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Identifying weak signals in the labor market: a machine learning approach for strategic policymaking

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ABSTRACT

This study introduces a novel machine learning-based methodology for detecting and forecasting the strength of weak signals in the labor market, using Greece as a case study and utilizing Eurostat time series data (2000–2023). Weak signals, conceptualized as subtle anomalies within otherwise stable labor market indicators, were identified through the Isolation Forest algorithm and projected using a Long Short-Term Memory neural network model. Findings highlight structural instability in male manufacturing employment and wholesale/retail trade, contrasted by stable trends in sectors such as agriculture, education, and public administration. This study contributes to labor market foresight by integrating anomaly detection with predictive analytics, offering valuable insights for proactive, scenario-based policy design in support of a sustainable and adaptive future of work.

Introduction

The concept of weak signals was originally introduced by Ansoff (1975) to refer to subtle emerging indicators that are too incomplete to allow accurate assessment of their impact. In complex systems, weak signals may refer to technical anomalies or performance variabilities (Van Veen & Ortt, 2021; Yu et al., 2022). When these signals are combined with systemic noise, they can produce detectable effects on the evolutionary capabilities of the system in question (Yu et al., 2022). Their timely detection and interpretation have strategic value, as they may signify impending change and the need for anticipatory action (Ha et al., 2023).

In this study, we propose a machine learning approach to identify potential weak signals as variations in performance in otherwise "strong" signals within the labor market, such as employment distribution per sector, economic performance indices, and rates of participation in training. The analysis data are obtained from the labor market-related time series from Eurostat from 2000 to 2023, focusing on Greece.

The detected anomalies (weak signals) are projected into the future to evaluate their significance and are compared to existing forecasts for the labor market. To this end, we utilized the isolation forest algorithm, which is ideal for detecting outliers and anomalies in data (Xu et al., 2023). The algorithm analyzes the variations in the variables and identifies those that show unusual changes, possibly due to impending changes in the labor market. To predict the development and strength of the detected weak signals, the Long Short-Term Memory (LSTM) neural network model was applied, as it is the most suitable for time-series processing and identifying future development trends (Chen et al., 2023).

The forecast analysis (2024–2030) revealed that while overall male and female employment in Greece was expected to follow stable trajectories, weak-signal intensity was strongest in manufacturing for males and wholesale/retail trade (both genders), suggesting that these sectors might have undergone significant structural shifts in contrast to more stable sectors such as agriculture, education, public administration and defense, and accommodation.

Given the limited research on combined labor market foresight and forecasting techniques (Kanzola & Petrakis, 2024), this study aims to analyze and detect important labor market anomaly indicators that could produce significant insights for shaping the future of work and employment. For instance, employment pattern variations in specific economic sectors could indicate the need for targeted active labor market policies to influence economic activity in those sectors. Pairing this approach with scenario analysis on proactive labor market policies,

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this study is relevant for policymakers and governments focusing on creating an early warning system for impending structural transformations. This, in turn, enables proactive, rather than reactive, policymaking in areas such as education and training, labor activation, and social and fertility policies, which are cardinal for mobilizing labor force participation and improving the interpretation of certain economic variables such as unemployment.

Theoretical background and conceptual framework

Conceptual foundations of weak signals and the labor market environment

Weak signals are signs of strategic discontinuities, such as an impending opportunity, threat, or attenuation of a present trend that permeates the environment for some time before maturing into a widely recognized force or megatrend (Soroui, 2023). These anomalies can be detected even in highly "structured" datasets (Reeves et al., 2021) and may originate from either internal factors (such as workers' absenteeism) or external factors (such as the impact of an exogenous shock) (Nicolaidou et al., 2021). Thus, in complex systems, weak signals could serve as crucial predictors of future collective behavior trajectories owing to the interconnected transmission mechanism of change. The transformation process from a weak to a strong signal offers both strategic knowledge and enhanced understanding of the operational dynamics within the system (Ji et al., 2023).

The labor market is one of the most fundamental depictions of a complex system within economics (Gomes & Gubareva, 2021). Labor markets are characterized by the emergence of social and economic phenomena resulting from the interaction of thousands of micro and macro decisions (Lloret-Climent et al., 2020). These relational dynamics have intensified with the adoption of new technologies, the pace of career development, changing tasks, and endogenization of shocks, such as the 2020 pandemic and its implications for labor. In other words, the increase in complexity makes the labor market environment more susceptible to anomalies or performance variations that could eventually be proven significant for the performance of the labor market system.

In the labor market environment, anomalies identified as signals of forecasting capacity concern the following aspects: (i) participation in education and training, which can be interpreted as a signal to employees when assessing job candidates (Liechti et al., 2017); (ii) sectoral employment patterns, which could indicate labor absorption patterns and can be used to forecast employment and unemployment in a multisectoral labor market (Nababan & Purba, 2023); (iii) job vacancy indicators to predict firm performance, showing that vacancy announcements can act as signals for future stock returns and operational growth (Lo et al., 2020); and (iv) frictions, in general, such as wage growth and labor share, could be significant predictors of credit market outcomes (Favilukis et al., 2020).

Research objective of the study

Despite the aforementioned contributions, the identification and analysis of weak signals to examine potential future labor market prospects remains unexplored in the labor economics literature, generating an interesting research gap. Therefore, this study aims to provide an original contribution toward a more profound understanding of the nature and impact of weak signals within the labor market using labor-related time series data, given that historical data play a critical role in interpreting weak signals (Yu et al., 2022).

Analyzing the life cycle[1] of these weak signals affects our understanding of the future of work. This approach differs from previous efforts to apply foresight and forecasting in the labor market because it is not based on deterministic relationships to produce forecasts and, subsequently, scenarios for the future (Wilkinson, 2016).

Utilizing existing research on the subject, we collected data on sectoral employment, unemployment, skill level, and overall financial performance for Greece from 2000 to 2023 to generate a continuous time-series dataset. Focusing on strong signals to predict weak signals involves identifying deviations in normal patterns that could be impactful on future developments. For example, even minor changes and fluctuations in employment patterns could yield significant developments for the future of work and the structure of an economy's occupational map.

Greece is characterized by an overall stable production structure (Bakinezos et al., 2020), which in turn creates a low-noise environment, improving the detection of subtle signals. This characteristic offers a unique and insightful framework for studying the mechanisms of structural change and the role of weak signals in shaping future development pathways. In other words, the Greek production paradigm evolves relatively slowly over time and is based on tradition, whereas alterations occur more frequently because of major global trends. In other words, the identification of weak signals and subsequent policymaking could foster impactful initiatives that could potentially generate new trends.

