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Chapter: Social and Human-Centered Dimensions of Sustainable Development

STRATEGIC LEADERSHIP AND EMPLOYMENT DYNAMICS IN EUROPEAN COUNTRIES INDUSTRIES: FORECASTING LABOUR FORCE EXPECTATIONS THROUGH SPACE-TIME ANALYSIS

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Annotation. This paper analyses the evolution of employment expectations in industry (BS-IEME-BAL) for the period 1992–2025, using data from the Business and Consumer Surveys (BCS) provided by the Directorate-General for Economic and Financial Affairs (DG ECFIN) of the European Commission. The study examines cyclical fluctuations, long-term trends and the impact of macroeconomic factors on the industrial labour market. To identify recurring patterns and anticipate future changes in employment, the analysis uses spatiotemporal forecasting in GIS, applying the Exponential Smoothing Forecast (Holt-Winters) model. This model allows the decomposition of the time series into trend, seasonality and residual components, providing a robust estimate of the evolution of employment expectations. Anomalies and turning points are also assessed, contributing to the understanding of the vulnerabilities of the industrial sector in times of economic uncertainty. The results obtained provide support for strategic leadership performed by formulating public policies and strategies for adapting to the digital transition, economic fluctuations and labour market challenges. The study highlights the usefulness of spatial analysis and temporal forecasting tools for data-based decision-making in the context of structural transformations of the economy.

Keywords: strategic leadership; employment; space-time forecasting; industry; public policies.

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JEL classification: C53, E24, J21, J23, J24.

Introduction

The past three decades brought European industries through the most extensive structural change in their history. Accelerated by technological innovation, globalisation, digitalisation, and geopolitical uncertainty, industrial employment dynamics have become increasingly complex and volatile (Autor, 2015; European Commission, 2023). Within this evolving landscape, strategic leadership, defined as the capacity to navigate long-term changes while adapting to short-term shocks, has emerged as a crucial factor for managing labour market transitions, sustaining competitiveness, and ensuring inclusive economic growth (Boal and Hooijberg, 2000; Samimi *et al.,* 2022). Labour policy and industrial strategy require a deep knowledge of employment predictions to develop public policies that match market trends along with socio-economic targets.

This research investigates the modifications in European industrial job expectations through Business and Consumer Surveys (BCS) data from 1992 to 2025 maintained by the Directorate-General for Economic and Financial Affairs (DG ECFIN). The methodology stands out by merging strategic leadership theory alongside spatial and temporal econometric forecasting with a Holt-Winters exponential smoothing model that runs within Geographic Information System software. The approach provides strategic foresight for policymaker's industry leaders and researchers by combining these methods to detect spatiotemporal trends and anomalies.

Public governance along with industrial policy strategies under strategic leadership control the direction taken by labour markets. The concept of strategic leadership goes beyond operational and transactional leadership through its emphasis on environmental adaptations achieved by long-term visioning and system analysis capabilities and adaptability to intricate environmental changes (Ireland and Hitt, 2005; Nassani *et al.,* 2024). European institutions use strategic leadership to create unified policies for labour mobility that work alongside innovation and resilience across different labour market regulatory contexts (Broecke, 2023).

Recent studies have shown that countries with proactive strategic leadership, characterised by anticipatory policymaking, public-private collaboration, and workforce investment, are better equipped to mitigate job displacement caused by automation, climate policy, and global competition (Griggs *et al.,* 2013; Pitelis and Wagner, 2019). Strategic leadership supports industrial restructuring by positioning labour force strategies to meet the European Green Deal and digital transition and regional cohesion targets (European Commission, 2020). Predicting employment patterns becomes complex because cyclic fluctuations meet unbalanced regional business sector recovery patterns.

Employment expectations determine both the sentiment within labour markets and the overall economic confidence. The BS-IEME-BAL series generated by the BCS gives European industries sustained access to employment projections information. Enterprises apply these expectations to control their workforce selection processes and future investment decisions and wage negotiations. Research on evolving employee expectations across time and space enables researchers to identify strategic decision-making behaviours of industrial organisations.

The employment patterns within the European Union have transformed under diverse impacts which included both intermittent disturbances (e.g. financial crisis in 2008, COVID-19 pandemic impact) and enduring system changes (e.g. industrial decline alongside changes in the energy sector) and workforce border migration. These dynamics are unevenly distributed across member states, reflecting different levels of productivity, innovation capacity, and institutional coordination (Bogliacino and Vivarelli, 2012; Grigsby, 2022). Strategic planning development depends on spatial segmentation as well as sectoral categorisation in labour market analysis to demonstrate market changes.

The need to predict future labour market trends has increased and become complex as we face an uncertain and disruptive period. Traditional macroeconomic models lack capability for modeling employment shifts because they fail to represent the dynamic processes in addition to non-linear and localised employment changes. To address this, the present study adopts the Holt-Winters exponential smoothing model, a time-series forecasting technique that decomposes historical data into trend, seasonal, and irregular components (Holt, 1957; Winters, 1960). The model reveals turning points together with anomalies, thus providing deeper insights into labour market actions.

Spatial analysis within forecasting helps to reveal how job opportunities differ across regions, simultaneously pointing out fast-growing employment clusters. The spatiotemporal analysis through GIS technology assists policy makers in identifying critical intervention areas and potential industrial transition zones affecting local resilience or vulnerability (Kudełko *et al.,* 2022; Lincaru *et al.,* 2024). By merging data on time and space, researchers today create what experts name as “strategic labour intelligence” which helps authorities design future-oriented workforce management (ILO, 2022).

The research adds value to scholarly works alongside policy implementation approaches. This study develops new connections between strategic leadership theory and labour economics through effective employment forecasting that supports organisational decisions. This study applies an innovative forecasting approach with Holt-Winters models inside Geographic Information Systems to analyse the underutilised BS-IEME-BAL dataset across temporal and spatial dimensions. The study employs empirical research to showcase employment expectation trends in European industry from 1990 to 2025 and beyond.

The outcomes of this research produce significant beneficial effects for industrial and labour market approaches while focusing on EU digital and green transition efforts. The evaluation of employment prediction patterns through this study allows policymakers together with industry leaders to create workforce development plans according to the economic requirements of the future. The analysis works to prevent harmful consequences that arise from imbalances between different regions and social inequality.

