Research Article / Araştırma Makalesi

Ekonomik ve Sosyal Araştırmalar Dergisi

The International Journal of Economic and Social Research

2025, 21(2)

Implications for Human Resources Management from Labour Force Participation Rates of Countries by Education Level

Eğitim Seviyesine Göre Ülkelerin İşgücüne Katılım Oranlarından İnsan Kaynakları Yönetimi İçin Çıkarımlar

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Geliş Tarihi (*Received*): 02.02.2025 **Kabul Tarihi (*Accepted*):** 23.06.2025 **Yayın Tarihi (*Published*):** 30.12.2025

Abstract: Labour force participation rates are a key indicator of economic structure, human capital development, and employment dynamics, with education level playing a crucial role in shaping workforce accessibility and productivity. This study examines the labour force participation rates across different education levels (basic, intermediate, high) in 34 European and surrounding countries between 2015 and 2023, aiming to provide strategic insights for human resources management (HRM). Using a quantitative approach, the study employs descriptive statistics and K-means clustering to analyse workforce segmentation, while Silhouette Scores assess the degree of convergence among countries over time. The findings indicate a significant decline in Labour force participation among individuals with lower education levels, particularly in countries such as Croatia and Latvia, whereas participation rates for highly educated individuals remain relatively stable. Additionally, clustering results suggest a gradual convergence in labour force dynamics, with certain countries shifting between clusters, reflecting structural shifts in workforce composition. These results highlight the need for targeted reskilling programs, flexible employment models, and education-driven labour policies to mitigate participation disparities. The study underscores the importance of international talent mobility, workforce digitalisation, and skill development initiatives in optimising HRM strategies. By providing an education-based labour market analysis, this research contributes to data-driven workforce planning and global HRM decision-making.

Keywords: Labour Force Participation, Education Levels, Human Resources Management, Workforce Segmentation, Talent Mobility

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Öz: İşgücüne katılım oranları ekonomik yapı, beşeri sermaye gelişimi ve istihdam dinamiklerinin önemli bir göstergesidir ve eğitim seviyesi işgücüne erişilebilirlik ve verimliliği şekillendirmede önemli bir rol oynamaktadır. Bu çalışma, insan kaynakları yönetimi (İKY) için stratejik öngörüler sağlamayı amaçlayarak, 2015-2023 yılları arasında 34 Avrupa ve çevre ülkesinde farklı eğitim seviyelerinde (temel, orta, yüksek) işgücüne katılım oranlarını incelemektedir. Nicel bir yaklaşım kullanan çalışmada, işgücü segmentasyonunu analiz etmek için tanımlayıcı istatistikler ve K-ortalamalar kümelemesi kullanılırken, Siluet Skorları zaman içinde ülkeler arasındaki yakınsama derecesini değerlendirmektedir. Bulgular, özellikle Hırvatistan ve Letonya gibi ülkelerde daha düşük eğitim seviyesine sahip bireyler arasında katılımda önemli bir düşüş olduğunu gösterirken, yüksek eğitimli bireyler için katılım oranları nispeten sabit kalmaktadır. Ayrıca, kümeleme sonuçları işgücü dinamiklerinde kademeli bir yakınsama olduğunu ve bazı ülkelerin kümeler arasında geçiş yaparak işgücü kompozisyonundaki yapısal değişimleri yansıttığını göstermektedir. Bu sonuçlar, katılım eşitsizliklerini azaltmak için hedefe yönelik yeniden beceri kazandırma programlarına, esnek istihdam modellerine ve eğitim odaklı işgücü politikalarına duyulan ihtiyacı vurgulamaktadır. Çalışma, İKY stratejilerinin optimize edilmesinde uluslararası yetenek hareketliliğinin, işgücünün dijitalleşmesinin ve beceri geliştirme girişimlerinin öneminin altını çizmektedir. Bu araştırma, eğitim temelli bir işgücü piyasası analizi sunarak, veri odaklı işgücü planlamasına ve küresel İKY karar alma süreçlerine katkıda bulunmaktadır.

Anahtar Kelimeler: İşgücüne Katılım, Eğitim Düzeyleri, İnsan Kaynakları Yönetimi, İşgücü Segmentasyonu, Yetenek Hareketliliği

Atıf/Cite as: Şimşek, T. (2025). Implications for Human Resources Management from Labour Force Participation Rates of Countries by Education Level. *Ekonomik ve Sosyal Araştırmalar Dergisi*, 21(2), 437-458.

İntihal-Plagiarism/Etik-Ethic: Bu makale, en az iki hakem tarafından incelenmiş ve intihal içermediği, araştırma ve yayın etiğine uyulduğu teyit edilmiştir. / This article has been reviewed by at least two referees and it has been confirmed that it is plagiarism-free and complies with research and publication ethics. https://dergipark.org.tr/tr/pub/ijaws

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1. Introduction

Labour force participation rate is a multidimensional indicator of the social, economic and demographic structure of an economy. The rates in these cases are influenced by a number of demographic factors such as age, gender and education level, and macroeconomic factors like market dynamics, economic fluctuations and social policies (Kumari, 2018; Perez-Arce & Prados, 2021). Given that, labour force participation rates do not only shed light on employment trends but also constitute a strategic instrument for grasping economic development, social equity and human resource management. By applying thematic classifications of labour force participation like gender, age, sector or education level, labour opportunities and inequalities can be analysed within specific population groups (Burdorf et al., 2023). Thematic analyses, especially at the education level, are imperative for evaluating a country's human capital structure and its capacity to respond to human resource labour market demand changes (Angrist et al., 2021). These ratios can tell us what changes over time and these changes can be used to provide important guidance for workforce planning and organisational training strategies (Gibson, 2015).

Previous research has shown that the level of education does have a strong impact on economic performance, labour force structure and institutional strategies. Peneder (2007) observes that education-intensive sectors perform better than other sectors in economic performance, while Lu et al. (2021) investigate how educational background of healthcare professionals affects service quality. Moreover, as per Weir-Smith (2018), even in the countries with a low level of education regional labour force disparities display the necessity for the region based workforce planning strategies. The study by Jarinto and Ridsomboon (2024) is also in line with broader talent management frameworks that categorise employees based on their educational background to determine workforce composition's effect on organisational performance.

Theoretically, educational analysis of labour force participation rates is in accordance with the Human Capital Theory that argues education facilitates increased corporate competitiveness through enhancing the individuals' productivity and employability (Gurgu & Savu, 2014). Economic Development Theory strengthens this perspective by suggesting that individual level employability as well as macroeconomic growth and sectoral development vary with education levels at the national level (Hanushek & Kimko, 2000). As such, human resource management (HRM) is crucial to determine which industries and countries provide the best talent pools. Additionally, the Competency Based Strategy Theory (Palpacuer, 2000) argues that the competencies of workforce (as a result of education) constitute the key organisation capabilities. In fact, however, Institutional Flexibility Theory (Englehardt & Simmons, 2002) reinforces that these competencies are sustainable only if firms can adapt to changing workforce dynamics. As an example, global labour mobility, the rise of flexible employment models, requires an education-based analysis of workforce participation trends, so that organisations are in the optimal locations and attract and retain talent.

In terms of analysing cross country variation of labour force participation for different educational attainment, this study contributes to the literature and by providing comparative insights through clustering techniques. This research adds a novel clustering-based approach to study education's role for employment dynamics in a category of similar labour force patterns by country and over time. The study shows with K-means clustering in combination with Silhouette Scores that the trends of labour market convergence can be described for the period from 2015 to 2023 and explains how educational disparities in workplace participation have developed.

This study's findings offer strategic insights to HRM professionals, policymakers and multinational organisations on:

- Discover areas where education improves their workforce access and competitiveness in a sectoral sense.
- Targeted reskilling programmes can be developed to address the declining participation trends of the individuals with lower educational backgrounds.

- Adaptive employment policies should be formulated which fit into the ongoing convergence of labour force participation among countries.
- It will help them understand how education-based workforce dynamics affect international talent mobility.

The rest of the study is organised as follows: Section 2 discusses the theoretical framework, including the relation between education and labour force participation and some points from the literature. In Section 3, the research methodology is presented including the sources of dataset, analytical techniques and clustering methods. Section 4 shows main findings applying descriptive statistics and cluster analysis to variations in the labour force participation depending on education levels. These findings are discussed in Section 5 with reference to their strategic implications for human resource management. Section 6 concludes the study and proposes future research.

2. Theoretical Framework

In this section, education is theorised as a determiner of labour market dynamics within a framework. Firstly, the basic relations between education and participation in the labour force are analysed, and their consequences on employability, wage levels and career perspective are investigated. Furthermore, different levels of education are evaluated regarding their adaptability to changing labour market needs and the strategic issues related to human resources planning.