During the 1970s, Greece transformed from a purely agricultural economy to a service economy (Galaní-Moutáfi, 1993). In Greece, service-oriented activities have high multipliers, whereas manufacturing activities feature lower total multipliers because of their low labor intensity (Bakinezos et al., 2020). In terms of production effects and value-added, Danchev et al. (2014) reported that trade and tourist operations, along with public administration and education, account for 23.3 % of the total value-added in the economy. However, forestry and fisheries provide <3.5 % of gross value-added but employ 13 % of the total employees, while the industrial sector features similar characteristics (Danchev et al., 2014). Similarly, Spinthiropoulos et al. (2020) consider tourism the "growth engine" of the Greek economy rather than manufacturing, which is "weak" (Louri, 1988). More specifically, since the 1980s, it has been observed that the importance of industry in terms of gross value added has declined (Vettas et al., 2020). According to some forecasts, economic activity will decline significantly in the primary, utilities, and manufacturing sectors by 2030, resulting in occupational shortages due to demographic factors such as population aging (European Centre for the Development of Vocational Training [CEDEFOP], 2020).

Techniques for identifying weak signals

In terms of weak-signal identification techniques, traditional anomaly detection methods that rely on predefined thresholds or specific assumptions about data distribution are becoming increasingly inadequate owing to their lack of flexibility and scalability (Iqbal & Amin, 2024). Furthermore, anomalies are often nonlinear but relational, meaning that they could appear at a later stage of an analysis, depending on the sensitivity of the monitoring method applied (Kozma et al., 1994).

Advances in machine learning have facilitated the identification of anomalies, leaving the filtering of potential weak-signal candidates to the capabilities of experts (Ahlqvist & Uotila, 2020; Ha et al., 2023; Iqbal & Amin, 2024). For instance, Ha et al. (2023) proposed a fully automated weak-signal detection process for extracting and subsequently inspecting the growth of literature-related weak signals through a trained predictive model. Another example is Huang (2019), who proposed an automatic technique for seismic signal recognition that takes advantage of unsupervised machine learning.

The distinctive feature of machine learning methods lies in their ability to extract the predefined features of signal data in supervised and

[1] The life cycle of a weak signal involves three stages: (i) identification, (ii) evaluation of its relevance, and (iii) communication to decision-makers through a foresight policy approach (Yu et al., 2022), such as alternative futures analysis (Reeves et al., 2021).

unsupervised learning models and create reliable signal prediction models (Ma et al., 2024). In this study, we utilized the isolation forest algorithm because of its good performance in high-dimensional settings, such as labor market datasets, offering an efficient and effective means of identifying anomalies (Agyemang, 2024).

Conceptual framework of the study

Fig. 1 presents the conceptual framework of the study.

Materials and methods

Research question and data

The research question is whether unsupervised machine learning techniques can effectively identify anomalies within the evolving complexities of contemporary labor markets, which can be forecasted and later contextualized into scenarios for the future of work. To address the research question, we used the Greek labor market as a case study. The data were derived from the Eurostat database and focused on direct or indirect labor market indicators from 2000 to 2023. Table 1 presents all the variables used in this study and their definitions and identification codes in the Eurostat database. The descriptive analytics of the sample are provided in a separate Excel file as supplementary material.

Methodology

To examine this research question, we generated a computational algorithm for the processing, analysis, and forecasting of anomalies within strong, structured, and labor-related data. To this end, machine and deep learning techniques were applied in the Python programming language. The applied methodology involved three broad stages: (i) preprocessing of the data, (ii) detection of anomalies in the time series, and (iii) forecast analysis using the LSTM neural network model. Each stage is described in detail below:

Stage 1. Data collection and preprocessing

The data presented in Table 1 were manually collected from Eurostat and systematically organized into an Excel file. All sheets from the Excel file were cleansed using the *Pandas* library. This library has functions for analyzing, cleaning, and exploring a dataset. Any anonymous columns and empty rows were removed. Subsequently, using label encoding, we converted categorical variables into numerical variables. This process assigns a unique integer to each category in the data, making it suitable for machine learning models that work with numerical inputs. Any missing inputs in the numerical columns were substituted using the median strategy, which replaced the missing values with the mean value of the corresponding feature or attribute in the complete dataset, also known as complete mean imputation (Alam et al., 2023). This approach was chosen because the number of missing values was small (Alam et al., 2023). All sheets were then unified to create a consistent dataset. Columns containing zero values were removed to eliminate redundant features. Finally, all numerical characteristics were standardized using the *StandardScaler* library from Scikit-learn to ensure consistency in data distribution. This stage resulted in 299 observations.[2]

Stage 2. Anomalies detection using the isolation forest algorithm

Anomalies in the dataset were identified using the isolation forest algorithm, which is often used in anomaly detection of time series because of its linear time complexity, scalability, and capability to handle high-dimensional data (Iuhasz et al., 2025). This is a tree-based ensemble method (Iuhasz et al., 2025) that isolates anomalies by randomly selecting features and splitting values, requiring fewer splits for anomalies than for normal points, thus capitalizing on the anomalies' inherent "susceptibility" to isolation (Agyemang, 2024), creating isolation trees. Anomalous data instances have shorter paths in trees, making them easier to isolate (Iuhasz et al., 2025). The time required for a data point to be isolated is measured as an anomaly score. This score represents the likelihood of the data point being an anomaly (Song et al., 2020).

In this study, anomaly detection was semi-supervised since, during training the algorithm, we assumed a contamination parameter of 5 % to define maximum tree depth and adjust the sensitivity threshold of detection to prevent the model from classifying too many points as anomalies. Once the training was completed, the model classified the data as normal or anomalous. Data points identified as anomalies (outliers) were assigned the label "−1″ and were categorized as weak signals. These signals represent potentially unusual but significant shifts in the labor market, which may influence future trends and provide early indications of structural changes. The selection of the most important signals was based on the variance-covariance subspace distance method (Karami et al., 2023). Essentially, the algorithm analyzed variable fluctuations and identified those with unusual changes, potentially signaling upcoming shifts in the labor market.

Stage 3. Forecasting future trends using the LSTM neural network approach

The most important weak signals were forecasted in a time series format using an LSTM neural network model to trace their behavior and strength over time.

Algorithms used for forecasting can be divided into two categories: regression analyses and neural network models. Traditional forecasting approaches such as linear regression, exponential smoothing, and autoregressive integrated moving average are considered foundational in time series forecasting but also have certain limitations, such as their inability to effectively capture nonlinear relationships and non-stationary patterns in data, which may lead to reduced accuracy when dealing with complex environments such as the labor market (Mitrea et al., 2009; Zhang et al., 1998).

However, neural network models have been found to outperform traditional forecasting models (Mitrea et al., 2009) because of their data-driven ability to process both linear and nonlinear data without relying on specific ad hoc hypotheses (Nababan & Purba, 2023). Over the past decades, to overcome certain limitations of traditional neural network forecasting, a specialized class of models has emerged: the recurrent neural networks (RNNs) (Yadav & Thakkar, 2024). RRNs are designed to model sequences of variable lengths by incorporating recurrently connected hidden layers that retain past information through feedback loops, thereby enabling the network to consider previous outputs during training (Bandara et al., 2020).