The paper is divided into the following sections. Section 1 conducts a review of research examining employment dynamics along with strategic leadership functions and forecasting method applications. Section 2 details data presentation along with the approach to build the Holt-Winters model followed by GIS application description. Section 3 contains results from spatiotemporal forecasting with detailed descriptions of significant anomalies and trends. Section 4 analyses implications toward strategic leadership and policy development and presents a summary of results along with proposed directions for future research.

1. Problem Statement

1.1 Strategic Leadership in Industry and Its Employment Implications

Organisation direction alongside flexible adaptability and future business sustainability depends significantly on proficient strategic leadership. The strategic leadership decision-making process creates impacts on firm performance alongside labour practices together with job quality and innovation capacity and workforce sustainability in industrial environments. The research traces current strategic leadership scholarship and evaluates industrial employment patterns in Europe to build foundation for future study.

A leader who displays strategic leadership navigates their organisation members toward decisions that enhance business longevity, as according to Boal and Hooijberg (2000) and Samimi *et al.* (2022). As a leadership style, this method requires leaders to develop visions accompanied by environmental assessment skills and elastic adaptability to changes. Industrial environments experience ongoing strategic leadership tests because of technological speed and both domestic workforce upheaval and international business competition.

According to Norzailan *et al.* (2016) along with Vera and Crossan (2004), the management at strategic levels needs to demonstrate three distinct competencies to establish a connection between the development of employment structures and the competencies identified by these authors. Companies need to integrate three core competencies which include innovation management combined with knowledge sharing and human capital empowerment (Vera and Crossan, 2004). These competencies guide officials in maintaining staff levels and workforce engagement and employment creation.

Research has built up evidence demonstrating how strategic leadership improves firm performance, while employee outcomes, such as engagement satisfaction and performance, act as mediators (Ambilichu *et al.,* 2023; Zia-ud-Din *et al.,* 2017). Ambilichu *et al.* (2023) studied small and medium-sized enterprises to reveal that strategic leadership promotes ambidextrous organisations through exploration and exploitation abilities that enhance employment innovation with improved job sustainability.

Research findings reveal that strategic leadership styles improve employee creativity and adaptability (Atiyeh, 2022; Krishnan *et al.,* 2019). Strategic leadership accelerates essential outcomes that support organisations operating in dynamic industrial landscapes through their adaptive workforce management policies and resilient staff capabilities.

Discoveries about strategic leadership as an innovation driver, particularly regarding workforce innovation, appear in numerous academic publications. Leaders who encourage their teams to participate in decision-making while promoting ongoing learning create environments supporting the development of skills and flexible adaptability (Pitelis and Wagner, 2019; Mahdi and Nassar, 2021). Managers in European industries facing digital transitions play a direct role in the training efforts aimed at adapting their current personnel.

Transcendent leadership introduced by Crossan, Vera, and Nanjad (2008) combines strategic leadership with learning dynamics to empower employees who adapt the organisation. These leadership methods serve essential functions for innovation and represent fundamental requirements for preserving employment security during prolonged periods.

Strategic leadership in uncertain industrial settings needs to address macroeconomic changes along with supply chain instabilities and workforce market dynamics. Research by Adobor, Darbi, and Damoah (2021) shows that strategic leaders play a critical role in steering “swan events” thatcause abrupt employment dynamic changes.

Strategic leaders serve a central role in sustaining employee morale together with workforce continuity during organisational crises, as stressed by Schaedler, Graf-Vlachy, and König (2022). The flexible nature of leadership enables organisations to keep employment steady through strategic transformation without disrupting workforce unity.

The relationship between strategic leadership and employment becomes more specific through sector-based analytical research. Abrudan *et al.* (2022) conducted research in the agribusiness sector and revealed that strategic leadership acts as a vital mediator between supply chain risks and environmental unpredictability to help stabilise employment conditions directly. The strategic leadership style in professional services sectors shaped organisational design alongside role definition, which directly affected employment quality (Ambilichu *et al.,* 2023).

Strategic leadership frameworks bring value to industries ranging from the public sector to non-profit organisations. Andrews (2023) identified leadership in value-driven organisations that prioritises change management as a factor which leads to better job satisfaction and decreased turnover rates. The study demonstrates how strategic leadership orientation affects employment stability together with its market appeal within various sectors.

Organisational culture, innovation capacity and knowledge management systems act as mediators through which strategic leadership impacts employment conditions. Research demonstrates that supportive cultures improve the effectiveness of strategic leadership and promote the connection between human resources and strategic objectives (Alateeg and Alhammadi, 2024; Kahwaji *et al.,* 2020).

Organisations need to manage operational requirements together with long-term innovative initiatives to achieve ambidexterity successfully. Organisations utilising strategic leadership as an ambidexterity enhancement tool discover improved workforce development results together with enhanced employee engagement (Ambilichu *et al.,* 2023).

Studies conducted throughout the world deliver insights that apply directly to European business circumstances. European labour markets rely heavily on digital transformation alongside sustainable development and workforce regulatory changes. The strategic leadership system needs to navigate rules and regulations as well as handle employee mobility across borders while managing social tensions.

According to Singh *et al.* (2023), strategic leadership requires a holistic interpretation which demonstrates its interaction with national economic and employment policy frameworks. The analysis of employment dynamics across time and space demands mindful leadership which shapes workforce structures in addition to creating regional and industrial employment variations. Fernandes *et al.* (2022) strengthens the argument for an integrated research design through bibliometric modeling that captures the complex effects of strategic leadership on organisations. The research shows leadership functions on two levels: advancing as an internal firm capacity and shaping systemic industrial and employment modifications.

The existing literature demonstrates extensive evidence of strategic leadership generating positive employment effects; yet, ongoing gaps exist within this field. Accurate studies about strategic leadership at the industry level and macroeconomic employment data system remain scarce in current research. The analysis of strategic leadership effects on employment changes during two crucial European policymaking concerns involving digital transformation and industrial shifts due to climate change remains underdeveloped.

Research needs to continue using longitudinal methods, as they offer essential insight into the impact of strategic leadership on employment patterns in various economic stages and technological developments. A space-time framework needs both temporal analysis and depth study of individual sectors due to its fundamentality for effective space-time frameworks.