2.1. Education and Labour Dynamics

According to Becker (1964), Human Capital Theory advocates that human capital is an economic growth contributing factor which increases the productivity of the individual. The literature supports this theory and it is stressed that education is a key factor for adoption of technological innovations, organisational flexibility and productivity growth (R. Becker & Blossfeld, 2017; Shamsuddinova, 2024). It is noted that low educated individuals have difficulties in being integrated in the labour market (Patzina & Wydra-Somaggio, 2020). Dual Labour Market Theory suggests that low educated people tend to work at low paid and insecure jobs that perpetuate inequality in the labour market (Schömann & Becker, 1995; Shamsuddinova, 2024).

Stegmaier, Krekel and Bellmann (2010) claim that vocational training programmes are an important instrument to increase employability for individuals with low educational attainment. Research on German apprenticeship system demonstrates that vocational training is an effective strategy for lowering youth unemployment and contributes to strengthening people's position in the labour market through growing their professional skills (Patzina & Wydra-Somaggio, 2020). In addition, vocational training is essential for people to adapt to changes in job and career development (R. Becker, 2019).

Becker and Blossfeld (2017) argue that employers' investments in employees' vocational training are strategic necessity for economic modernisation and adaptation to structural changes in the labour market. R. Becker (2019) explains that these investments in vocational training enhance people's capacity to adapt to job changes and increase job security.

According to Shamsuddinova (2024), lifelong learning is not only aimed at improving the individual skill, but also to enhance the ability to respond to the changing needs of the labour market. In this context, the European Union's Youth Guarantee programme stands out as an important policy that aims to increase young people's access to employment, education or vocational training opportunities (Shamsuddinova, 2024).

However, this literature shows that investments in education could enable decrease of inequality in labor market and also boost the level of economic development overall and at an individual level as well. This implies that education is key in human resource management and policy development processes.

2.2. Education and Economic Productivity

Many of the literatures often highlight the conceptual foundation of the relationship between education and economic productivity. According to Schumpeter's theory of innovation, education plays an important role in economic growth through promoting innovation. As stated by Mok, Yu and Ku (2013), research and development (R&D) investments made by higher education institutions in Taiwan are a key factor in raising the global competitiveness of the country. Within this framework, with the increase in level of education, productivity rises and economic development, especially in technology-based industries, is supported.

The concept of global value chains (GVCs) is emphasised by Jegede and Muchie (2024) as the importance of education and innovation in the knowledge sharing and economic productivity at international level. GVCs are integrated into the open innovation model as they enhances the innovative capabilities of individuals and organisation through knowledge exchange across countries. This implies that education has microeconomic impact, and also has microeconomic impact on macroeconomy.

Neethirajan (2023) addresses the impacts of artificial intelligence (AI) and sensor technologies on productivity and sustainability, particularly in the agriculture and livestock sectors. The adoption of these technologies is possible through increased training and technological competences so that the sectors can effectively adopt these technologies and thereby increase their global competitiveness. In addition, such innovations also lead to the optimisation of the business process and the efficiency is in line with Schumpeter's theory of innovation.

As mentioned by Tahsin et al. (2025), one of the main obstacles to technological adaptation in developing countries is the lack of education and awareness. Higher level of education helps the adaptation of individuals to technology and helps in adoption of innovative ways that help to promote economic productivity. This result suggests that the effects of education on economic productivity are multi-dimensional and help develop both at the sectoral and individual levels.

The effect of education on economic productivity is discussed in the literature in terms of innovation, technological adaptation and integration in global value chains. This relationship provides a basis for the contributions to the economic systems by means of the increase of the knowledge and skills of individuals, and at the same time the increase of the countries' global competitiveness. Increasing the level of education not only advanced economic growth but also enhances social and technological transformation in society.

2.3. Human Resources Management and Strategies According to Education Levels

Strategies based on education levels are a critical element for human resource management in the process of creating value at both individual and organisational levels. Zuzana (2017) states that education levels shape workforce competencies and individuals with higher education levels are preferred, especially in roles that require expertise such as branding. This situation reveals that organisations should prioritise the level of education in recruitment processes in order to gain competitive advantage.

Lv (2011) examined that increasing education funding improves regional labour force competencies and its impact on employees' wage expectations. He emphasised that the earning potential of individuals with higher levels of education increases and this should be taken into account in organisational strategies. Training investments both increase individual competencies and create a stock of human capital that supports organisational performance.

Sozen et al.(2016) states that recruitment strategies based on educational level play an important role in the social capital development process of organisations. It is stated that educated individuals expand social networks and these networks strengthen organisational connections, therefore, not only technical competencies but also social relations should be taken into consideration in recruitment processes.

Carraher et al. (2006) examined the effect of education level on remuneration and employee satisfaction policies and found that higher education levels positively affect employees' perceptions of remuneration policies. It indicates that compensation and career planning processes should be based on the educational level, as different strategies are needed for each educational level.

Yang et al. (2020) argues that education level should be taken into account in the management of ageing workforce and that education level of management team is important for the sustainability of the services. This finding implies that the HRM strategies for different age groups should be planned based on the level of education.

El Ouirdi et al. (2016) also demonstrate that individuals with higher education are more preferred for job applications when they use social media and digital tools in recruitment processes. This situation shows that technology can be a strategic tool in attracting high educated talents.

Educational attainment based HRM strategies not only help in improving the individual skill and knowledge levels but also help organisations to improve their competitive advantage. Organisations using these strategy strategies to implement them in areas such as the recruitment, remuneration and planning of the career are able to both consolidate human resources and in many cases achieve sustainable performance.

2.4. Global Workforce Diversity and Education

Globalisation has brought the factors of global workforce diversity and training as key factors for organisations to gain competitive advantage in today's globalised economic order. Schim, Doorenbos and Borse (2005) state that cultural competence training should help strengthen effective management of global workforce diversity. This implies that the degree of education and cultural awareness strategies are essential in the adaptation of individuals to global workforce dynamics. Cultural diversity and training affect organisations' international human resource management (IHRM) strategies.

The synergy between educational attainment and cultural diversity was not only to boost the individual skills but also strengthen the global competence of organizations. Marrocu and Paci (2012) study the impact of human capital and creativity on economic performance in Europe and that education increases innovation. This shows the need for organisations' strategies to attract and retain highly skilled workforce. But the educational attainment has not only a technical impact, because cultural awareness and creativity are vital factors for organisations to remain alive in the global market.

In such a context, Busse, Sun and Zhu (2015) claim that cultural diversity and education levels determine the value priorities of the international workforce in particular. Education level was found to be a strong factor in segmentation and management of the workforce in a study between German and Chinese managers. Diverse cultural backgrounds in the workforce can be a useful tool to improve organisational performance. However, managing this process requires the successful implementation of cultural adaptation policies.

Osmancevic, Großschädl and Lohrmann (2023) analysed the effects of cultural diversity in the European healthcare sector, showing that high levels of education and cultural awareness training increase employees' cultural adaptability. This can be seen as a key component of organisational success not only in the healthcare sector but in all sectors. Global workforce diversity enables organisations to build a well-rounded talent pool by increasing communication and collaboration between individuals with different educational backgrounds.

The effects of increasing educational attainment on women's labour force participation are also important. Buchmann and Malti (2012) stated that in developed industrial countries women outperform men in education , but they do not achieve the same level of success in the labour market. Due to this insurmountable Glass Ceiling syndrome, the female labour force is not only not allowed to take part in top management positions but also treated differently in the labour market (Akdemir & Duman, 2017). This reveals that gender-based education and labour policies should be taken into account in the global competitiveness strategies of organisations. More effective inclusion of women in the workforce can further enhance the organisational benefits of diversity and training.

Global labour diversity and education are also considered in political and economic contexts. As implied by Ehsan and Sloam (2020), young cosmopolitans who are ready to embrace cultural diversity are likely to support economic and social reforms in the context of globalisation. This indicates that education and cultural diversity do not only affect the organisational level but also macroeconomic policies. Younger generations are educated with an important tool in shaping global labour dynamics.

Organisations need to develop a relationship between global workforce diversity and education to achieve their strategic objectives. In general, the talent strategies based on educational attainment improve both individual and organisational performance but, on the other hand, the cultural diversity provides organisations with a sustainable competitive advantage in global markets. Thus, training and diversity should be handled in an integrated manner and be incorporated in the organisational strategies in international human resource management.

3. Research Methodology

In this study the labour force participation rates of countries are examined by levels of education from 2015 to 2023, and these data are analysed from a human resource management perspective. The indicators analysed in the study are as follows: Labour force at basic education level (K1) refers to the labour force participation rate of individuals with primary education. The labour force with intermediate level of education (K2) reflects the labour force participation rate of individuals with high school or equivalent level of education. The highly educated labour force (K3) represents the labour force participation rate of individuals with a university degree or higher. In this context, indicators for a total of 34 countries in and around Europe were obtained from the World Bank database (Data set is presented in the Appendices (Table 9-11)).