The LSTM network was introduced in the late 1990s to extend the RNN architecture by incorporating a standalone memory cell and a gating mechanism that regulates the information flow across the network (Nababan & Purba, 2023). Since then, LSTMs have been successfully used in diverse forecasting contexts, including energy demand (Dimoulkas et al., 2019), product demand (Abbasimehr et al., 2020), unemployment rates (Yurtsever, 2023), and workforce planning (Cao & Sing, 2024).

In this study, the LSTM neural network model was chosen because of its ability to consider temporal dependencies in linear and nonlinear time series data, capture long-range dependencies, maintain temporal information, and serve as a robust building block for encoder–decoder forecasting architectures (Hochreiter & Schmidhuber, 1997; Yadav & Thakkar, 2024). Furthermore, the LSTM approach was very suitable for this study due to the observation that in the labor market context, a short-to-medium-term forecast approach is more effective and robust owing to demographic, behavioral, and modeling complexity (Higgins et al., 2019). Therefore, the historical data of the most important weak signals, as indicated by the isolation forest algorithm, were trained using an LSTM network aimed at producing forecasts for their patterns up to

[2] Raw data are provided in a separate Excel file as supplementary material.

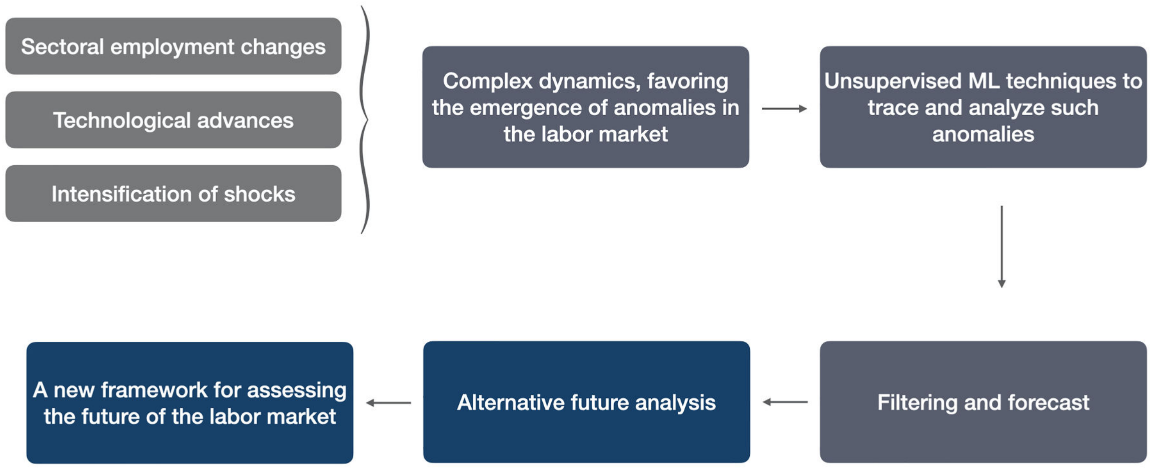

Fig. 1. Conceptual framework.

Table 1
Variables used.

Indicator Name	Eurostat Code	Definition
Indicators for labor market performance		
Unemployment Rate	une_rt_m	Percentage of unemployed individuals by gender, age, and region.
Employment by Sector	lfsq_egan2	Sectoral employment distribution based on economic activity.
Underemployment	lfsa_ugad	Individuals working fewer hours than their preferred workload.
Indicators for employment structure		
Part-time Employment	lfsa_eppga	Proportion of workforce engaged in part-time employment.
Involuntary Part-time Employment	lfsa_eppgi	Proportion of part-time workers employed involuntarily.
Job Vacancies	jvs_q_nace2	Number of job vacancies reported across economic sectors.
Human capital and skills development indicators		
Lifelong Learning Participation	trng_lfse_01	Rate of participation in lifelong learning programs.
Early Leavers from Education	edat_lfse_14	Proportion of individuals leaving formal education prematurely.
Digital Skills Levels	isoc_sk_dskl_i	Share of workforce possessing digital competency levels.
Demographic and socioeconomic indicators		
Population by age, gender, and education level	demo_pjanind	Key demographic factors influencing labor market trends.
Migrant Employment	lfsa_ergan	Rate of employment among migrant populations.
Population by sex, age, and participation in education and training	lfsa_pgaied	Distribution of population engaged in education and training.
Macroeconomic indicators		
GDP Growth Rate	nama_10_gdp	Annual GDP growth as an indicator of economic performance.

Source: Authors' creation based on Eurostat datasets.

2030, offering a quantitative evaluation of future variations and facilitating policymaking for the future.

It is important to emphasize that the forecasting of significant weak signals over time is not carried out solely for reasons of predictive accuracy but primarily to highlight their dynamics over a medium-term horizon. A weak signal that appears significant today may diminish or even lose its semantic relevance in future. This limitation should be attributed to the very definition of weak signals as anomalies that may eventually "flatten" or dissipate. Consequently, the assessment of each weak signal, as with any non-deterministic foresight process, requires interpretation within a broader and holistic analytical framework (Saritas & Smith, 2011).

The framework for the present study is the labor market. Accordingly, the forecasting of weak signals is not considered in isolation but rather through the combined examination of two key dimensions: (i) their dynamic trajectory, which is explored through forecasting using an LSTM network, and (ii) their evaluation in relation to existing trends, as well as to the (already) identified challenges concerning productivity and the broader labor market system.

Findings

Building on the methodology described above, we extracted ten significant variables indicating potential space for weak signals. Given that they all concerned important aspects of the labor market structure, all the extracted variables were considered useful for forecasting and foresight. The following variables indicate the potential space for weak signals:

(i) Total male employment in all Nomenclature of Economic Activities (NACE) activities
(ii) Total female employment in all NACE activities
(iii) Male employment in the manufacturing sector
(iv) Male employment in wholesale and retail trade; repair of motor vehicles and motorcycles
(v) Female employment in wholesale and retail trade; repair of motor vehicles and motorcycles
(vi) Male employment in the agriculture, forestry, and fishing sector
(vii) Female employment in the education sector
(viii) Male employment in the public administration and defense sector
(ix) Female employment in the human health and social work sector
(x) Male employment in the accommodation and food services sector

To investigate the evolution of these variables within the Greek labor market up to 2030, we forecasted them using the LSTM network model, as described in the Methods section. The heatmap in Fig. 2 depicts the forecasted standardized values of weak-signal strength for the years 2024–2030.