Strategic leadership proves essential in defining contemporary industrial employment patterns. Such leaders achieve workforce development goals by setting visions along with enhancing adaptability and developing human capital thus directing the organisational talent acquisition, maintenance, and advancement. European countries undergoing technological changes and sustainability challenges should understand how employment system leadership functions for successful navigation. The existing literature serves as a base to explore space-time employment patterns by connecting strategic leadership practices to economic and social effects.

1.2 Employment Dynamics in Industry with Emphasis on European Contexts

The dynamic nature of industrial employment stems from changing relationships among labour markets and technological change along with economic structures and institutional policies. A complete understanding of these dynamics serves as the foundation for studying labour demand shifts as well as new work patterns and job geographical distribution. Theories of creative destruction and technological displacement and structural transformation define conceptual frameworks for understanding employment changes. According to Van Reenen (1997), in UK manufacturing, innovative processes perform a dual function between job creation and destruction, which remains consistent in modern advanced economies. Research shows innovation produces long-run employment expansion even though it causes immediate work interruptions (Bogliacino and Pianta, 2010; Kunapatarawong and Martínez-Ros, 2016).

Aaronson *et al.* (2018) developed a “putty-clay” framework that demonstrates the relationship between wage policies and labour costs and capital intensity and firm dynamics. The researchers determined that minimum wage adjustments modify the capital-labour ratio while causing specific changes to employment within selected sectors. Acs and Mueller (2008) demonstrated the significance of “gazelle” high-growth businesses together with state-of-the-art business demography in creating employment variations.

The COVID-19 crisis demonstrated how employment systems remain vulnerable and adjustable worldwide. Analysis by Sobieralski (2020) revealed that airline employment patterns track historical economic volatility requiring nimble labour policy frameworks for unstable industries. The pandemic period has also influenced the unemployment inequalities (Cojocaru *et al.,* 2025) and health systems of various countries worldwide, facing difficulties for achieving sustainable development, with impact on employment policy as well (Copcă *et al.,* 2024).

A combination of industrial structures, regulatory environments and technological readiness creates distinctive patterns in European labour markets. Cörvers and Dupuy (2010) developed employment models which tracked European sector employment changes alongside occupational movement and sector transformation. The research reveals that employment results prove highly responsive to unique characteristics inherent to different industries, including innovation level, skill demands and globalisation penetration.

Technological interdependencies are particularly influential. Cresti, Dosi, and Fagiolo (2023) explored the relationship between technological exchanges across different sectors and their impact on European industry employment. Employment growth in sectors linked through dense innovation networks becomes stronger because knowledge transfers and improved adaptive capabilities emerge as key factors in this process.

Digitalisation is another key factor. Gallipoli and Makridis (2022) found employment shock recovery speeds to be higher among digital production-intensive industries, especially in the post-COVID period. Digital systems enable remote operations, while automation and adaptable work organisation principles contribute to business resilience.

The employment patterns of Europe display geographical differences across regions, according to research studies. Based on Kudełko *et al.* (2022), Poland’s regional smart specialisations show how employment structures move towards knowledge-intensive services, yet present variations because of distinct regional capabilities and industrial policies.

The impact of innovation on employment dynamics remains complex. Research shows that automation fears about job loss often present complex results in real-world situations. Jestl (2024) studied how industrial robots and ICT impact EU labour markets by showing routine jobs decrease while skilled labour demand increases. The research of Grigsby (2022) supports the notion that diverse skill levels act as a fundamental determinant of total employment patterns.

Mossig (2011) demonstrated that German cultural and creative industries show regional employment expansion because of creative clusters and urban agglomeration. Research results support the experience economy and knowledge-intensive employment theories outlined in Smidt-Jensen *et al.* (2009).

The shift toward green economies alongside environmental innovation directly affects employment patterns in industries. Kunapatarawong and Martínez-Ros (2016) established that green innovation does not automatically result in employment reductions. The employment growth in new emerging sectors becomes possible through policy incentives that support such initiatives. Costantini, Crespi, and Paglialunga (2018) presented that public and private energy efficiency policies in European industries create positive employment impacts.

Artificial intelligence (AI) and Industry 4.0 technologies continue to transform employment patterns in ways that cannot be easily predicted (Lazzeretti *et al.,* 2023). Lazzeretti *et al.* (2023) examined AI and big data adoption by firms and clusters while analysing their effects on job structures and required competencies. According to Zhang (2023), AI has caused both job elimination and substantial sectoral reshaping which manifests most strongly in digital-intensive fields.

Shen and Zhang (2024) developed the concept of “virtual agglomeration” to describe employment hubs formed by AI-driven industries that can exist outside traditional geographical boundaries. The evolution demands new employment geography frameworks to replace traditional regional development models.

O’Clery and Kinsella (2022) demonstrated that labour networks create “skill basins” which attract digital jobs to clustered competency areas. The data indicates industrial employment now depends on skill-based networks instead of fixed geographical boundaries.

The way institutions operate creates specific influences on employment patterns. Durand and Miroudot (2015) revealed how financial globalisation leads capital mobility and shareholder value orientation to replace workers in vulnerable sectors. The research identified that labour regulations together with institutional protections can minimise these effects across numerous countries.

Forde (2023) applied historical case study research to demonstrate how UK temporary employment agency policies drove industrial labour structures over extended time periods with implications for the state’s impact on workplace development. In research by Zalmanov (2024), shift-share analysis illustrated the dependency of regional employment patterns on local policies working together with economic structures.

European governance structures require integrated industrial and workforce policies which ensure the support of employee development by technological progress. Core regions exhibit substantial differences in workforce conditions when compared with peripheral regions. Gravina and Pappalardo (2022) explored how technological progress in affluent nations poses potential employment challenges for developing economies thus affecting their value chains. The researchers have presented evidence about technological divergence risks despite questioning direct links between these elements.

Kordić and Milićević (2020) demonstrated the role of human capital in developing tourism employment in Serbia. Mölk *et al.* (2022) examined employment perception shifts using multilevel narratives across sectors with volatile conditions such as hospitality, whereas Ruiz *et al.* (2014) created an index of human development. Research findings indicate that workplace resilience stems from both national sector plans and community storytelling alongside vocational competencies and town identity.