In this study, the countries were chosen based on a comparison of labour force participation by education level. Data availability, geographical, economic diversity and variation in education policies and differences in labour market dynamics were the criteria of inclusion. The sample also includes both advanced and developing economies that permit an assessment of the workforce participation across different economic structures, thereby improving validity of findings. The countries included in the analysis are as follows: Austria (AUT), Belgium (BEL), Bosnia and Herzegovina (BIH), Bulgaria (BGR), Croatia (HRV), Cyprus (CYP), Czechia (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Iceland (ISL), Ireland (IRL), Italy (ITA), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Moldova (MDA), Netherlands (NLD), North Macedonia (MKD), Norway (NOR), Poland (POL), Portugal (PRT), Romania (ROU), Serbia (SRB), Slovenia (SVN), Spain (ESP), Sweden (SWE), Switzerland (CHE), Türkiye (TUR), and the United Kingdom (GBR).

This research, which is structured within the framework of quantitative research design, proceeds in two parts. i) Statistical analysis of the data, in this context, descriptive statistics was used to analyse. ii) Cluster analysis was carried out by k-means method to group the labour force profiles of countries according to their similarities.

3.1. Cluster Analysis (K-Means)

In the study, the K-means algorithm was used to group countries. This method aims to create meaningful clusters among countries by taking into account labour force participation rates based on education levels. The K-means clustering algorithm is a very popular clustering technique because it can be applied to almost any data set and is relatively simple and computationally efficient. Nevertheless, the K-means clustering algorithm may present one of the biggest obstacles which is related to the sensitivity of initial states that result in the final solution to be reached at one of the local optima (Karaboga & Ozturk, 2011). In order to mitigate the difficulties associated with the K-means method, many scholars have proposed changes that would help to improve its efficiency and effectiveness (Celebi et al., 2013; Fahim et al., 2006; Kanungo et al., 2002). Pokharel et al.(2021) used the K-means algorithm and its variations to compare their performances in the clustering tasks. While the k-means clustering algorithm is a fundamental method in cluster analysis, ongoing research aims to improve its performance, address its limitations, and explore its applications in various domains.

K-means clustering algorithm is frequently preferred in various fields. Wahyuni et al. (2023) used the K-means algorithm to predict electoral clusters based on voter patterns and aims to reduce budgeting risks by identifying areas with high abstention rates. Muttaqin (2022) used K-means cluster analysis to classify Sumatra's districts and cities into high, medium and low areas according to Human Development Index indicators. Wang (2023) utilised K-means cluster analysis to create a student health monitoring system that aids physical health planning based on biochemical data. Zamani et al. (2023) analysed public service satisfaction using the K-means Clustering algorithm to categories data into different clusters based on similarities and differences. Fa'rifah & Pramesti (2022) used K-means cluster analysis to group East Java districts according to overarching economic development indicators and to identify clusters with above or below average economic growth. Chi (2021) applied K-means clustering to analyses student achievement data, aid project grouping, assist personalised teaching and estimate course importance for educational improvements. Muttaqin & Zulkarnain (2020) used K-mean cluster analysis to classify Indonesia's districts/cities according to the Human Development Index and identify high, medium and low areas with different characteristics.

The stages of the K-means algorithm with an iterative process are as follows (Jain, 2010).

1. An initial clustering is formed by randomly determining k cluster centres from the dataset.

$C = \{c_1, c_2, \ldots, c_k\}$ consists of k randomly selected cluster centres.

Each c_i centre represents a data point. $D = \{x_1, x_2, \ldots, x_n\}$ is the set of data points.

2. For each data point, the distances from all cluster centres are calculated and the data is assigned to the cluster which is closer to the cluster centre.

For each data point x_i , assign it to the nearest cluster centre. If x_i is assigned to c_j , then $x_i \in S_j$

$S_j = \{x_i : \|x_i - c_j\| \leq \|x_i - c_l\| \; \forall \, l, 1 \leq l \leq k\}$ where$\| \quad \|$ represents the Euclidean norm.

3. The new cluster centres are recalculated with the average of all data points assigned to clusters.

$$c_j = \frac{1}{|S_j|} \sum_{x_i \in S_j} x_i$$

4. If the centre points of the formed clusters are the same as the previous centre points, the process is terminated, if not, the process is repeated over the new cluster centres from step 2.

The quality of clustering is assessed by the internal consistency of clusters and the distinction between different clusters. As a result of a good clustering, elements in the same cluster should be similar to each other while elements in different clusters should be different from each other. In this study, clustering quality is evaluated with the Silhouette Score. For each data point, the Silhouette Score measures the difference between the similarity of that point to other points in its cluster and the similarity of that point to points in the nearest cluster. It takes values between -1 and +1. Values close to +1 indicate that the data points are well placed in their clusters and that there is good separation between different clusters. The analysis is completed with the number of clusters with the highest Silhouette Score among the clusters with different k values.

4. Findings

In this section, the labour force participation rates of 34 countries in and around Europe between 2015-2023 are analysed in detail according to basic (K1), intermediate (K2) and high (K3) education levels. Firstly, the changes in labour force participation rates by years and countries were analysed. Then, by using the K-means clustering method, countries were grouped according to their similarities, and with the help of Silhouette scores, it was evaluated how the differences between the clusters decreased over time. The findings provide a basis for important implications for human resource management strategies discussed in the next section.

4.1. Findings from Statistical Analysis of Labour Force Participation Rates by Education Level

The year-by-year statistics of labour force participation rates of individuals with basic education between 2015 and 2023 are shown in Table 1. The statistics show a gradual decline, with the mean value decreasing from 39.55% to 37.79% and the median from 38.01% to 35.20%. The standard deviation decreased (from 13.54% to 12.00%), while the coefficients of skewness and kurtosis indicate an even distribution of labour force participation rates. The maximum participation rate decreased from 73.40% to 66.80% and the minimum from 16.50% to 15.50%. These findings indicate that the labour force participation of individuals with basic education has decreased. The decline in labour force participation among individuals with basic education levels can be explained by the Skill-Biased Technological Change hypothesis, which suggests that technological advances reduce demand for low-skilled jobs. Additionally, changing labour market conditions, globalisation, and flexible working models have further reduced participation by forcing these individuals into low-paid and insecure jobs.

Table 1: Year-based statistics for K1 criterion

	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	39.55	39.07	38.84	38.63	38.66	37.69	37.12	37.39	37.79
Median	38.01	37.85	36.30	36.59	37.12	37.37	34.43	35.55	35.20
Standard Deviation	13.54	13.74	13.36	13.43	13.19	13.04	12.89	12.34	12.00
Kurtosis	0.54	0.61	0.40	0.22	0.20	0.27	0.22	0.09	-0.03
Skewness	0.80	0.81	0.75	0.69	0.69	0.73	0.82	0.69	0.58
Range	56.91	58.88	55.10	53.00	51.07	50.61	51.78	51.92	51.30
Minimum	16.50	15.60	16.49	17.77	17.79	16.92	18.21	17.17	15.50
Maximum	73.40	74.48	71.59	70.77	68.86	67.53	69.98	69.10	66.80

Country-by-country statistics of labour force participation rates of individuals with basic education between 2015 and 2023 are shown in Table 2. The statistics show significant differences between countries, with Iceland (68.05%) having the highest average, while Croatia (18.46%) shows the lowest value. The standard deviation and range values highlight the heterogeneity in the distribution of labour force participation rates; Estonia (3.78%) and Iceland (14.42%) have a wide variance, while Czechia (0.69%) and Denmark (1.26%) show a more homogeneous distribution. These differences may stem from factors such as national education policies, the strength of informal labour markets, and the degree of economic development. Countries like Iceland often provide stronger adult education pathways and inclusive labour policies, whereas countries like Croatia may face structural barriers including higher informality and lower demand for low-skilled labour. The skewness and kurtosis coefficients indicate the symmetric or asymmetric nature of the distribution across countries, while the minimum and maximum values draw attention to the level of inequality in labour force participation of individuals with basic education.