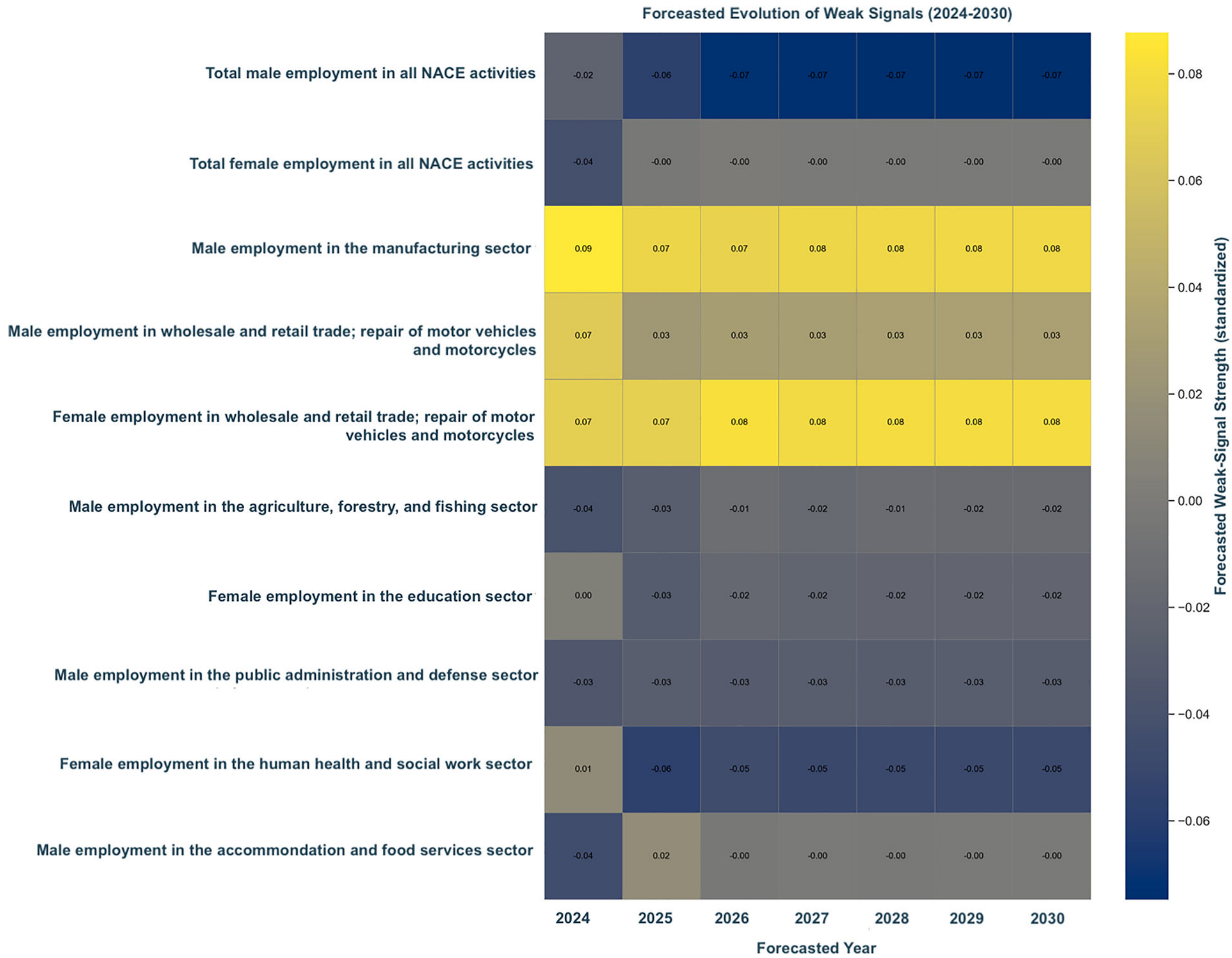

Fig. 2. Heatmap of projected weak signal strength from 2024 up to 2030.
Note: The color scale indicates the standardized weak-signal strength, where yellow shades indicate higher intensity (i.e., greater potential for unexpected structural changes) and darker shades correspond to lower intensity (i.e., more stable or predictable employment patterns).

In terms of male and female employment in all NACE activities, the LSTM model predicted a decline in weak-signal strength. The results suggest a reduced probability of imminent structural shifts in overall employment patterns, indicating that both male and female employment are expected to follow relatively stable or predictable trajectories by 2030. This observation leads to an inevitable connection between current labor market conditions and employment forecasts.

Recent analyses and forecasts have indicated underutilization of human capital in the Greek labor market, combined with an overall decline in employment, which is connected to factors such as population aging, retirement of workers, and labor migration (Antonopoulos et al., 2022). Such factors contribute to labor market tightness, as technological advancements have driven higher labor demand that is not adequately met by supply, a situation further exacerbated by elevated levels of involuntary part-time employment and stagnating real compensation per worker in relation to labor productivity (Theofilakou & Vasardani, 2024). In addition, long-term unemployment levels are negatively influenced by the high percentage of long-term unemployed individuals, a phenomenon referred to as “negative unemployment duration dependence” (Mitrakos & Nicolitsas, 2006). Essentially, the longer an individual remains jobless, the harder it is to reenter the labor market. This situation is primarily cultivated by employer bias on the demand side, which eventually limits the effective labor supply and can lead to permanent withdrawal from job searching, resulting in workforce underutilization.

In terms of employment in the agriculture, healthcare, education, accommodation, and public administration and defense sectors, the LSTM model estimated low, weak-signal intensity for the forecasted period of 2024–2030, which can be interpreted as a period of stable or predictable trajectories. In other words, employment in these sectors is likely to follow the current estimations. The analysis below critically discusses the current trends in these sectors.

The agricultural sector is considered vital for the rural population in Greece; however, the absolute number of employed individuals has decreased significantly over time owing to the aging phenomenon and the lack of desire for young people to work in it (Paschalidis et al., 2021). This phenomenon has been prominent in the last 20 years despite the availability of several opportunities for growth in the sector, particularly in the last few years with Agriculture 4.0, which concerns the adoption of new techniques to optimize resources, reduce production costs, provide real-time information, and enable informed decision-making in farming and agriculture. The effective utilization of these opportunities, when combined with governmental support measures targeting young farmers, may contribute to alleviating prevailing perceptions of low-income and unfavorable working conditions in the sector, thereby facilitating a reversal of the negative trend (Staboulis et al., 2022).

Given the low weak-signal intensity in female employment in the healthcare sector, it is anticipated that it will also follow current trend expectations. In general, healthcare occupations experience significant social recognition and are of vital importance in the field of life sciences and service provision because of the broader perception that health is the most important asset (Hafferty & Light, 1995). The rise in healthcare workforce demand is attributed to population aging and post-pandemic-driven growth in roles, such as nursing, which is typically associated with females (World Economic Forum [WEF], 2025).

Following the same reasoning, stable patterns are anticipated for female employment in the educational sector, which is particularly influenced by new technologies and the changing nature of working activities (WORLD ECONOMIC FORUM, 2025). Combining this with the overall aging phenomenon and the need for lifelong learning, a significant growth is anticipated in the adult training and lifelong learning field (WORLD ECONOMIC FORUM, 2025).

The accommodation and food services sector in Greece is considered one of the most dynamic targets for increasing tourist arrivals by 2030 (Kasimati et al., 2024). However, it is currently undergoing an important transformation by introducing more sustainable practices and technological adaptations, which might result in diverse demands in terms of human capital during 2025 to support this transition (Kasimati et al., 2024). This was probably the reason for the slight increase in the significance of the weak signals during that time. This sector experiences an upward trend in employment flows and in the wages of new hires, which may be indicative of potential emerging market pressures (Antonopoulos et al., 2022), explaining the slight increase in weak-signal intensity from 2024 to 2030.