Job markets within the industry experience transformation through interconnected driving factors. Designs based on innovation and technology combine with regional sector expertise and labour regulations to adapt to global economic fluctuations. Digital and green transitions present fresh employment prospects together with potential risks that create inequality and workforce disruption. The numerous industrial systems and policy regimes across Europe generate different employment effects, which demand both space-time analysis and valuable insights. Future research should combine global developments with localised specifics to better understand how labour evolves in industrial sectors while also creating solutions for building employment systems that are inclusive and resistant to change.

1.3 Forecasting Methods for Employment Dynamics, with Emphasis on European Contexts

When modeling employment forecasting, scientists face challenges because they need to examine economic systems together with technological advancements, demographic patterns and institutional changes. Different quantitative to qualitative research methods produce labour market predictions by using econometric models, machine learning tools, and shift-share analysis alongside scenario-based predictive models. Employment dynamics forecasting remains crucial across Europe to support regional planification and workforce movement and Europe's digital transformation and sustainability changes.

Employment forecasting used mainly three types of econometric models including autoregressive integrated moving average (ARIMA) and vector autoregression (VAR) along with dynamic panel data models. The approaches calculate employment levels by considering factors such as GDP, labour costs, productivity, sectoral output and investment. Dutta Roy (2004) utilised structural econometric modeling to study Indian industrial employment lag durations while illustrating how institutions restrict labour fluidity.

Shift-share analysis remains a widely adopted traditional method that divides employment shifts across three main sectors including national average, industrial composition and local competition levels. Zalmanov (2024) implemented this method for studying city and regional employment relationships, which constructed a useful framework to analyse labour movements as economies transform.

CGE and I-O models have come into use during recent years for examining employment effects in environmental and innovation-related policy scenarios. Costantini *et al.* (2018) demonstrated the employment effects of European industries from energy efficient policy changes through I-O modeling of the value chain within individual sectors.

European employment forecasting takes place through the policy structures of both European Centre for the Development of Vocational Training (CEDEFOP) and European Commission's Joint Research Centre (JRC). The institutions apply comprehensive macro-sectoral models (e.g. E3ME, QUEST) to generate predictions related to employment sectors together with occupations and skill requirements.

Cörvers and Dupuy (2010) demonstrated how structural decomposition models which integrate sectoral employment statistics alongside occupational trend patterns enhance forecasting productivity. By incorporating technological change and demographic elements into their model, this research produced predicted outcomes that delivered higher accuracy, particularly when studying the relationship between education systems and changing labour market requirements in specific regions.

Forecasts about employment change now rely more on scenario analysis and foresight exercises to handle unexpected events. The research methods integrate predictions based on expert knowledge and calculated forecast trends with consultations from stakeholders to develop multiple future scenarios. The effects of automation and climate policy on European labour markets were anticipated through these methods (Jestl, 2024; Cresti *et al.,* 2023).

Big data and machine learning methods continue to increase in popularity among researchers. AI models evaluated in Zhang (2023) and Shen and Zhang (2024) examine their ability to process big labour data for pattern recognition and employment forecast predictions within digital economy settings. The speed and flexibility of these methods match well with traditional models, so they enhance their capabilities rather than fully replace them.

Despite methodological advances, some challenges still remain. Current forecasting models fail to detect quick major changes in economic structures, which arise from natural disasters and sudden technological changes. The spatial dynamics of the forecasted data face simplification from models which do not reflect regional labour market heterogeneity properly, which is a crucial weakness for European applications that present high intra-EU variations.

O'Clery and Kinsella (2022) present network analysis and modular labour market integration through their skill basin framework that locates labour capability clusters. Researchers develop these modeling approaches to achieve better precision in spatial forecasts.

Future research should merge methodologies between econometric modeling, scenario planning, and machine learning to boost predictive accuracy without compromising interpretability. Forecasts of employment require models to connect with education and migration policies as well as innovation policy to enable managers to plan for the workforce holistically.

2. Research Questions and Methods

The present study aims to analyse the employment in industrial sector and to identify trends, fluctuations, seasonality and resilience, and the relationship with the strategic leadership. Considering the twin transitions with intense implications and effects on labour market, the study addresses the following research questions (RQs):

RQ1: Could a space-time analysis and forecast offer consistent insights for policy makers about the employment dynamics and strategic leadership?

RQ2: Is Exponential Smoothing Forecast (Holt-Winters) model appropriate for exploring the labour market expectations?

The study applied Exponential Smoothing Forecast (Holt-Winters) model to consider the dataset of labour force in industry (BS-IEME-BAL) for the period of 1992–2025, as suggested by the Directorate-General for Economic and Financial Affairs (DG ECFIN) of European Comision. The data are collected through Business and Consumer Surveys (BCS) for European countries. Unfortunately, countries do not provide data systematically, so the study covers 13 countries: Belgium, Bulgaria, Denmark, Finland, France, Greece, Italy, Luxembourg, Netherlands, Portugal, Romania, Spain, and Sweden. These countries were selected based on data availability and series continuity for the BS-IEME-BAL indicator from 1992 to 2025.

The Exponential Smoothing Forecast (Holt-Winters) model, as applied in ArcGIS, is a robust time-series forecasting method used to model and predict future values based on historical data. This method is particularly effective for data exhibiting both trend and seasonal components, making it suitable for economic, environmental, and demographic analyses.

ArcGIS implements the additive form of the Holt-Winters model, which is appropriate when seasonal variations are relatively constant over time. The model decomposes a time series into three main components:

- Level – the base value of the series;
- Trend – the direction and rate of change over time;
- Seasonality – the repeated cyclical patterns within the data.

The model works by applying exponentially decreasing weights to past observations, giving more importance to recent data while not discarding older data completely. Three smoothing parameters: alpha (level), beta (trend), and gamma (seasonality), are optimised automatically in ArcGIS to minimise forecast errors.

Mathematically, the additive Holt-Winters model consists of the following equations:

- Level:
  $L_t = \alpha (Y_t - S_{t-p}) + (1 - \alpha) (L_{t-1} + T_{t-1})$
- Trend:

$T_t = \beta (L_t - L_{t-1}) + (1-\beta) T_{t-1}$

- Seasonality:

$S_t = \gamma (Y_t - L_t) + (1-\gamma) S_{t-p}$

- Forecast:
  $Y_{t+h} = L_t + hT_t + S_{t+h-p}$

Where:

- Y_t is the observed value at time t;
- L_t is the level;
- T_t is the trend;
- S_t is the seasonal component;
- p is the season length;
- h is the forecast horizon.