Table 2: Country-based statistics for K1 criterion

	AUT	BEL	BIH	BGR	HRV	CYP	CZE	DNK	EST	FIN	FRA	DEU
Mean	37.47	28.34	23.76	27.55	18.46	37.05	21.70	43.75	40.68	28.78	29.13	41.33
Median	37.28	28.39	24.34	27.23	17.80	36.81	21.48	43.24	40.78	28.11	28.72	40.90
Standard Deviation	0.77	1.33	1.54	1.39	2.22	1.31	0.69	1.26	3.78	2.22	1.07	2.73
Kurtosis	0.21	-1.31	-0.96	0.14	0.74	-0.23	-1.50	0.35	-0.62	2.43	-1.20	-0.64
Skewness	0.68	0.16	-0.67	0.05	0.97	0.60	-0.16	1.24	-0.31	1.54	0.33	0.68
Range	2.53	3.82	4.29	4.68	7.30	4.13	1.88	3.59	11.70	7.38	3.19	7.83
Minimum	36.40	26.62	21.15	25.16	15.50	35.23	20.63	42.54	34.31	26.27	27.62	38.04
Maximum	38.93	30.45	25.44	29.84	22.80	39.35	22.50	46.13	46.01	33.65	30.81	45.87
	GRC	HUN	ISL	IRL	ITA	LVA	LTU	LUX	MDA	NLD	MKD	NOR
Mean	30.09	29.00	68.05	31.03	33.91	35.33	19.00	39.81	67.58	45.91	32.57	50.86
Median	28.76	28.52	68.86	30.96	34.54	37.85	18.64	39.52	67.53	45.07	33.32	50.67
Standard Deviation	2.70	1.92	4.98	1.43	1.09	4.61	2.76	1.84	1.64	2.01	2.97	1.53

Kurtosis	-1.54	1.20	-1.23	-0.05	-2.33	-0.58	-0.64	2.64	-1.23	-0.21	0.10	5.59
Skewness	0.46	0.88	-0.29	0.16	-0.23	-1.06	0.55	0.51	-0.01	0.64	0.33	2.20
Range	7.40	6.58	14.42	4.47	2.49	12.24	8.29	6.96	4.90	6.44	9.83	5.15
Minimum	26.87	26.29	60.06	28.68	32.60	26.85	15.60	36.62	65.08	43.11	28.16	49.49
Maximum	34.27	32.87	74.48	33.15	35.09	39.10	23.89	43.58	69.98	49.55	37.99	54.64
	POL	PRT	ROU	SRB	SVN	ESP	SWE	CHE	TUR	GBR		
Mean	43.16	48.38	30.28	33.46	25.64	47.27	47.14	51.33	48.88	65.68		
Median	43.53	49.17	31.98	33.46	26.02	47.47	47.31	51.44	49.65	68.48		
Standard Deviation	1.60	3.25	3.28	1.32	2.40	2.30	2.18	0.55	1.87	4.75		
Kurtosis	-0.51	-1.73	-1.20	0.50	-1.34	-1.54	-0.57	-0.25	-1.00	0.44		
Skewness	-0.80	-0.21	-0.81	-0.72	-0.09	0.31	-0.61	-0.21	-0.54	-1.45		
Range	4.75	8.89	8.92	4.28	6.67	6.09	6.55	1.77	5.46	11.84		
Minimum	40.24	43.66	25.02	30.89	22.51	44.85	43.28	50.39	45.63	56.94		
Maximum	44.99	52.55	33.94	35.17	29.18	50.94	49.83	52.15	51.09	68.78		

Table 3 reveals that the labour force participation rates of individuals with secondary level education showed a slight decrease between 2015 and 2023 (from 66.04% to 63.84%) and the distribution evolved into a more balanced structure. The decrease in the standard deviation and range values (from 27.48% to 18.34%) indicates that the inequality in participation rates has decreased. The decrease in the skewness and kurtosis coefficients indicates that the distribution has become symmetric and more homogenous. However, the decrease in the maximum values from 84.74% to 74.94% indicates a significant decline even in countries with the highest participation rates.

Table 3: Year-based statistics for K2 criterion

	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	66.04	65.83	65.80	65.71	65.39	64.39	63.73	63.96	63.84
Median	64.12	64.70	64.45	64.26	64.55	62.90	62.74	62.85	62.90
Standard Deviation	6.14	6.18	6.25	6.16	6.36	6.39	5.24	4.98	5.17
Kurtosis	1.23	1.25	1.46	0.95	0.43	0.02	-0.36	-0.35	-0.59
Skewness	1.06	0.98	1.06	0.92	0.76	0.86	0.66	0.63	0.63
Range	27.48	29.32	30.15	29.10	28.93	25.05	18.66	18.98	18.34
Minimum	57.27	55.20	54.58	54.18	53.34	55.03	56.72	56.25	56.61
Maximum	84.74	84.52	84.73	83.29	82.27	80.08	75.38	75.23	74.94

Country-based statistics on labour force participation rates of individuals with secondary level education are shown in Table 4. The statistics show significant differences between countries, with Iceland having the highest average of 79.59% and Bosnia and Herzegovina the lowest at 57.19%. The standard deviation and range values reveal that the distribution of participation rates has a wider variance in some countries (e.g. Moldova 2.10%, Estonia 2.94%) and a more homogeneous distribution in others (e.g. Czechia 0.59%, Denmark 0.42%). The skewness and kurtosis coefficients indicate that the distribution is more asymmetric in countries such as Estonia (2.06%) and North Macedonia (-1.54%). The maximum value for Iceland (84.74%) and the minimum value for Bosnia and Herzegovina (53.34%) highlight inequality in labour markets.

Table 4: Country-based statistics for K2 criterion

	AUT	BEL	BIH	BGR	HRV	CYP	CZE	DNK	EST	FIN	FRA	DEU
Mean	63.28	58.50	57.19	60.51	59.92	67.13	63.13	65.95	72.58	65.95	59.92	63.99
Median	63.50	58.54	57.27	60.83	59.44	67.34	63.31	65.89	74.06	66.12	59.30	64.05
Standard Deviation	0.73	1.47	3.06	1.21	1.15	1.02	0.59	0.42	2.94	0.86	1.65	0.86
Kurtosis	0.32	-1.82	-1.76	-1.04	-0.27	-0.33	-1.36	-0.82	-0.35	-0.57	-0.40	-2.18
Skewness	-1.38	0.04	0.22	-0.44	0.64	-1.02	-0.39	-0.14	-1.05	-0.37	-0.05	0.02
Range	1.87	3.69	7.97	3.43	3.66	2.70	1.65	1.29	8.04	2.69	5.24	2.01
Minimum	62.00	56.71	53.34	58.55	58.33	65.42	62.24	65.27	67.06	64.48	57.11	63.01
Maximum	63.87	60.40	61.31	61.98	61.99	68.11	63.89	66.57	75.10	67.16	62.35	65.02

	GRC	HUN	ISL	IRL	ITA	LVA	LTU	LUX	MDA	NLD	MKD	NOR
Mean	59.64	64.19	79.59	66.70	62.97	66.57	61.50	59.24	71.95	69.95	64.88	68.14
Median	59.74	64.12	82.27	66.76	63.18	68.54	61.48	59.15	71.39	69.47	66.05	69.44
Standard Deviation	0.82	0.57	5.73	1.20	1.14	4.13	1.18	2.10	2.24	1.16	2.80	3.41
Kurtosis	-0.01	-1.16	-1.73	1.85	-1.36	-1.58	-1.60	-0.39	-0.50	-0.62	2.57	0.53
Skewness	-1.08	0.39	-0.65	-1.18	-0.29	-0.73	-0.18	0.31	0.34	0.92	-1.54	-1.44
Range	2.26	1.59	12.99	4.04	3.19	10.21	3.09	6.70	6.72	3.26	8.93	9.34
Minimum	58.20	63.48	71.76	64.15	61.18	60.39	59.88	56.25	68.51	68.77	58.64	62.00
Maximum	60.46	65.08	84.74	68.19	64.38	70.60	62.96	62.95	75.23	72.02	67.57	71.34
	POL	PRT	ROU	SRB	SVN	ESP	SWE	CHE	TUR	GBR		
Mean	58.97	74.22	60.98	61.26	59.70	65.37	74.05	66.33	59.08	75.47		
Median	59.17	74.69	62.57	60.73	60.08	65.80	76.54	66.09	59.63	76.50		
Standard Deviation	0.90	1.23	3.16	1.41	1.15	2.35	4.08	0.65	1.83	2.06		
Kurtosis	-0.52	0.28	-1.72	-0.90	-1.13	-1.50	-1.61	-1.35	2.42	0.37		
Skewness	-0.64	-1.30	-0.69	0.50	-0.26	0.27	-0.87	0.47	-1.62	-1.44		
Range	2.72	3.45	7.22	4.24	3.44	6.11	9.06	1.79	5.85	5.09		
Minimum	57.39	71.91	56.61	59.33	57.85	62.62	67.97	65.56	55.03	71.78		
Maximum	60.11	75.36	63.83	63.58	61.29	68.73	77.03	67.35	60.87	76.86		

The statistics presented in Table 5 show that the labour force participation rates of individuals with advanced education remained highly stable between 2015 and 2023, but the inequality decreased; the average rate decreased from 78.88% to 78.56% and the range decreased from 22.10% to 18.79%. The decrease in the standard deviation (from 4.50% to 3.89%) shows that the distribution has become more homogenous, and the decrease in skewness and kurtosis values shows that the distribution has become more balanced. The decrease in the minimum and maximum values from 69.62% to 68.50% and from 91.71% to 87.29%, respectively, indicates a decline even in countries with the highest participation rates.