The public administration and defense sector had one of the highest vacancy rates in 2023; however, it is also undergoing structural changes due to military reform packages that are going to require investment in training for the armed forces' human capital and slight automation effects (CEDEFOP, n.d.). Although the current weak-signal intensity suggests relatively stable employment trajectories, the convergence of technological adaptation, digital transformation, and geopolitical drivers could generate rising pressures in this sector, and, given its significance and tense geopolitical situation in the Eastern Mediterranean area, could also affect employment patterns and preferences. In other words, the provision of appropriate incentives is important to fill job vacancies.

Finally, the strongest significance in weak signals is found in the manufacturing sector for male employment and in the wholesale and retail trade for both male and female employment in the motor vehicle and motorcycle repair branch. According to the LSTM model, these sectors may experience employment fluctuations, with future trajectories potentially differing significantly from current estimations. It should be noted that the current estimations indicate an increase in employment in the manufacturing sector as well as the total wholesale and retail sector (CEDEFOP, n.d.). The weak-signal intensity in these sectors could also be due to changes in the anticipated composition of skills and work tasks.

Discussion

Weak signals and labor market foresight

Weak signals can be used to map or hinder potential capabilities for the future of the labor market, particularly if their analysis is combined with alternative scenarios. In turn, the revealed insights generate opportunities to design active labor market policies aimed at achieving a desirable future.

Foresight in the labor market is a relatively underexplored field because of the dominance of forecasting techniques for the main labor-related variables. However, because weak signals contain latent information whose significance may evolve, scenario analysis as a foresight technique emerges as a particularly suitable method for examining potential implications in the labor market. Scenarios use intuitive logistics and observations to anticipate and undertake risks and discover strategic options for the future (Wack, 1985).

In general, the future of the Greek labor market involves four scenarios (Kanzola & Petrakis, 2024). The *first scenario* entails a sustainable transformation of the production framework, marked by equitable sectoral expansion, inclusive employment, skill enhancement, and elevated intertemporal welfare via a coordinated transition. The *second scenario* describes a slow transformation of the production structure characterized by sectoral adjustments, moderate skill requirements, escalating polarization, and medium social and demographic pressures. The *third scenario* pertains to automation and counterbalancing demographics, depicting a polarized labor market characterized by selective sector support, talent shortages, and increasing structural unemployment, mitigated by skilled migration influxes. The *fourth scenario* refers to a high-automation era characterized by a unilateral production framework, exhibiting a markedly polarized and inequitable labor market dominated by the service sector, featuring elevated unemployment, a disheartened workforce, and significant brain drain.

The above scenarios synthesize complex trajectories within the Greek labor market, leveraging points of interconnectedness, such as gender dynamics, sectoral growth, training preferences, and demographics. Our weak-signal analysis reflected stability in macrostructural trends in terms of labor force participation. Furthermore, low weak-signal intensity in agriculture, education, public administration, defense, and accommodation suggests predictable employment patterns at the sectoral level, at least in the short-to-medium term. The sectors with high weak-signal strength—manufacturing (for males) and wholesale and retail trade (for both genders)—will probably diverge from the predicted business-as-usual employment trajectories, possibly due to structural transformations such as automation, shifts in consumer behavior, global value chain reconfigurations, and evolving skill demands. Such fluctuations can be positive or negative. Therefore, to arrive at the first scenario, which is the most favorable, early responses to active labor market policies are critical for navigating uncertain futures.

Essentially, the intensity or absence of weak signals in the distribution of employment across the various critical sectors of the Greek economy highlights broader systemic trajectories. Specifically, the absence of weak signals generates a probabilistic evolution of a "business-as-usual scenario" in many sectors that may currently face adverse prospects despite their crucial importance. In other words, the business-as-usual scenario is not necessarily a positive outcome, because it can mask risks, inertia, or deterioration in key areas. However, the partial presence of weak-signal intensity in the manufacturing sector suggests the possible existence of transitional factors, although the quality of these factors, whether positive or negative, remains unknown. In any case, weak signals function as possible indicators, and therefore, they should be monitored holistically. Their absence also indicates the need for proactive rather than reactive policymaking.

Implications for policy development: labor market policies in Greece

As mentioned above, one of the main findings of this study concerns the absence of weak-signal intensity for critical sectors, which could modify the production structure in Greece. This phenomenon is an overall pathology of the Greek economy, which is characterized by high uncertainty intolerance and rigidity in accepting structural changes. Such cultural characteristics, on the one hand, produce relatively predetermined scenarios (such as those in subsection 5.1), but on the other hand, positive change requires effective and case-fit labor market policymaking to rejuvenate the production structure. Given the potential disruptions in the manufacturing, wholesale, and retail sectors, it is crucial to design proactive policies to either stabilize negative developments or capitalize on positive ones. To this end, flexibility and proactivity are significant. Some policy implications of our study are the following.

Active labor market policies aim to increase employment opportunities and match jobs (vacancies) with workers. Such policies are concerned with providing incentives for individuals to enter the labor force. Particularly, in the case of Greece, which has recorded one of the lowest rates of female participation in the labor force in European countries in 2022 (Antonopoulos et al., 2022), such policies should incentivize female labor force participation. An increase in female labor force participation can be achieved directly through training and internship programs or indirectly through access to free or subsidized public childcare.

Another important dimension of labor-related policy is the development of comprehensive family policies, which often embody the principle of "the family as the first line of support" (Zhan & Huang, 2023). These policies are increasingly leveraged as strategic instruments to address declining fertility rates and mitigate the demographic challenges associated with population aging in the long term (Zhan & Huang, 2023). Practically, an integrated policy framework that includes child allowance programs, particularly within competitive market contexts, can incentivize fertility in rural areas. Poland provides a notable example of such a policy in action (Topińska, 2018). Targeted support measures aimed at reducing disparities in living standards between urban and rural populations can further enhance these efforts. If complemented by the strategic deployment of advanced agricultural technologies, such policies have the potential to rejuvenate Greece's agricultural economy and contribute to a more sustainable rural development trajectory.

In general, to rejuvenate the occupational and production structure, it is important to account for the behavioral factors that impact human decision-making. According to Kaufman (1999), social norms concerning occupational status play a significant role in occupational choice. For instance, in Greece, vocational training is perceived by students as a less efficient version of academic studies (Bulman, 2020; Sidiropoulou-Dimakakou et al., 2012), a perception that negatively impacts the structure of the labor market, particularly in the primary and secondary sectors. To change this dynamic, it is important to introduce educational reforms aimed at supporting the 2040 workforce, referring, among others, to children entering education today.

Hence, schools in Greece should focus on (i) providing an adequate framework of general knowledge in all fields, (ii) generating fundamental skills such as critical thinking, and (iii) compensating for the socioeconomic background of their students. Another objective of Greece's schooling system relates to effective school career guidance and counseling, as well as the empowerment of vocational skills and vocational education in general. Such policies support the sustainable transformation of the production structure and ensure resilience in the labor market (Brewer, 1916).