ArcGIS's Space Time Pattern Mining toolbox supports Holt-Winters forecasting by analysing spatiotemporal cubes, 3D data structures that represent location, time, and observed value. The tool detects trends, estimates future values, and identifies anomalies or turning points, simultaneously providing insights into spatial patterns and temporal dynamics. By integrating Holt-Winters smoothing with GIS, ArcGIS enables analysts to perform not only accurate forecasting but also map-based visualisation of predicted changes, enhancing spatial decision-making in fields like labour market analysis, environmental monitoring, and infrastructure planning.

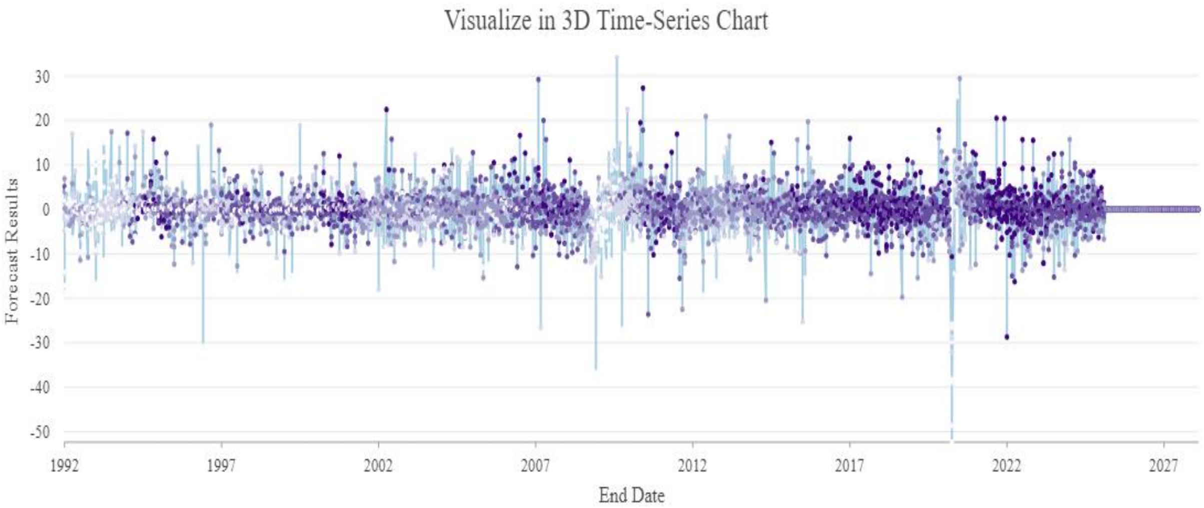
The indicators used to evaluate the employment expectations are Renewable Energy Adoption (%) as green energy share by region and Green Leadership Index as leadership commitment to sustainability initiatives by region. The Employment Expectations Indicator (EEI) is a monthly composite indicator which summarises managers' employment plans in four surveyed business sectors (industry, services, retail trade, and construction) and thus provides a timely indication of expected changes in dependent employment. The present study considered the industry values for EEI for 13 countries from 1992 to 2025.

Detailed methodological information about the BCS surveys and indicators is provided in a user guide to the *Joint Harmonised EU Programme of Business and Consumer* (European Commission, 2025).

3. Model and Results

3.1 Model Forecast Results

The cube-time for Employment Expectation Index for 13 locations from 1992 to 2025 was built. The forecast results are presented in *Figure 1*.



Source: authors' research results.

Figure 1. **The Forecast Results of Employment Expectations (BS-IEME-BAL), 1992–2025**

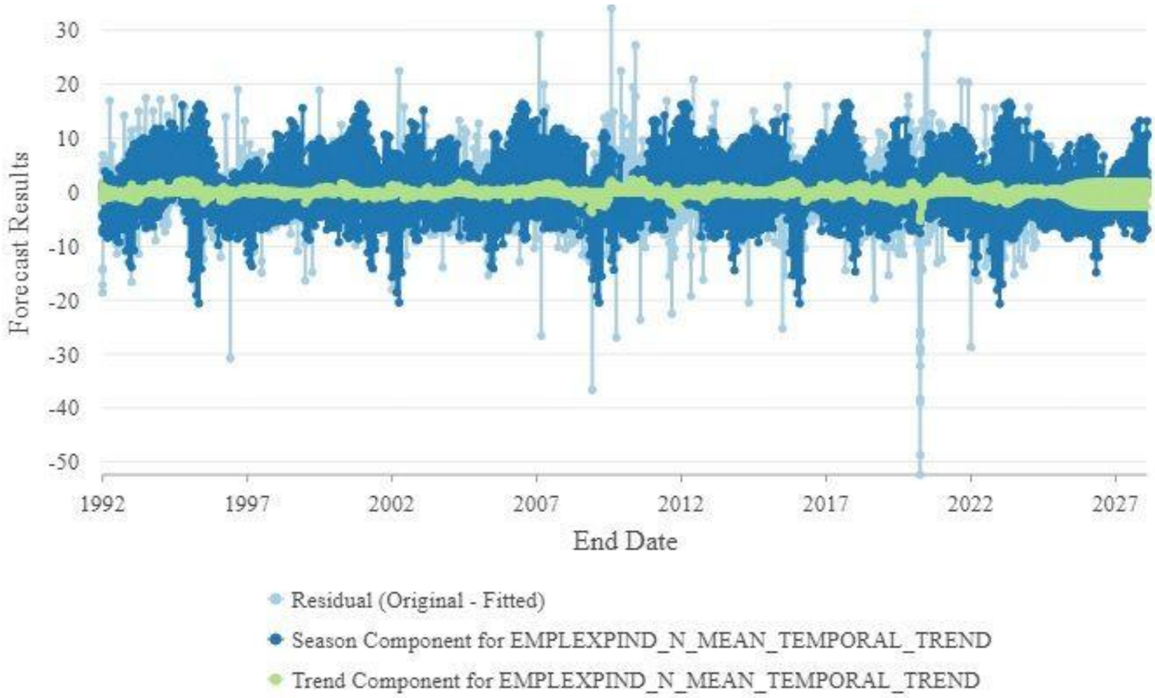
The predicted values are between -50 to +30, illustrated by dark purple points. For the entire studied period of time, they are placed below and above "zero" value. The light blue bars reflect the ranges of variation, uncertainty, or prediction errors.