Table 5: Year-based statistics for K3 criterion

	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	78.88	78.95	78.95	78.92	79.09	78.44	78.39	78.81	78.56
Median	79.59	79.31	79.90	79.47	79.30	79.21	77.78	78.58	78.00
Standard Deviation	4.50	4.48	4.44	4.36	4.45	4.44	3.61	3.49	3.89
Kurtosis	0.61	0.57	0.27	-0.28	-0.42	-0.87	-0.49	-0.14	0.40
Skewness	0.35	0.38	0.30	0.23	0.31	0.01	0.16	0.40	-0.13
Range	22.10	21.46	20.12	18.58	18.42	17.71	14.85	13.98	18.79
Minimum	69.62	70.29	71.21	71.63	71.75	70.36	71.11	72.71	68.50
Maximum	91.71	91.75	91.33	90.21	90.17	88.07	85.96	86.69	87.29

The statistics presented in Table 6 show that there are significant differences between countries in the labour force participation rates of individuals with advanced education, with Iceland having the highest average of 89.03%, North Macedonia 73.63% and Croatia 72.25%. Standard deviation and range values show that labour force participation rates have a wider variance in some countries (Sweden 2.76%, North Macedonia 13.93%) and a more homogeneous distribution in others (Luxembourg 0.55%, Denmark 0.75%). Skewness and kurtosis values indicate that the symmetric nature of the distribution varies across countries; for example, North Macedonia (-2.93%) exhibits a significant negative skewness, while Czechia (1.71%) shows a positive skewness.

Table 6: Country-based statistics for K3 criterion

	AUT	BEL	BIH	BGR	HRV	CYP	CZE	DNK	EST	FIN	FRA	DEU
Mean	77.47	75.38	78.65	75.15	72.25	82.63	76.34	77.07	80.25	74.40	76.90	73.52
Median	76.77	75.31	78.96	74.66	72.24	82.44	76.21	76.95	81.22	74.07	77.22	73.63
Standard Deviation	1.36	0.42	2.09	1.19	0.71	0.75	0.78	0.32	2.18	0.63	0.60	0.59
Kurtosis	0.64	-1.37	0.34	-1.61	-0.86	-0.70	0.17	3.33	-1.22	-0.11	1.20	-1.49
Skewness	1.56	0.31	-0.88	0.02	-0.11	0.57	0.91	1.71	-0.89	1.01	-1.19	-0.03

Range	3.34	1.17	6.70	3.33	2.08	2.14	2.34	1.01	5.50	1.84	1.86	1.68
Minimum	76.61	74.82	74.60	73.38	71.11	81.77	75.51	76.80	76.64	73.75	75.65	72.69
Maximum	79.95	75.99	81.29	76.72	73.19	83.91	77.85	77.81	82.14	75.60	77.52	74.37
	GRC	HUN	ISL	IRL	ITA	LVA	LTU	LUX	MDA	NLD	MKD	NOR
Mean	75.15	74.44	89.03	81.53	74.98	82.00	82.43	79.77	73.63	79.51	79.55	83.09
Median	75.60	73.23	90.17	81.15	75.07	83.22	82.78	79.60	73.74	79.38	81.03	83.35
Standard Deviation	0.82	2.31	2.54	0.88	0.65	3.69	0.87	0.55	1.46	0.57	4.17	1.41
Kurtosis	-1.26	-1.43	-1.78	-0.27	1.39	-1.54	-1.73	4.03	-0.32	0.14	8.69	0.51
Skewness	-0.57	0.72	-0.36	1.03	-0.78	-0.58	-0.48	1.97	-0.54	1.14	-2.93	-1.08
Range	2.26	5.97	6.38	2.52	2.26	9.76	2.09	1.76	4.52	1.59	13.00	4.23
Minimum	73.75	71.79	85.37	80.61	73.66	76.79	81.28	79.31	71.21	78.97	68.50	80.38
Maximum	76.01	77.76	91.75	83.13	75.92	86.55	83.37	81.07	75.72	80.56	81.50	84.61
	POL	PRT	ROU	SRB	SVN	ESP	SWE	CHE	TUR	GBR		
Mean	80.99	83.01	82.29	72.09	79.40	79.59	81.76	80.89	78.24	85.10		
Median	80.89	83.00	82.15	71.95	79.90	79.41	83.53	80.99	79.19	84.57		
Standard Deviation	0.45	0.54	0.44	1.84	1.13	0.98	2.76	0.57	1.73	1.18		
Kurtosis	-1.24	-1.51	-1.42	-0.91	1.21	-1.23	-1.63	0.75	-0.05	-0.20		
Skewness	0.21	-0.08	0.10	0.28	-1.38	0.49	-0.87	-0.71	-0.93	1.02		
Range	1.26	1.46	1.28	5.43	3.41	2.60	6.12	1.93	5.13	3.27		
Minimum	80.32	82.30	81.67	69.62	77.06	78.51	77.83	79.77	74.91	84.02		
Maximum	81.58	83.76	82.95	75.04	80.46	81.11	83.94	81.69	80.04	87.29		

4.2. Trends in Labour Force Participation Rates and Variability Analysis Findings

The analysis of trends and variations of labour force participation rates at basic (K1), intermediate (K2) and advanced (K3) education levels is shown in Table 7. At the K1 level, Germany (0.97%) and Lithuania (0.97%) show an increase, while Iceland (-1.66%) and the United Kingdom (-1.44%) experience a significant decrease; the highest variation is observed in Croatia (11.35%) and Latvia (12.30%). At the K2 level, labour force participation is broadly stable, but declines are notable in countries such as Spain (-0.78%) and Sweden (-1.23%). At the K3 level, labour force participation is more stable, with Germany (0.34%) and Serbia (0.56%) showing a positive trend, while Estonia (-0.56%) and Latvia (-1.02%) show a decline. These findings suggest that the dynamics of labour force participation across countries differ significantly by education level and that education level-specific strategies should be developed in human resources management.

The high coefficient of variation in K1 for transition economies (HRV, LVA, EST, LTU, MKD, ROU, SVK) stems from their shift from planned to market economies, marked by rapid privatization, economic restructuring, and global market adaptation. This has destabilized labor force participation, especially for those with basic education, due to limited technological adaptability and misaligned education systems, restricting employability and causing fluctuations. Varying reform speeds and economic diversification levels across these countries further contribute to the observed variability.

Table 7: Trends and variability of countries on the basis of criteria

	K1		K2		K3	
Country	Slope	Var. Coef.	Slope	Var. Coef.	Slope	Var. Coef.
AUT	0.23	1.94%	-0.10	1.09%	0.34	1.65%
BEL	-0.40	4.44%	-0.45	2.36%	0.10	0.52%
BIH	0.07	6.10%	0.80	5.05%	0.36	2.51%
BGR	0.25	4.76%	-0.20	1.89%	0.34	1.50%
HRV	-0.72	11.35%	-0.39	1.82%	0.00	0.92%
CYP	-0.34	3.34%	0.03	1.43%	0.05	0.85%
CZE	0.18	2.99%	-0.16	0.88%	0.18	0.96%
DNK	0.37	2.72%	-0.06	0.60%	0.06	0.39%
EST	-0.92	8.77%	-0.69	3.82%	-0.56	2.56%
FIN	0.61	7.26%	-0.17	1.22%	-0.05	0.80%
FRA	-0.32	3.47%	-0.48	2.59%	-0.01	0.73%
DEU	0.97	6.23%	-0.22	1.27%	-0.14	0.76%
GRC	-0.89	8.45%	-0.17	1.30%	-0.24	1.02%

	K1		K2		K3	
Country	Slope	Var. Coef.	Slope	Var. Coef.	Slope	Var. Coef.
HUN	0.65	6.23%	0.15	0.83%	0.63	2.93%
ISL	-1.66	6.90%	-1.90	6.78%	-0.89	2.69%
IRL	-0.34	4.34%	-0.04	1.69%	0.25	1.02%
ITA	-0.34	3.04%	-0.34	1.70%	0.11	0.82%
LVA	-1.21	12.30%	-1.12	5.85%	-1.02	4.24%
LTU	0.97	13.71%	-0.42	1.80%	-0.23	0.99%
LUX	-0.07	4.35%	-0.68	3.34%	-0.02	0.65%
MDA	0.06	2.29%	0.56	2.93%	0.28	1.87%
NLD	0.45	4.12%	0.32	1.56%	0.12	0.68%
MKD	-1.01	8.60%	-0.92	4.07%	-0.90	4.94%
NOR	0.01	2.84%	-1.03	4.72%	-0.45	1.60%
POL	-0.56	3.50%	0.06	1.43%	0.10	0.53%
PRT	-1.12	6.34%	-0.17	1.57%	0.10	0.62%
ROU	-0.98	10.20%	-1.02	4.89%	0.04	0.51%
SRB	0.38	3.71%	0.45	2.17%	0.56	2.41%
SVN	-0.62	8.84%	-0.11	1.81%	0.25	1.34%
ESP	-0.80	4.59%	-0.78	3.39%	-0.32	1.16%
SWE	-0.40	4.37%	-1.23	5.20%	-0.81	3.18%
CHE	0.07	1.00%	-0.21	0.92%	-0.08	0.67%
TUR	-0.46	3.61%	-0.03	2.93%	-0.43	2.08%
GBR	-1.44	6.82%	-0.58	2.57%	0.39	1.31%

4.3. Findings of K-Means Clustering Analysis of Labour Force Participation Rates

Table 8 presents the results of clustering analyses based on the labour force participation rates of countries between 2015 and 2023 and Silhouette scores measuring the quality of decomposition of these analyses. Two clusters (C1 and C2) were formed in each year and Silhouette scores decreased from 0.421 in 2015 to 0.363 in 2023, indicating that the differences between clusters are decreasing and there is a convergence trend in the labour force participation dynamics of countries. This convergence may be driven by policy harmonisation efforts within the EU, greater alignment of education and employment systems, and the diffusion of digital technologies and flexible work models, all of which contribute to reducing structural disparities in labour force participation across countries. While most countries have remained in the same cluster for all years (e.g. Germany and Austria have consistently been in cluster C1, while Sweden and the United Kingdom have been in cluster C2), some countries, such as Estonia and Spain, have shifted between clusters, indicating that these countries have experienced fluctuations in their labour force participation rates over time. The decline in Silhouette scores suggests that cross-country differences are gradually decreasing and labour force participation is becoming more homogeneous. These findings emphasise that human resource management strategies should focus on countries' unique labour force dynamics rather than general trends and that international strategies should be re-evaluated with these changing structures in mind.

