PLF Persons in the labor force
 NULCP Nominal unit labor cost based on persons

Appendix A

Table A1. Cluster membership.

Country	Cluster	Distance	UGAI_3M	UGAI_PP	UGAI_WP	UGAI_FE	PLF	NULCP
Austria	1	3.813	43.98	35.61	27.64	12.80	82.0	2.7
Belgium	1	9.543	47.71	38.97	31.29	4.89	77.1	2.5
Cyprus	1	13.68	49.46	48.65	29.62	12.27	84.8	1.3
Czechia	1	16.155	36.11	30.69	19.25	1.06	85.2	4.2
Denmark	1	9.783	50.36	36.55	35.08	12.20	85.0	0.5
Estonia	1	10.976	51.34	41.53	32.14	12.81	88.5	2.7
Finland	1	9.923	51.24	33.04	34.53	7.86	83.9	1.9
France	1	9.603	40.67	30.89	24.11	4.77	81.4	1.5
Germany	1	13.872	36.34	30.61	20.04	5.23	84.7	5.0
Greece	1	12.928	49.22	45.65	24.61	5.01	78.2	3.2
Ireland	1	7.928	45.03	31.87	28.46	7.12	83.7	−3.1
Latvia	1	15.692	35.96	29.17	18.87	4.95	84.7	6.2
Lithuania	1	6.323	42.25	37.26	25.23	6.94	86.2	6.3
Luxembourg	1	9.522	47.10	40.35	34.24	7.59	78.6	3.6
Malta	1	16.168	51.78	41.46	36.15	19.99	86.9	4.0
Netherlands	1	11.56	49.19	30.85	36.56	7.82	86.4	3.4
Portugal	1	4.348	42.57	36.90	25.85	11.10	85.0	5.1
Slovenia	1	8.556	41.88	35.80	21.94	5.03	81.5	4.6
Spain	1	7.75	41.31	33.75	23.92	13.29	80.6	4.2
Sweden	1	20.168	44.91	36.59	28.89	28.89	88.2	−0.5
Cluster 1 mean		10.91	44.92	36.31	27.92	9.58	83.63	2.97
Bulgaria	2	5.057	25.23	23.19	12.38	1.88	79.6	7.3
Croatia	2	12.803	31.86	28.54	13.35	11.44	77.9	8.2
Hungary	2	21.205	31.91	2.78	1.77	0.66	84.9	8.8
Italy	2	10.907	21.11	14.48	11.25	3.59	72.1	4.0
Poland	2	5.023	26.03	22.75	12.62	2.05	81.6	6.5
Romania	2	10.498	20.98	18.13	8.40	0.77	73.5	1.2
Slovakia	2	13.95	34.88	29.46	15.26	7.35	82.6	4.4
Cluster 2 mean		11.35	27.43	19.90	10.72	3.96	78.89	5.77
EU mean		11.03	40.39	32.06	23.46	8.12	82.40	3.69

Source: authors' design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

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