The forecast indicates that the employment expectations series shows general stability around the zero axis, most of the predicted values are in the range -10 / +10. After 2000, the dispersion becomes tighter around the zero axis, highlighting that the model is more stable. The results signal that the modelled phenomenon does not have a long-term increasing or decreasing trend but oscillates around the average. Significant negative and positive spikes appear in 2007–2009 and 2020–2022 (i.e. sudden decreases below -30). The time of the spikes appearance directly corresponds with the global financial crisis and the COVID-19 pandemic. The model captures the impact of major external shocks on the analysed phenomenon. The bars of uncertainty increased around and during crises periods. After 2022, uncertainty seems to progressively decrease in forecasts.

Based on the forecast results we can appreciate that the time series is largely stable, with moderate variations outside crisis periods. External shocks are clearly visible in 2008 and 2020–2022, with sharp decreases. The model provides a conservative long-term forecast, returning to the mean aftershocks, providing information about the resilience of the system. Uncertainty decreases in future forecasts, suggesting a possible stabilisation of the phenomenon analysed.

3.2 Time Series Decomposition Model

The analysis of the time series on three components: residuals, seasonal, and trend, for the studied variable employment expectations is presented in *Figure 2*.



Source: authors' research results.

Figure 2. **Time Series Decomposition: Trend, Seasonal, and Residual Components**

The time series decomposition model was applied to the EMPLEXPIND_N_MEAN_TEMPORAL_TREND variable to identify the components behaviour.

Trend component (light green in the graph)

The general trend of the phenomenon is stable, with minor variations over time. A slight decrease is observed in the 1990s, followed by a long period of stabilisation after 2000. The lack of sudden fluctuations or significant changes in the trend indicates that the underlying dynamics of the modelled phenomenon have not undergone major long-term transformations. The model correctly captures the general direction of the phenomenon, which indicates a good adjustment of the trend component.

In the graph, the light green line is almost flat, with minimal variations. This postulates that, in the long term, the phenomenon has a stable trend, without major changes. The model says that there is no clear increase or decrease over time, so the phenomenon is “around a constant”.

Seasonal component (dark blue in the graph)

The seasonal component exhibits visible variations but maintains a regular behaviour around the zero axis. The range of variation observed in the graph is approximately -20 to +20 units. This amplitude indicates that seasonality has a visible, but controllable effect on the modelled phenomenon. It can be appreciated that there is a moderate seasonal effect, which suggests that during a period of the year or observation cycle, the phenomenon experiences predictable variations, which can be integrated into the model. The model does not capture these external shocks with the seasonal component, so external explanations are important.

Residual component (light blue in the graph)

The residuals oscillate around zero, but in certain periods significant spikes are recorded:

• 2007–2008 — correspondence to the global financial crisis;

• 2012–2013 — the post-crisis period, marked by austerity measures in Europe;

• 2020–2022 — the economic impact of the COVID-19 pandemic.

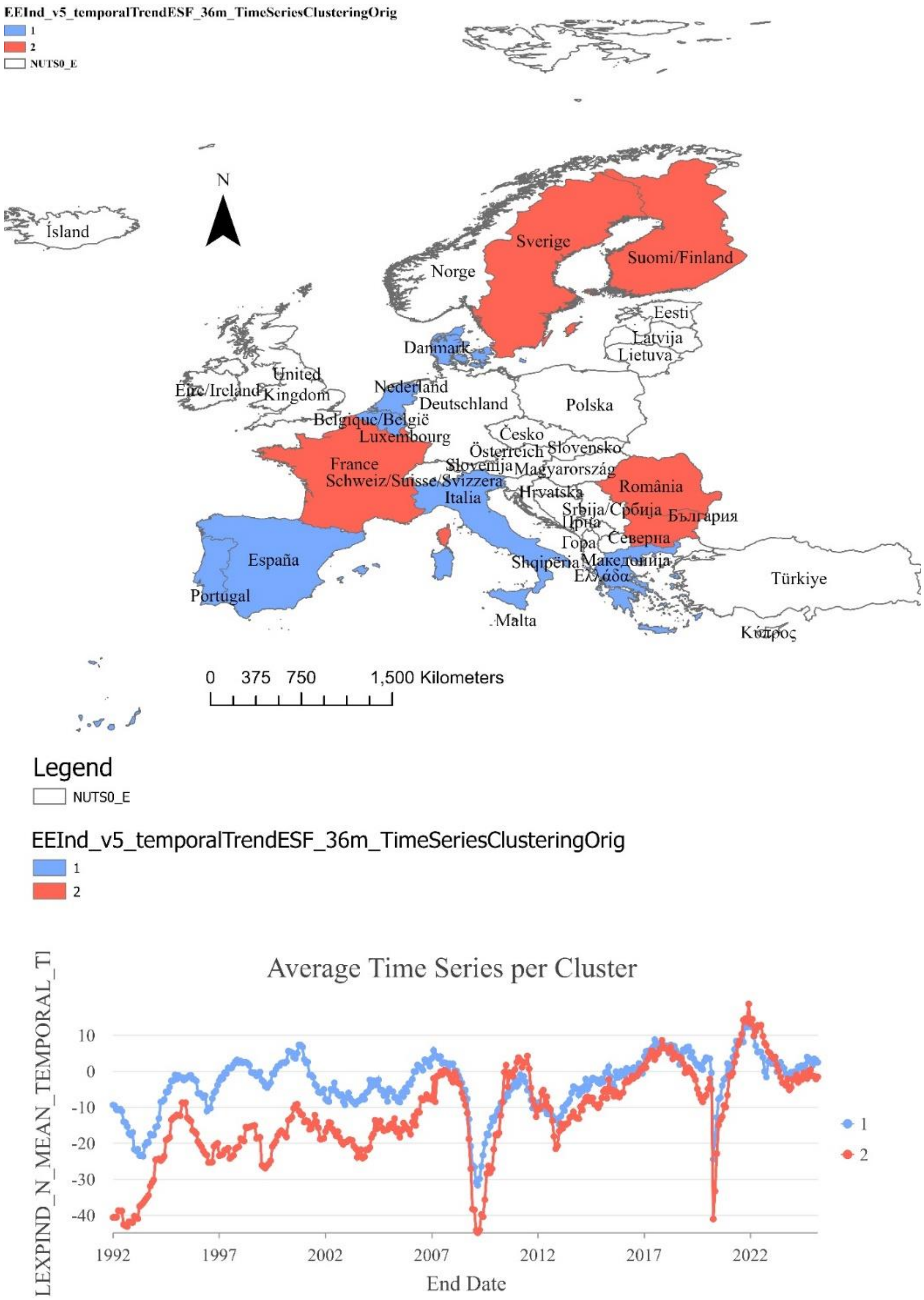
The residual values vary between -73.8 and +37.3, with an average of -7.29, which signals a slight underestimation of the phenomenon by the model. In periods of shock mentioned above, the errors explode capturing the effects of external hits. Outside these moments of shock, the residuals are well distributed around the zero axis, with no visible patterns of autocorrelation. The applied model correctly captures the underlying trend and correctly reflects the lack of strong seasonality. The residuals signal the presence of external shocks, such as the financial crisis or the COVID-19 pandemic, which are not explained by the model variables, but are the effect of the economic and social context.