Table 8: Year-based clustering analysis results

Silhouette Scores	0.421	0.418	0.405	0.400	0.406	0.431	0.429	0.350	0.363
# of Clusters	2	2	2	2	2	2	2	2	2
	2015	2016	2017	2018	2019	2020	2021	2022	2023
AUT	C1	C1	C1	C1	C1	C1	C1	C1	C1
BEL	C1	C1	C1	C1	C1	C1	C1	C1	C1
BIH	C1	C1	C1	C1	C1	C1	C1	C1	C1
BGR	C1	C1	C1	C1	C1	C1	C1	C1	C1
HRV	C1	C1	C1	C1	C1	C1	C1	C1	C1
CYP	C2	C1	C1	C2	C2	C2	C2	C2	C2
CZE	C1	C1	C1	C1	C1	C1	C1	C1	C1
DNK	C1	C1	C1	C1	C1	C1	C1	C2	C2

Silhouette Scores	0.421	0.418	0.405	0.400	0.406	0.431	0.429	0.350	0.363
# of Clusters	2	2	2	2	2	2	2	2	2
	2015	2016	2017	2018	2019	2020	2021	2022	2023
EST	C2	C2	C2	C2	C2	C2	C1	C2	C2
FIN	C1	C1	C1	C1	C1	C1	C1	C1	C1
FRA	C1	C1	C1	C1	C1	C1	C1	C1	C1
DEU	C1	C1	C1	C1	C1	C1	C1	C1	C1
GRC	C1	C1	C1	C1	C1	C1	C1	C1	C1
HUN	C1	C1	C1	C1	C1	C1	C1	C1	C1
ISL	C2	C2	C2	C2	C2	C2	C2	C2	C2
IRL	C1	C1	C1	C1	C1	C1	C1	C2	C2
ITA	C1	C1	C1	C1	C1	C1	C1	C1	C1
LVA	C2	C2	C2	C2	C2	C2	C1	C1	C1
LTU	C1	C1	C1	C1	C1	C1	C1	C1	C1
LUX	C1	C1	C1	C1	C1	C1	C1	C1	C1
MDA	C2	C2	C2	C2	C2	C2	C2	C2	C2
NLD	C2	C2	C2	C2	C2	C2	C2	C2	C2
MKD	C1	C1	C1	C1	C1	C1	C1	C1	C1
NOR	C2	C2	C2	C2	C2	C2	C2	C2	C2
POL	C1	C1	C1	C1	C1	C1	C1	C1	C1
PRT	C2	C2	C2	C2	C2	C2	C2	C2	C2
ROU	C1	C1	C1	C1	C1	C1	C1	C1	C1
SRB	C1	C1	C1	C1	C1	C1	C1	C1	C1
SVN	C1	C1	C1	C1	C1	C1	C1	C1	C1
ESP	C2	C2	C2	C2	C2	C1	C1	C2	C1
SWE	C2	C2	C2	C2	C2	C2	C2	C2	C2
CHE	C2	C2	C2	C2	C2	C2	C2	C2	C2
TUR	C1	C1	C1	C1	C1	C1	C1	C1	C1
GBR	C2	C2	C2	C2	C2	C2	C2	C2	C2

5. Managerial Implications

The findings reveal how labour force participation rates vary across years and countries according to education levels and how these dynamics can provide meaningful implications for human resources management. Based on the findings, the following managerial implications can be drawn.

5.1. Education Level and Labour Productivity

The fact that the labour force participation rates of individuals with higher levels of education remain at a stable level and inequalities are decreasing is clearly supported by the findings in Table 5 and Table 6. The fact that the average values of the labour force participation rates of individuals with higher levels of education showed only a small decline between 2015 and 2023 (from 78.88% to 78.56%) reveals the stability and priority of this group in the labour force. Moreover, the decreases in the values of the standard deviation (from 4.50% to 3.89%) and the range (from 22.10% to 18.79%) indicate that inequalities in this group are decreasing and the distribution is becoming more homogenous. Table 6 shows that this group maintains high participation rates in different countries, reaching the highest values in countries such as Iceland (89.03%).

These findings have important strategic implications for human resource management. Firstly, highly educated individuals represent a critical talent pool to fill positions requiring innovative leadership in organisations. In this context, human resource management can take the following steps to strengthen the position of this group in the labour market:

- **Skill Development Programmes:** Leadership and expertise-oriented skills development programmes designed for highly educated individuals can enhance the contribution of this group to organisational productivity. For example, while the findings in Table 5 show that this group has a generally stable structure, it requires investment in digital skills training to enable them to take a more active role in technological transformation processes.

- **Inclusive and Flexible Working Models:** The cross-country differences in Table 6 show that organisations need to design different working models according to the needs of this group. For example, the relatively low participation rates in countries such as North Macedonia (73.63%) and Croatia (72.25%) may encourage innovative approaches such as flexible working hours and remote working models in these regions. Empirical evidence suggests that flexible work arrangements significantly enhance labour force participation by allowing employees to better manage work-life conflicts, thus increasing job satisfaction, organizational commitment, and overall productivity (Maket et al., 2015)
- **Strategies for Attracting and Retaining International Talent:** High rates of labour force participation of highly educated individuals increase the role of this group in international labour mobility. The findings in Table 6 show that in countries such as Iceland (89.03%) and Switzerland (81.76%), for example, this group finds an attractive work environment. Accordingly, the promotion of education-based migration policies and the development of integration programmes are recommended to facilitate international labour mobility.

5.2. Reduction of Differences between Clusters

The decreasing differences between clusters are clearly supported by the clustering analysis and Silhouette scores presented in Table 8. The analysis shows that countries are grouped into two main clusters according to labour force participation rates between 2015 and 2023 and the differences between the clusters are decreasing over time. The decrease in Silhouette scores from 0.421 in 2015 to 0.363 in 2023 indicates a convergence trend in labour force participation dynamics across countries. For instance, countries in cluster C1 are permanently situated in cluster C1 while countries in cluster C2 have moved between clusters in some years. They indicate unstable or convergence processes in the labour force participation rates of countries.

Implications for human resource management of global companies are important for the reshaping of their talent management strategies:

- **Decline in Silhouette scores:** As labour force dynamics converge in different countries, the talent pool becomes wider and more accessible, and expanding the international talent pool. As an example, the cross training programmes and talent transfer policies can be adopted between countries of converging labour dynamics. Secondly, this can help global companies to take advantage from a broader talent pool without being dependent upon being a particular region.
- **Reduced cross country differences:** Global companies can develop more standardised and integrated human resources policies due to reduced cross country differences. For instance, there are policies including career development, compensation and benefits which can be more harmonised between countries in terms of labour profile. Countries in cluster C1, such as Germany, Austria and France, are countries that have been consistently ranked, and are therefore countries where such integrated policies can be carried out.
- **Global Mobility and Flexibility:** Cluster analysis reveals that fluctuations in labour force participation rates in countries such as Estonia and Spain indicate that these countries need to adapt to labour mobility and flexible working models. Global companies can respond more effectively to labour market fluctuations by establishing flexible recruitment models or temporary workforce programmes in such countries. Although flexible recruitment and temporary workforce programmes may offer short-term responsiveness to labour market fluctuations, evidence also suggests that these models can increase employment precarity and labour segmentation if not supported by strong institutional safeguards (Kalleberg, 2001).
- **Talent Management Technologies:** The convergence of Silhouette scores offers opportunities for more integrated analysis of labour data and the use of AI-based human resource management systems. These systems can support strategic decision-making processes by analysing labour trends across countries more quickly and accurately.