According to the Organization for Economic Co-operation and Development (2020), the future of schooling will range between more traditional education and education that takes place everywhere in the form of lifelong learning, without distinguishing it as formal or informal. Thus, rethinking lifelong learning is essential in the context of ongoing changes in the labor market because future education and training systems should be flexible and prepare individuals to learn continuously over their lives. For individuals already active in the labor market, certified lifelong learning structures offer significant benefits because of their flexibility and capacity to rapidly develop skill-building processes. A promising approach in this context is the development of diversified skill and knowledge portfolios, a combination of technical, cognitive, and soft skills that enables individuals to adapt to various roles, occupations, or economic sectors (Kanzola & Petrakis, 2024).

Besides education, policymakers should transform Greece's overall economic profile into an investment-friendly environment and battle the long-lasting pathogenies of (i) overregulation and slow implementation of institutional changes, (ii) high concentrations of small- and medium-sized firms, and (iii) failure to support innovation due to the relatively slow integration of technological development (Petrakis, 2024). Addressing these challenges can foster a safer, more uncertainty-tolerant, and investment-attractive environment.

Limitations, recommendations for future research, and contributions of this study

This study aimed to provide a new methodological framework for the evaluation and analysis of the labor market. Provided that the interactions in the labor market are both micro and macro in nature, our approach would benefit from a broader dataset incorporating occupational choice models, as well as an extended analysis of employer demand through online advertisements. The latter was partially provided by CEDEFOP with the project Skills Online Vacancy Analysis Tool for Europe; however, the project's data were limited, and thus, it was not possible to use them.

Future research could address these limitations and generate larger datasets for future use. Additionally, we anticipate that the model could lead to the co-creation and analysis of a series of elaborate scenarios to predict the future of the labor market and find sustainable paths through narrative scenarios (Wright et al., 2020). To this end, the method combines the analysis of hard and soft data using the quantum computing ideas for bibliometric studies (Sáez-Ortuño et al., 2024) to conduct market research and skill forecasting.

In terms of contribution, the methodological approach of the present study advances the integration of machine learning into the social sciences by expanding their analytical framework, particularly in labor market analysis, enabling the transformation of obscured or fragmented information into actionable scenarios for informed policy making. Our methodology differs from the traditional macroeconomic analysis of the labor market because it goes beyond structural relationships to reveal hindered signals to anticipate future change and prepare for it.

Thus, it should be emphasized that the methodology of this study is distinguished by its high applicability in several contexts and geographic regions. On the one hand, the exact methodology can be applied to effectively assess weak-signal intensity in these labor market indicators in any country because it is based on Eurostat data and official classifications. However, this methodology can be further extended to more specialized analyses, such as sectoral analysis. Sectoral analysis concerns the individual assessment of each sector of an economy to understand its performance dynamics, drivers of change, and employability prospects. Provided that the input variables will be adjusted based on the targeted sector and country, our approach could be helpful in preparation to face uncertainty and change per sector, while it could also be extended to enhance sectoral technology foresight and innovation (Gaponenko, 2022). Such extensions could further facilitate skills anticipation regarding specific occupations and sectors based on analyzing both strong trends and potential weak signals.

For instance, the proposed methodology could be applied to the eight key sectors of economic activity identified by the Recovery and Resilience Fund as vital for the Greek economy. These sectors are (i) Materials, Construction, and Manufacturing Industry; (ii) Tourism, Culture, and Creative Industries; (iii) Agri-food Value Chain; (iv) Environment and Circular Economy; (v) Life Sciences, Healthcare, and the Pharmaceutical Industry; (vi) Transport and Logistics; (vii) Sustainable Energy; and (viii) Digital Technologies.

These sectors are regarded as strategic because of their growth potential, capacity for digital transformation, and substantial impact on employment. Nonetheless, prioritization alone does not ensure that they will develop as expected. A critical limiting factor is the availability of skilled labor; without a sufficiently trained workforce, financial investment alone will not be sufficient to drive sustainable growth. In this context, applying weak-signal analysis to each sector individually could reveal anomalies with the potential to evolve into strategic advantages, particularly in terms of upskilling and reskilling the workforce, while also creating the right incentives for individuals to enter the labor market.

Therefore, the identification and interpretation of weak signals are valuable tools for monitoring development policy and enabling the utilization of signals and information that are usually not available to policymakers when they allocate large-scale resources to specific development initiatives. This type of analysis can also be extended to weak signals related to innovation, offering critical insights into whether proposed development plans can, for instance, effectively support an endogenous growth policy.

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Declaration of competing interest

All authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in Journal of Innovation & Knowledge.

CRediT authorship contribution statement

Anna-Maria Kanzola: Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Conceptualization. **Konstantina Papaioannou:** Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Panagiotis E. Petrakis:** Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

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Supplementary materials

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References

Abbasimehr, H., Shabani, M., & Yousefi, M. (2020). An optimized model using LSTM network for demand forecasting. *Computers & Industrial Engineering, 143*, Article 106435. https://doi.org/10.1016/j.cie.2020.106435

Agyemang, E. F. (2024). Anomaly detection using unsupervised machine learning algorithms: A simulation study. *Scientific African, 26*, Article e02386. https://doi.org/10.1016/j.sciaf.2024.e02386

Ahlqvist, T., & Uotila, T. (2020). Contextualising weak signals: Towards a relational theory of futures knowledge. *Futures, 119*, Article 102543. https://doi.org/10.1016/j.futures.2020.102543

Alam, S., Ayub, M. S., Arora, S., & Khan, M. A. (2023). An investigation of the imputation techniques for missing values in ordinal data enhancing clustering and classification analysis validity. *Decision Analytics Journal, 9*, Article 100341. https://doi.org/10.1016/j.dajour.2023.100341

Ansoff, H. I. (1975). Managing strategic surprise by response to weak signals. *California Management Review, 18*(2), 21–33. https://doi.org/10.2307/41164635

Antonopoulos, C., Anyfantaki, S., Balfoussia, H., Kosma, T., Papapetrou, E., Petroulakis, F., Petroulas, P., & Zioutou, P. (2022). The Greek labour market before and after the pandemic: Slack, tightness and skills mismatch. *Economic Bulletin. Bank of Greece*, (56), 45–74. https://doi.org/10.52903/econbull20225602

Bakinezos, C., Panagiotou, S., & Vourvachaki, E. (2020). Multiplier effects by sector: An input–output analysis of the Greek economy. *Economic Bulletin. Bank of Greece*, (52), 7–28. https://doi.org/10.52903/econbull20205201

Bandara, K., Bergmeir, C., & Smyl, S. (2020). Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach. *Expert Systems with Applications, 140*, Article 112896. https://doi.org/10.1016/j.eswa.2019.112896

Brewer, J. M. (1916). Vocational guidance in school and occupation. *Annals of the American Academy of Political and Social Science, 67*(1), 54–63. https://doi.org/10.1177/000271621606700109

Bulman, T. (2020). *(OECD Economics Department Working Papers, no. 1622*. OECD Publishing. https://doi.org/10.1787/8ea5033a-en

Cao, N., & Sing, M. C. P. (2024). Workforce forecasting in the building maintenance and repair work: Evaluating machine learning and LSTM models. *Journal of Building Engineering, 95*, Article 110125. https://doi.org/10.1016/j.jobe.2024.110125

Cedefop. (2020). *2020 skills forecast: Greece [Report]*. Cedefop. https://www.cedefop.europa.eu/files/skills_forecast_2020_greece.pdf.