The model can be considered robust for forecasting, but to improve performance, it is recommended to integrate additional variables that capture the impact of external shocks. The seasonal component plays a determining role in the dynamics of the analysed phenomenon, exceeding the amplitude of the underlying trend. The phenomenon presents moderate to strong seasonality, being influenced more by periodic fluctuations than by the long-term trend. The model signals the need to integrate additional explanatory factors to reduce the margin of error in shock periods. This analysis validates the application of a forecast model with an active seasonal component and reveals the importance of constant monitoring of external influences on the phenomenon.

3.3 Spatial Representation and Cluster Analysis

Space-time model representation for the countries studied is presented in *Figure 3*. The model identifies two main clusters from the employment expectations, dividing the 13 countries in half. Cluster 1 (blue) covers countries from Western and Southern Europe: Spain, Portugal, Italy, Benelux, Germany, and Greece. The average series is above zero in most periods, and they have less severe dynamics in crises. The years 2008 and 2020 show consistent decreases, but the amplitude of the shocks is smaller than those of the Cluster 2. In addition, the trend recovers quickly after the crisis. Countries from cluster 1 seem to have greater resilience to economic and social shocks, which suggests a more robust structure of the labour market or economy.

Cluster 2 (red) includes countries from Eastern, Central, and Northern Europe: Romania, Bulgaria, Serbia, Finland, Sweden, France, and Switzerland. They are characterised by average values of the net negative throughout almost the entire period. Steep drops are observed in the 2008 financial crisis and in 2020 during the COVID-19 pandemic. After the crises, the recovery is slow and incomplete. The amplitude of the decrease is noticeably greater than in Cluster 1. Countries in this cluster are much more vulnerable to external shocks, with prolonged effects on the trend of the analysed phenomenon. This behaviour can be linked to labour market rigidity, less diversified economic structure, and higher exposure to external risk factors.



Source: authors' research results.

Figure 3. **Spatiotemporal Clustering of Employment Expectations in 13 European Countries**

This spatiotemporal analysis highlights the existence of two distinct European clusters from the perspective of the evolution of the EMPLEXPIND_N_MEAN_TEMPORAL_TREND indicator:

- Cluster 1 (blue): countries with better resilience to shocks, rapid recovery, and moderate fluctuations;
- Cluster 2 (red): countries with significant vulnerabilities, steep declines in crises, and slow recovery.

Romania belongs to Cluster 2, which suggests the need for proactive policies to increase economic and social resilience, especially to cope with external shocks.

4. Discussion

This research posed two research questions. It was found that the results of spatiotemporal clustering confirm that this analysis provides clear insights for policymakers, especially regarding regional resilience, with reference to RQ1. Moroever, the Holt-Winters model proved adequate for cyclical employment data, especially in capturing anomalies like 2008 and 2020 shocks, with reference to RQ2.

The findings of this study contribute to a deeper understanding of employment dynamics in European industry by leveraging space-time analysis and strategic leadership frameworks. Applying the Holt-Winters exponential smoothing model integrated with GIS, employment expectations across 13 European countries over the period of 1992–2025 were forecasted. The analysis confirms the model's ability to identify major structural shocks, namely the 2008 financial crisis and the 2020–2022 COVID-19 pandemic, and distinguish between regions of high resilience and vulnerability.

These insights offer both theoretical enrichment and practical guidance for strategic leaders and policymakers navigating the complex landscape of labour market transitions. In addition, the model highlighted the role of strategic leadership used by the more stable and resilient countries, with high capacity to recover after falls generated by external shocks.

The use of spatiotemporal forecasting in this study aligns with recent literature emphasising the regional heterogeneity of employment responses to macroeconomic shocks and technological transformations. The clustering results obtained resonate with earlier findings from Kudełko *et al. (*2022), who documented similar regional polarisation in Poland's labour market during periods of structural change. Similarly, the identification of recovery speed and resilience in countries with more diversified industrial structures confirms findings from Gallipoli and Makridis (2022), who showed that digital-intense sectors recover faster post-shock.

The dynamic responsiveness of employment expectations, particularly visible in the residual analysis, echoes the work of Jestl (2024) and Cresti *et al.* (2023), both of whom linked digital and technological interdependencies with labour market adaptability. The analysis also builds on Cörvers and Dupuy's (2010) insights into occupational and sectoral employment shifts, emphasising how external disruptions shape expectations unevenly across economies.

By applying Holt-Winters model in a spatial GIS-enabled environment, this study expands upon prior quantitative approaches, such as the ARIMA or CGE models used in earlier forecasting research (Dutta Roy, 2004; Costantini *et al.,* 2018). The study illustrates how modern tools can enhance prediction robustness when spatial-temporal specificity is vital.