5.3. Strategic Importance of Education Investments

The decline in labour force participation rates at basic and secondary education levels is clearly visible in the data presented in Table 1 and Table 3. At the basic education level, the mean value of labour force participation rates decreased from 39.55% to 37.79% between 2015 and 2023 and the median values showed a similar decrease. The decrease in the standard deviation (from 13.54% to 12.00%) reveals that inequalities in this group have decreased slightly, but the overall participation rate has decreased. Similarly, a decline in the labour force participation rate of individuals with secondary education (from 66.04% to 63.84%) is also noteworthy. These findings point to a weakness in the capacity of individuals with basic and secondary education to adapt to skills and labour market requirements.

This situation indicates that education investments should be considered as a strategic priority in terms of human resources management:

- **Design of Targeted Education Programmes:** Customised training programmes should be created for individuals at basic and secondary education level. For example, topics such as digital skills and adaptation to technology can increase the competitiveness of these groups in the labour market. The data show that the labour force participation of individuals at this level should particularly focus on sectoral needs-oriented training.
- **Sectoral Training Incentives:** The country-level findings in Table 2 and Table 4 show that in some regions labour force participation rates are quite low (e.g. Croatia and North Macedonia). This calls for sectoral training incentives to be applied in specific sectors. For example, regional training centres could be established to meet labour demand in agriculture, health and service sectors.
- **Vocational Development and Career Support:** In order to increase labour force participation, it is important to structure vocational development programmes in line with individuals' career expectations. For individuals at the basic education level, apprenticeship and vocational certification programmes can be developed to facilitate their transition to the labour market. At the secondary education level, programmes focusing on leadership and technical skills can be implemented.
- **Innovative Solutions in Low Participation Regions:** Table 2 and Table 4 underline the low levels of labour force participation rates in certain regions. In these regions, innovative solutions to respond to labour needs, such as distance learning, flexible working models and regional development projects, can be implemented.

5.4. Demographic and Regional Differences

Demographic and regional differences are clearly illustrated by the country-based findings in Table 2, Table 4 and Table 6. At the basic education level, labour force participation rates show large differences between Iceland (68.05%) and Croatia (18.46%), indicating that demographic and economic conditions across countries have a significant impact on labour force dynamics. Similarly, at the secondary level, Bosnia and Herzegovina has the lowest participation rate at 57.19% and Iceland has the highest at 79.59%, indicating that sectoral needs and policies vary across countries. The differences between North Macedonia (73.63%) and Iceland (89.03%) at the level of further education show that even in this group, countries' education and employment policies have different results.

These findings suggest that human resource management should develop strategies tailored to countries' specific labour force dynamics and regional needs:

- **Country-specific employment incentives:** In countries or regions with low labour force participation rates, employment incentives can be implemented, particularly targeting individuals with basic and secondary education. For example, in countries such as Croatia and Bosnia and Herzegovina, special projects can be implemented to increase job opportunities in the agriculture and service sectors. These incentives can both increase labour force participation and support regional economic development.

- **Flexible Working Models:** The disparity in the labour force participation rates of individuals with advanced education in different countries in Table 6 shows that flexible working models can be an effective solution in some regions. In particular, in countries with low participation rates, such as North Macedonia, a broader labour force base can be created by implementing teleworking, part-time employment or project-based work models.
- **Demographic Targeting:** The cross-country differences seen in Table 2, Table 4 and Table 6 emphasise the importance of strategies specific to demographic groups. For example, in countries with young populations (e.g. Moldova) internship programmes and apprenticeship systems can be strengthened for education and labour integration. In countries with a higher proportion of older population (e.g. Germany), reskilling and lifelong learning programmes can be implemented.
- **Sectoral Focus:** Differences between countries necessitate the development of sector-based strategies. For example, in agriculture-based economies such as Bosnia and Herzegovina, training programmes for modern agricultural techniques can be implemented. In countries with a high concentration of individuals with advanced education, such as Iceland, investments in high technology and innovative industries may be prioritised.

5.5. Other Strategic Implications

The differences in labour force participation rates by education level and their trends are clearly supported by the findings in Table 1 to Table 6. For instance, the decline in labour force participation rates at the basic education level between 2015 and 2023 (from 39.55% to 37.79%) and the relative reduction in inequalities suggest that tailored strategies should be developed to enhance the competencies of this group. The persistence of disparities in participation rates at the secondary and advanced education levels and the confirmation of inequalities across countries by the data in Table 6 require human resources management to adapt its global strategies based on these data.

In the light of these findings, the following strategic implications can be made in terms of human resources management:

- **Competitive Advantage and Sectoral Concentration:** The data in Table 6 show that labour force participation rates of individuals with higher levels of education are high in countries such as Iceland (89.03%) and Germany (87.29%). These findings encourage global companies to invest in high-skill sectors in such regions. On the other hand, countries with low participation rates, such as North Macedonia and Croatia, can be considered as labour markets that can offer cost advantages.
- **International Labour Mobility and Flexible Business Models:** As the cluster analysis in Table 8 shows, decreasing differences between countries enable global organisations to manage international labour mobility more efficiently. The trend of convergence across countries, along with the decline in Silhouette scores, requires the expansion of flexible work models and optimisation of location-based talent strategies.
- **Specialised Training and Development Programmes:** The low labour force participation rates of individuals with secondary and basic education underline the strategic importance of vocational development and skills enhancement programmes. Table 2 and Table 4 show that sectoral training programmes need to be implemented, especially in countries such as Croatia (18.46% basic level) and Bosnia and Herzegovina (57.19% intermediate level). These investments play a critical role in meeting the future talent needs of companies.
- **Skills Development for Digital Transformation:** The high labour force participation rates of individuals with advanced education (Table 5 and Table 6) indicate that this group can quickly adapt to digitalisation and automation processes. In particular, in countries such as Iceland and Germany, digital skills development programmes can contribute to the digital transformation of organisations.

6. Conclusion

This study, which examines labour force participation rates by education level, provides important outputs for human resources management and policy making. The study reveals that labour force dynamics change according to education levels and analysing this change together with cross-country differences generates new information.

First of all, the study examined the effects of educational attainment on labour force participation in a multidimensional manner and produced original findings on how these effects have transformed over time. The level of education is found to stabilize labour force participation, but this stability performs very differently across countries and regions. Thus, education policies should be appraised in a wider context.

The research also offers a new view via cluster analysis in which a convergence trend in labour dynamics among countries is empirically found. It implies that global companies and policy makers can take advantage of the narrowing of differences between countries as a strategic option. New knowledge about the global trading and speed mismatch leads to new means of optimising the international labour mobility, as well as new ways of designing flexible business models.

The other important outcome of the study is that concrete recommendations for enhancing competencies of these groups are needed as labour force participation rates at the basic and secondary education level are declining. Thus, it is in fact possible that training and skills development programmes not only increase the employability of individuals, but also contribute to reducing economic inequalities. This has led to a new evidence on how customised training and employment incentives can play an important role in terms of economic development, particularly in regions where participation rates are low.

The study points to the necessity of more integrated and flexible strategies in terms of human resources management. The analysis of education-based workforce dynamics shows that skills suitable for digitalisation and automation processes need to be developed and that organisations can gain competitive advantage if these processes are supported by inclusive policies.

The results of this study have contributed both to the academic literature and to applied human resource management and policy development processes, generating new insights on how education level-based labour force analyses can create strategic advantages. Future research can provide a deeper understanding of labour force dynamics by adapting these findings to wider geographical areas and different sectors.