Cedefop. (n.d.). Future employment and growth indicators for Greece (2022–2035) [Data set]. *Cedefop Skills Intelligence*. https://www.cedefop.europa.eu/en/tools/skills-intelligence/future-employment-growth?country=EL&year=2022-2035#5.

Chen, H., Lu, T., Huang, J., He, X., Yu, K., Sun, X., Ma, X., & Huang, Z. (2023). An improved VMD-LSTM model for time-varying GNSS time series prediction with temporally correlated noise. *Remote Sensing, 15*(14), 3694. https://doi.org/10.3390/rs15143694

Danchev, S., Pavlou, G., & Kostarakos, I. (2014). Input–output analysis of sectoral labor dynamism. In P. E. Petrakis (Ed.), *The rebirth of the greek labor market* (pp. 153–180). Palgrave MacMillan. https://doi.org/10.1057/9781137460820_9.

Dimoulkas, I., Mazidi, P., & Herre, L. (2019). Neural networks for GEFCom2017 probabilistic load forecasting. *International Journal of Forecasting, 35*(4), 1409–1423. https://doi.org/10.1016/j.ijforecast.2018.09.007

Favilukis, J., Lin, X., & Zhao, X. (2020). The elephant in the room: The impact of labor obligations on credit markets. *American Economic Review, 110*(6), 1673–1712. https://doi.org/10.1257/aer.20170156

Galaní-Moutáfi, V. (1993). From agriculture to tourism: Property, labor, gender, and kinship in a Greek island village (Part one). *Journal of Modern Greek Studies, 11*(2), 241–270. https://doi.org/10.1353/mgs.2010.0288

Gaponenko, N. (2022). In search of sectoral foresight methodology: Bridging foresight and sectoral system of innovation and production. *Futures, 135*, Article 102859. https://doi.org/10.1016/j.futures.2021.102859

Gomes, O., & Gubareva, M. (2021). Complex systems in economics and where to find them. *Journal of Systems Science and Complexity, 34*(1), 314–338. https://doi.org/10.1007/s11424-020-9149-1

Ha, T., Yang, H., & Hong, S. (2023). Automated weak signal detection and prediction using keyword network clustering and graph convolutional network. *Futures, 152*, Article 103202. https://doi.org/10.1016/j.futures.2023.103202

Hafferty, F. W., & Light, D. W. (1995). Professional dynamics and the changing nature of medical work. *Journal of Health and Social Behavior, Spec*, 132–153. https://doi.org/10.2307/2626961

Higgins, P., Hotchkiss, J. L., & Terry, E. (2019). Evolution of behavior, uncertainty, and the difficulty of predicting labor force participation. *Business and Economic Research, 9*(4), 157–176. https://doi.org/10.5296/ber.v9i4.15350

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Huang, W. (2019). Seismic signal recognition by unsupervised machine learning. *Geophysical Journal International, 219*(2), 1163–1180. https://doi.org/10.1093/gji/ggz366

Topińska, I. (2018). *ESPN Flash Report 2018/34: Poland: Effects of the child allowance programme "Family 500+" [Report]*. European Social Policy Network (ESPN). https://ec.europa.eu/social/BlobServlet?docId=19760&langId=en.

Iqbal, A., & Amin, R. (2024). Time series forecasting and anomaly detection using deep learning. *Computers & Chemical Engineering, 182*, Article 108560. https://doi.org/10.1016/j.compchemeng.2023.108560

Iuhasz, G., Fortiş, T. F., & Panica, S. (2025). Exploring machine learning methods for the identification of production cycles and anomaly detection. *Internet of Things, 30*, Article 101508. https://doi.org/10.1016/j.iot.2025.101508

Ji, P., Ye, J., Mu, Y., Lin, W., Tian, Y., Hens, C., Perc, M., Tang, Y., Sun, J., & Kurths, J. (2023). Signal propagation in complex networks. *Physics Reports, 1017*, 1–96. https://doi.org/10.1016/j.physrep.2023.03.005

Kanzola, A. M., & Petrakis, P. E. (2024). A foresight framework for the labor market with special reference to managerial roles: Toward diversified skill portfolios. *Forecasting, 6*(4), 49. https://doi.org/10.3390/forecast6040049

Karami, S., Saberi-Movahed, F., Tiwari, P., Marttinen, P., & Vahdati, S. (2023). Unsupervised feature selection based on variance–covariance subspace distance. *Neural Networks, 166*, 188–203. https://doi.org/10.1016/j.neunet.2023.06.018

Kasimati, E., Rentifi, A., & Vagionis, N. (2024). Tourism agenda 2030 in Greece. *Metaverse and tourism* (pp. 133–147). Routledge. https://doi.org/10.4324/9781003497004-10

Kaufman, B. E. (1999). Expanding the behavioral foundations of labor economics. *Industrial and Labor Relations Review, 52*(3), 361–392. https://doi.org/10.2307/2525140

Kozma, R., Kitamura, M., Sakuma, M., & Yokoyama, Y. (1994). Anomaly detection by neural network models and statistical time series analysis. In *, 5. Proceedings of the 1994 IEEE International Conference on Neural Networks (ICNN'94)*. IEEE. https://doi.org/10.1109/ICNN.1994.374748.

Liechti, F., Fossati, F., Bonoli, G., & Auer, D. (2017). The signalling value of labour market programmes. *European Sociological Review, 32*(4), 546–560. https://doi.org/10.1093/esr/jcw061

Lloret-Climent, M., Nescolarde-Selva, J. A., Mora-Mora, H., Alonso-Stenberg, K., & Molla-Sirvent, R. (2020). Modelling complex social systems: A new network point of view in labour markets. *IEEE Access : Practical Innovations, Open Solutions, 8*, Article 90910. https://doi.org/10.1109/ACCESS.2020.2994622

Lo, H. C., Koedijk, K. G., Gao, X., & Hsu, Y. T. (2020). How do job vacancy rates predict firm performance? A web crawling massive data perspective. *Pacific-Basin Finance Journal, 62*, Article 101371. https://doi.org/10.1016/j.pacfin.2020.101371

Louri, H. (1988). Urban growth and productivity: The case of Greece. *Urban Studies, 25*(5), 433–438. https://doi.org/10.1080/00420988820080551

Ma, M., Mao, J., & Li, G. (2024). Discovering weak signals of emerging topics with a triple-dimensional framework. *Information Processing & Management, 61*(5), Article 103793. https://doi.org/10.1016/j.ipm.2024.103793

Mitrakos, T., & Nicolitsas, D. (2006). Long-term unemployment in Greece: Developments, incidence and composition. *Economic Bulletin, 27*, 7–41. *Bank of Greece* https://www.bankofgreece.gr/Publications/2720060701_en.pdf.