Conclusions

Theoretically, the study reinforces the value of strategic leadership in managing labour market change. As Ireland and Hitt (2005) argued, strategic leaders must anticipate external pressure and craft adaptable frameworks for workforce evolution. The present research supports that position by demonstrating how employment expectations are not only reactive to external shocks but also embedded in national strategic capacity. The integration of time-series forecasting with spatial clustering introduces a new dimension to strategic labour intelligence (Dewan *et al.,* 2022). It also advances research in the field of labour economics by bridging predictive modeling and regional economic development, offering a multidimensional view of labour expectations.

Practically, the paper offers tools for evidence-based policy design. First, it provides early-warning indicators of labour vulnerability. Countries identified in Cluster 2, exhibiting prolonged downturns and weak recovery, may require targeted support through workforce training, industrial diversification, or safety net reform. Second, for countries in Cluster 1, which display resilience, the findings can help reinforce the best practices in digital adoption, energy transition alignment, and cross-sectoral labour adaptability.

Furthermore, the seasonality and cyclical patterns identified by the model can support policy synchronisation, helping governments' interventions, such as wage subsidies or reskilling programs, around expected downturns. In addition, private-sector firms can use these insights to guide strategic decisions around hiring, investment, and capacity expansion, aligning with broader policy frameworks such as the European Green Deal and the EU's Digital Compass.

While the Holt-Winters model provides strong predictive capacity and interpretability, it is not without limitations. The primary constraint lies in its inability to endogenously incorporate explanatory variables, such as policy changes, innovation indices, or sector-specific shocks. As noted in our residual analysis, major external events (e.g. COVID-19) produce forecast errors that the model cannot account for due to its reliance solely on historical values of the forecasted variable.

Moreover, the additive version of the model assumes constant seasonality and may underestimate dynamics in contexts where seasonal effects are evolving due to climate policy, globalisation, or technological disruption. While the smoothing parameters (alpha, beta, and gamma) are optimised for performance, the model remains deterministic, limiting its ability to capture non-linear behaviours or threshold effects present in some labour market dynamics.

The incompleteness of data for several European countries further narrows the generalisability of the results. Although the 13-country sample provides broad geographic and economic diversity, gaps in data availability reduce the capacity to build a fully EU-representative model. Besides, the model treats all shocks as symmetric in nature; yet, as noted in employment literature (Grigsby, 2022; O'Clery and Kinsella, 2022), labour market responses to different types of shocks may vary in magnitude and persistence.

This research opens several avenues for future work. First, integrating multivariate models such as Vector Auto Regression (VAR) or Vector Error Correction Models (VECM) would allow researchers to examine the interaction between employment expectations and external factors like innovation investment, energy pricing, or education policy. Second, machine learning methods, including long short-term memory (LSTM) neural networks, or random forest regressors, could be employed to compare forecast accuracy and provide probabilistic outputs. These models would complement Holt-Winters by identifying non-linear and non-parametric trends, although at the cost of interpretability. Third, expanding spatial scope by incorporating data from all EU countries, and potentially neighbouring regions, would improve regional labour market planning and EU-wide cohesion strategies. This is particularly relevant as the EU strengthens mechanisms for economic governance, climate transition, and digital innovation. Fourth, future research could explore employment expectations at the sub-national level using NUTS2 or NUTS3 spatial units, especially given the emerging interest in urban-rural employment resilience and smart specialisation strategies (Kudełko *et al.,* 2022). Finally, researchers should explore scenario-based forecasting, combining historical time series data with foresight techniques to simulate labour responses under various digital, demographic, and ecological transformation pathways. Such approaches would provide strategic leadership with tools to manage uncertainty, consistent with calls for anticipatory governance (Griggs *et al.,* 2013; Samimi *et al.,* 2022).

This study provides a novel contribution to the literature on employment dynamics and strategic leadership by combining a time-tested forecasting model with modern spatial analysis tools. It highlights the varying resilience of European countries to economic and social shocks, offering robust insights for labour market governance in an era of digital transformation and structural change. The Holt-Winters model, when embedded within a GIS framework, demonstrates value not only in technical forecasting but also in strategic interpretation. Its results offer actionable evidence for policymakers, industry stakeholders, and researchers committed to developing labour markets that are adaptive, inclusive, and resilient.

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STRATEGINĖS LYDERYSTĖS IR UŽIMTUMO DINAMIKA EUROPOS ŠALIŲ PRAMONĖS SEKTORIUOSE: DARBO JĖGOS LŪKESČIŲ PROGNOZAVIMAS PER ERDVĖS IR LAIKO ANALIZĘ

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Santrauka. Straipsnyje analizuojama užimtumo prognozių pramonės sektoriuje (angl. *BS-IEME-BAL*) raida 1992–2025 m. remiantis Europos Komisijos Ekonomikos ir finansų reikalų generalinio direktorato (angl. *DG ECFIN*) pateiktais verslo ir vartotojų nuomonės tyrimų (angl. *BCS*) duomenimis. Tyrime nagrinėjami cikliniai svyravimai, ilgalaikės tendencijos ir makroekonominių veiksnių įtaka pramonės darbo rinkai. Siekiant nustatyti pasikartojančius modelius ir numatyti būsimus užimtumo pokyčius, taikytas erdvės ir laiko prognozavimas GIS su eksponentinio išlyginimo prognozės (*Holt-Winters*) modeliu. Šis modelis leidžia išskaidyti laiko eilutes į tendencijos, sezoniškumo ir likučio komponentus, taip pateikti patikimą užimtumo lūkesčių raidos įvertinimą. Be to, analizuojamos anomalijos ir lūžio taškai, padedantys suprasti pramonės sektoriaus pažeidžiamumą ekonominio neapibrėžtumo metu. Gauti rezultatai leis strateginei lyderystei formuluoti viešosios politikos teiginius ir strategijas, skirtas prisitaikyti prie skaitmeninės transformacijos, ekonomikos svyravimų ir darbo rinkos iššūkių. Šiuo tyrimu pabrėžiama erdvės analizės ir laiko prognozavimo priemonių nauda priimant duomenimis pagrįstus sprendimus ekonomikos struktūrinių pokyčių kontekste.

Reikšminiai žodžiai: strateginė lyderystė; užimtumas; erdvės ir laiko prognozavimas; pramonė; viešoji politika.