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Appendices

Table 9: Countries' K1 indicator data

Country	2015	2016	2017	2018	2019	2020	2021	2022	2023
AUT	36.40	37.57	37.00	36.99	36.93	37.28	38.08	38.04	38.93
BEL	29.62	29.08	30.45	28.39	29.17	26.91	27.12	27.70	26.62
BIH	25.38	24.34	23.87	21.15	22.01	22.44	24.52	24.72	25.44
BGR	26.55	25.16	27.18	27.23	29.84	28.88	27.14	28.69	27.31
HRV	22.80	21.05	18.94	17.80	17.79	16.92	18.21	17.17	15.50
CYP	39.35	38.67	35.97	36.19	37.31	37.45	36.81	36.45	35.23
CZE	20.63	21.48	21.32	21.03	22.48	22.33	21.38	22.19	22.50
DNK	42.54	43.56	43.24	42.64	43.23	43.00	43.86	45.56	46.13
EST	40.70	42.58	44.76	46.01	42.29	40.78	34.31	36.93	37.74
FIN	28.11	26.27	27.82	28.53	27.69	27.37	28.64	30.93	33.65
FRA	30.81	30.23	30.15	29.41	28.48	27.62	28.28	28.45	28.72
DEU	38.04	38.61	39.61	39.90	40.90	41.41	42.49	45.10	45.87
GRC	34.27	33.31	32.25	31.16	28.76	26.87	27.99	28.29	27.90
HUN	26.29	27.49	28.20	28.52	28.64	28.40	30.13	30.46	32.87
ISL	73.40	74.48	71.59	70.77	68.86	66.26	60.06	63.22	63.83
IRL	33.15	33.06	31.20	30.57	30.96	28.68	30.49	29.80	31.37
ITA	34.54	34.93	35.09	34.92	34.59	33.00	32.61	32.91	32.60
LVA	38.20	38.12	37.85	37.63	39.10	38.86	26.85	30.08	31.28
LTU	16.50	15.60	16.49	17.77	18.64	19.43	21.01	21.67	23.89
LUX	43.58	39.42	36.62	38.64	39.47	40.44	40.47	39.52	40.14
MDA	69.10	68.26	66.16	65.08	66.20	67.53	69.98	69.10	66.80
NLD	45.88	45.07	44.60	44.67	44.93	43.11	47.55	47.79	49.55
MKD	37.99	34.91	33.45	33.32	33.61	31.66	29.85	28.16	30.18
NOR	51.14	51.18	50.67	49.49	50.70	49.85	54.64	49.99	50.05
POL	44.99	44.39	44.50	44.02	43.53	43.46	41.71	41.64	40.24
PRT	52.55	51.30	51.36	50.29	49.17	46.76	43.66	45.40	44.94
ROU	33.94	31.98	32.22	31.66	32.48	32.09	25.02	25.94	27.23
SRB	30.89	33.46	33.24	32.91	33.89	32.37	34.56	34.66	35.17
SVN	29.18	26.48	27.86	27.54	25.19	22.59	22.51	23.41	26.02
ESP	50.94	49.58	49.04	48.20	47.47	45.26	44.95	44.85	45.19
SWE	47.31	47.12	48.20	49.26	49.83	48.79	43.28	44.77	45.72
CHE	51.44	51.14	50.39	51.91	51.61	50.83	51.03	51.47	52.15
TUR	49.65	50.14	50.64	51.09	50.15	45.63	47.33	48.01	47.30
GBR	68.75	68.48	68.72	68.78	68.61	67.18	65.58	58.13	56.94

Data show the labour force participation rate of individuals at the relevant education level.

Table 10: Countries' K2 indicator data

Country	2015	2016	2017	2018	2019	2020	2021	2022	2023
AUT	63.72	63.78	63.50	63.87	63.42	62.05	62.00	63.81	63.37
BEL	60.40	59.31	58.54	60.28	59.62	57.48	56.72	57.42	56.71
BIH	57.27	55.20	54.58	54.18	53.34	57.62	60.52	60.67	61.31
BGR	60.98	59.42	61.95	61.11	61.98	60.83	59.15	60.65	58.55
HRV	61.99	60.65	61.18	59.99	59.44	59.03	59.32	59.34	58.33
CYP	68.11	65.56	67.34	67.94	67.31	65.42	66.85	68.02	67.66
CZE	63.31	63.55	63.57	63.89	63.59	62.80	62.37	62.24	62.83
DNK	66.57	65.88	65.66	66.19	66.40	65.51	65.27	66.16	65.89
EST	73.22	74.06	74.60	75.10	74.73	74.83	67.06	69.34	70.26
FIN	67.16	66.51	66.34	65.73	66.12	64.48	65.22	66.77	65.27
FRA	62.35	61.85	61.03	60.47	59.14	57.11	59.16	59.30	58.87
DEU	64.05	65.02	64.75	64.57	64.99	63.01	63.05	63.20	63.30
GRC	60.28	60.40	60.46	59.94	59.71	58.40	58.20	59.67	59.74
HUN	63.55	63.88	64.14	63.94	64.12	63.48	64.85	65.08	64.70
ISL	84.74	84.52	84.73	83.29	82.27	80.08	71.76	71.84	73.08

IRL	66.76	67.63	66.54	67.44	67.35	64.15	65.80	66.44	68.19
ITA	64.18	64.38	63.93	63.55	63.18	61.18	61.72	62.30	62.34
LVA	68.54	68.55	69.64	70.26	67.97	70.60	60.39	61.72	61.47
LTU	62.96	62.90	62.24	62.23	61.35	61.48	60.32	60.14	59.88
LUX	60.32	62.95	60.80	60.44	59.15	58.47	57.40	56.25	57.36
MDA	71.23	71.18	70.09	68.51	71.41	71.39	75.19	75.23	73.32
NLD	69.71	69.08	69.04	69.33	69.47	68.77	70.78	71.39	72.02
MKD	67.57	67.34	66.59	66.08	66.05	64.45	64.43	62.78	58.64
NOR	71.34	70.01	69.44	70.16	69.65	69.24	68.96	62.50	62.00
POL	58.93	59.55	59.17	58.42	57.94	57.39	59.81	60.11	59.42
PRT	74.69	74.69	75.05	74.94	75.36	72.40	71.91	73.96	74.94
ROU	63.68	62.63	63.82	63.83	62.57	61.69	57.06	56.95	56.61
SRB	59.33	60.32	60.73	61.21	60.72	60.14	62.44	62.93	63.58
SVN	60.29	59.12	60.44	61.29	60.08	58.79	57.85	58.65	60.83
ESP	68.51	68.73	66.61	65.80	66.13	62.62	63.10	63.88	62.98
SWE	76.97	76.38	77.03	76.54	76.66	76.97	69.25	67.97	68.66
CHE	67.07	67.35	66.88	66.46	66.03	65.56	66.09	65.74	65.75
TUR	59.07	59.63	60.04	60.30	59.24	55.03	57.29	60.21	60.87
GBR	76.50	76.29	76.86	76.78	76.79	76.73	75.38	72.09	71.78

Data show the labour force participation rate of individuals at the relevant education level.

Table 11: Countries' K3 indicator data

Country	2015	2016	2017	2018	2019	2020	2021	2022	2023
AUT	76.79	76.75	77.23	76.64	76.61	76.77	76.77	79.95	79.74
BEL	75.02	75.05	75.72	74.82	75.14	75.47	75.31	75.99	75.91
BIH	78.96	78.92	77.48	76.56	74.60	79.67	80.05	80.30	81.29
BGR	73.38	74.63	74.30	74.08	76.49	74.66	76.23	76.72	75.87
HRV	73.16	71.68	72.48	72.24	72.06	71.66	71.11	72.71	73.19
CYP	83.91	81.93	81.77	81.87	82.88	82.44	82.44	82.88	83.54
CZE	75.63	75.68	76.21	76.96	76.24	75.51	76.01	76.96	77.85
DNK	77.21	76.80	76.90	76.83	77.20	76.95	76.81	77.13	77.81
EST	81.22	81.15	81.99	81.65	82.14	81.85	76.64	77.46	78.16
FIN	75.09	74.37	73.91	74.80	73.75	74.07	75.60	74.04	73.94
FRA	77.52	77.29	76.60	76.55	76.64	75.65	77.38	77.27	77.22
DEU	73.63	74.03	74.07	73.74	74.37	72.69	72.98	73.25	72.90
GRC	76.01	75.89	75.60	75.78	75.71	74.39	73.75	74.64	74.57
HUN	72.85	73.61	73.07	73.23	73.09	71.79	76.80	77.76	77.73
ISL	91.71	91.75	91.33	90.21	90.17	88.07	85.96	86.69	85.37
IRL	80.93	80.82	81.11	81.31	81.15	80.61	81.97	83.13	82.72
ITA	74.51	75.08	75.07	74.91	74.76	73.66	75.37	75.55	75.92
LVA	83.22	84.25	84.54	84.61	86.55	83.04	77.64	76.79	77.40
LTU	82.44	83.37	82.85	83.09	83.34	82.78	81.39	81.28	81.36
LUX	79.60	79.41	81.07	79.50	79.61	79.44	80.17	79.31	79.82
MDA	73.74	73.66	71.21	71.63	74.85	73.14	74.26	75.72	74.49
NLD	79.58	79.22	79.11	79.44	78.97	78.97	79.38	80.32	80.56
MKD	80.49	81.34	81.50	81.38	81.07	81.03	80.27	80.34	68.50
NOR	84.61	84.52	83.28	83.35	83.80	83.58	82.98	81.29	80.38
POL	80.89	80.93	80.60	80.83	80.73	80.32	81.58	81.50	81.55
PRT	82.35	82.95	82.30	83.43	83.76	82.47	83.00	83.21	83.59
ROU	81.95	81.67	82.74	82.62	82.56	82.15	81.84	82.95	82.14
SRB	69.62	70.29	71.95	72.49	71.75	70.36	73.03	74.30	75.04
SVN	77.06	78.12	79.90	80.06	80.46	80.17	79.31	79.31	80.17
ESP	80.91	81.11	79.89	80.12	79.41	78.71	78.51	78.59	79.09
SWE	83.39	83.54	83.58	83.57	83.94	83.53	77.92	78.57	77.83
CHE	80.57	80.99	81.04	81.36	81.69	81.27	80.85	79.77	80.44
TUR	79.60	79.55	80.04	79.32	79.19	74.91	76.55	77.42	77.58
GBR	84.23	84.12	84.02	84.29	84.57	85.34	85.45	86.63	87.29

Data show the labour force participation rate of individuals at the relevant education level.