Mitrea, C. A., Lee, C. K. M., & Wu, Z. (2009). A comparison between neural networks and traditional forecasting methods: A case study. *International Journal of Engineering Business Management, 1*, Article 11. https://doi.org/10.5772/6777

Nababan, T. S., & Purba, E. F. (2023). Labour absorption in manufacturing industry in Indonesia: Anomalous and regressive phenomena [Preprint]. *arXiv* https://arxiv.org/abs/2311.01787.

Nicolaidou, O., Dimopoulos, C., Varianou-Mikellidou, C., Boustras, G., & Mikellides, N. (2021). The use of weak signals in occupational safety and health: An investigation. *Safety Science, 139*, Article 105253. https://doi.org/10.1016/j.ssci.2021.105253

Organization for Economic Co-operation and Development. (2020). Back to the future of education: Four OECD scenarios for schooling. *Educational research and innovation*. OECD Publishing. https://doi.org/10.1787/178ef527-en

Paschalidis, C. D., Petropoulos, D. P., Sotiropoulos, S. S., Paschalidis, D. C., Christodoulou, C. N., & Papakonstantinou, L. D. (2021). The evolution of agricultural employment in Greece. *Advances in Management and Applied Economics, 11*(6), 95–103. https://doi.org/10.47260/amae/1146

Petrakis, P. E. (2024). The legislative process and regulatory interventions in the Greek democracy: Deep-rooted weaknesses and recommendations for improvement. *Statute Law Review, 45*(1), 1–11. https://doi.org/10.1093/slr/hmae001

Reeves, M., Godson, N., & Whitaker, K. (2021). The power of anomaly: To achieve strategic advantage, scan the market for surprises. *Harvard Business Review*. https://hbr.org/2021/07/the-power-of-anomaly.

Sáez-Ortuño, L., Huertas-Garcia, R., Forgas-Coll, S., Sánchez-García, J., & Puertas-Prats, E. (2024). Quantum computing for market research. *Journal of Innovation & Knowledge, 9*(3), Article 100510. https://doi.org/10.1016/j.jik.2024.100510

Saritas, O., & Smith, J. E. (2011). The big picture: Trends, drivers, wild cards, discontinuities and weak signals. *Futures, 43*(3), 292–312. https://doi.org/10.1016/j.futures.2010.11.007

Sidiropoulou-Dimakakou, D., Argyropoulou, K., Drosos, N., & Terzaki, M. (2012). Career beliefs of Greek and non-Greek vocational education students. *Creative Education, 3*(7), 1241–1250. https://doi.org/10.4236/ce.2012.37183

Song, X., Liu, Y., Xue, L., Wang, J., Zhang, J., Wang, J., Jiang, L., & Cheng, Z. (2020). Time-series well performance prediction based on long short-term memory (LSTM) neural network model. *Journal of Petroleum Science and Engineering, 186*, Article 106682. https://doi.org/10.1016/j.petrol.2019.106682

Soroui, S. T. (2023). Encountering weak signals: Economic development practitioners' perceptions of remote work arrangements. *Local Economy, 38*(1), 3–21. https://doi.org/10.1177/02690942231180283

Spinthiropoulos, K., Zafeiriou, E., & Nikas, C. (2020). Sector analysis and economic growth in Greece: The domination of tourism over other sectors. In C. Nikas (Ed.), *Economic growth in the European Union, contributions to economics* (pp. 167–176). Springer. https://doi.org/10.1007/978-3-030-48210-7_12.

Staboulis, C., Natos, D., Gkatsikos, A., Tsakiridou, E., Mattas, K., Bojar, W., Baranowski, P., Krzyszczak, J., Rivero, O. P., & Roldán, Á. O. (2022). Assessing the role of the Young Farmer Scheme in the export orientation of Greek agriculture. *Sustainability, 14*(6), Article 3287. https://doi.org/10.3390/su14063287

Theofilakou, A., & Vasardani, M. (2024). Labour market tightness in the post-COVID-19 era. *Economic Bulletin. Bank of Greece, 2024*(59), 73–88. https://doi.org/10.52903/econbull20245904

Van Veen, B. L., & Ortt, J. R. (2021). Unifying weak signals definitions to improve construct understanding. *Futures, 134*, Article 102837. https://doi.org/10.1016/j.futures.2021.102837

Vettas, N., Peppas, K., Stavraki, S., & Vasileiadis, M. (2020). The contribution of industry to the Greek economy: Facts and prospects. *Economic Bulletin. Bank of Greece*, (52), 29–67. https://doi.org/10.52903/econbull20205202

Wack, P. (1985). Scenarios: Shooting the rapids. *Harvard Business Review, 63*(6), 139–150.

Wilkinson, A. (2016). Using strategic foresight methods to anticipate and prepare for the jobs-scarce economy. *European Journal of Futures Research, 4*(1), Article 12. https://doi.org/10.1007/s40309-016-0094-0

World Economic Forum. (2025). *The future of jobs report [Report]*. World Economic Forum. https://www.weforum.org/reports/the-future-of-jobs-report-2025.

Wright, D., Stahl, B., & Hatzakis, T. (2020). Policy scenarios as an instrument for policymakers. *Technological Forecasting and Social Change, 154*, Article 119972. https://doi.org/10.1016/j.techfore.2020.119972

Xu, H., Pang, G., Wang, Y., & Wang, Y. (2023). Deep isolation forest for anomaly detection. *IEEE Transactions on Knowledge and Data Engineering, 35*(12), 12591–12604. https://doi.org/10.1109/TKDE.2023.3270293

Yadav, H., & Thakkar, A. (2024). NOA-LSTM: An efficient LSTM cell architecture for time series forecasting. *Expert Systems with Applications, 238*, Article 122333. https://doi.org/10.1016/j.eswa.2023.122333

Yu, M., Pasman, H., Erraguntla, M., Quddus, N., & Kravaris, C. (2022). A framework to identify and respond to weak signals of disastrous process incidents based on FRAM and machine learning techniques. *Process Safety and Environmental Protection, 158*, 98–114. https://doi.org/10.1016/j.psep.2021.11.030

Yurtsever, M. (2023). Unemployment rate forecasting: LSTM-GRU hybrid approach. *Journal for Labour Market Research, 57*(1), Article 9. https://doi.org/10.1186/s12651-023-00345-8

Zhan, S., & Huang, L. (2023). State familism in action: Aging policy and intergenerational support in Singapore. *China Population and Development Studies, 7*(2), 111–129. https://doi.org/10.1007/s42379-023-00132-5

Zhang, G., Eddy Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks. *International Journal of Forecasting, 14*(1), 35–62. https://doi.org/10.1016/S0169-2070(97)00044-7