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# A Data-Driven Approach to Labour Market Alignment with Renewable Innovation in the UK and US

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***Abstract*— As the development of renewable energy technologies accelerates, the need for a highly skilled workforce becomes increasingly critical. However, empirical evidence remains limited regarding whether current labour markets are adequately responding to this growing demand. This paper analyses the demand for skills in electrical engineering as the energy sector transitions to renewables. We focus on the United States (US) and the United Kingdom (UK) markets and employ the enhanced Latent Dirichlet Allocation model with incorporated hierarchical skill relationships and automated variation handling, enabling deeper insights into skill interactions. The findings highlight both shared global priorities, such as practical and technical competencies, and distinct regional differences shaped by national energy transitions, as well as an evident gap between the projected future skill requirements for the renewable energy sector and the current labour market demand. To further investigate the influence of professional skills within a specific occupational group in the energy industry on national innovation output, we used a Bayesian regression model. The results indicate a robust, positive relationship between skills and innovation, with consistent effects across both countries despite differing broader innovation ecosystems. The study contributes to understanding the role of occupational skill development in the national innovation systems.**

***Keywords*—industry employment, innovation, job skills, machine learning, renewable energy**

## I. Introduction

The ambitious goal of eliminating carbon emissions relies on the skills, dedication, and collaboration of the workforce [1] interacting within the energy and industrial sectors. The expertise of industry professionals is an essential resource, equally as vital as technology, for developing and implementing the innovative solutions and policies needed to drive the transition towards renewable energy and a sustainable future. However, in the light of the rapid growth of renewable energy outpacing the development of a suitably skilled workforce [2] and driving workforce migration, it is still not clear how technological developments affect the labour market in the renewable energy sector.

In particular, most publications on skills requirements are based on the analysis of employer surveys (for instance, [2], [3], [4]). Consequently, there is a substantial gap in understanding whether the skills required for the future energy sector workforce are consistent with the trends in today's labour market and what the relationship is between these requirements and the country's competitiveness and growth.

There is a compelling case for examining market-specific characteristics using the example of the UK and the US, due to the simultaneous growth of the renewable energy sector and the comparable levels and dynamics of unemployment in both markets (Fig. 1). Both countries experienced significant labour market disruptions caused by the COVID-19 pandemic and, in the aftermath, faced challenges such as labour shortages and shifts in employment patterns [5], which by the end of 2023 reached the comparable levels.

Thus, analysing labour market trends in these countries provides insights into how the post-pandemic industrial recovery is progressing, particularly regarding the adoption of advanced technologies, the integration of sustainable practices, and the evolving skill demands driven by the acceleration of renewable energy technologies.

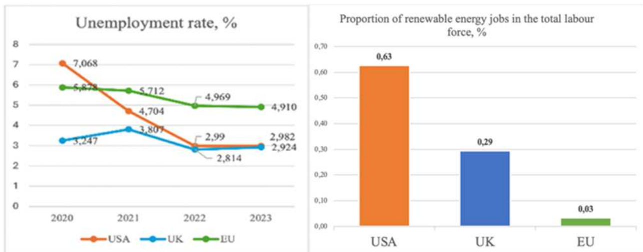


Fig.1. Comparison of the UK, the US, and the EU labour market characteristics

This paper proposes an adapted and robust approach to utilising machine learning to enhance the understanding of the patterns in skills demanded from electrical engineering professionals and to support labour market analysis. The approach involves (i) extracting relevant information from an extensive dataset, (ii) applying an enhanced machine learning model to uncover patterns and trends, and (iii) conducting comprehensive statistical analyses using Bayesian regression modelling to uncover the impact of the skills in a specific occupational group in the energy industry on the innovation output of the country and potentially its competitiveness. The results provide valuable insights that can guide the development of a skilled and future-ready energy sector workforce.

## II. Review of State-of-the-art

The topic of workforce development in the power and energy sectors faces several critical gaps. Firstly, there is a dearth of publicly available, detailed datasets. This data gap limits the ability of researchers and policymakers to conduct comprehensive analyses of the subject.

Secondly, data scarcity directly affects the scope of research on the future energy jobs. An analysis of the Scopus database, displayed in Fig. 2, shows a rather slow trend in the development of this topic.

Fig. 2 reveals that, in general, renewable energy is a large research topic with a substantial volume of research published every year. When narrowing the focus to publications specifically addressing the topic of energy sector jobs, they account for only 5% or less of the total publications on

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renewable energy. Moreover, in terms of research in renewable energy jobs, the numbers of publications are even more reduced, with less than 1% of the total research output dedicated to this area. This highlights a significant gap in the research on workforce development for the renewable energy sector, despite its recognised importance for achieving global sustainability goals.

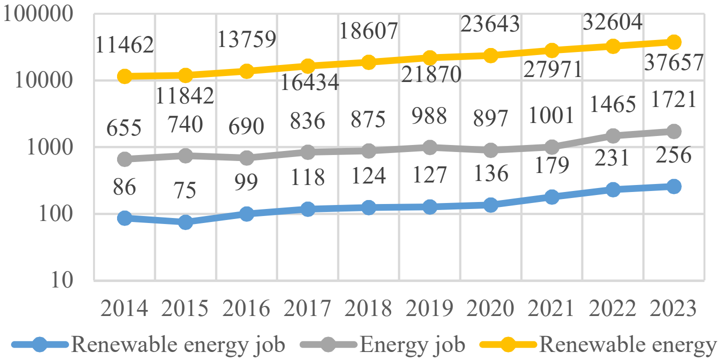


Fig.2. Representation of the research topicality on renewable energy employment

The methodology used in this study was shaped by the following recent research.

Paper [6] presents a comprehensive skills dictionary for the renewable energy sector workforce that establishes future skill requirements in this sector. This list integrates renewable energy-related professional profiles with their associated current and future technical, transversal, and green skill requirements. The methodology employed by the authors integrates systematic processes and expert validation to analyse the current and future skills needs in the renewable energy sector. The work is based on the analysis of the comprehensive European Commission initiative, as the primary resource for identifying professional profiles and current skill requirements.

Paper [7] conducted a comprehensive analysis by employing a systematic approach to monitor professional skills within job advertisements. It utilised specific search strings to flag each skill, focusing on the job skills and description sections of the postings. This method ensures precise identification of skills directly relevant to the renewable energy sector, enabling the extraction of both current and emerging skill requirements. This methodology enhances the understanding of workforce trends, aligning with the sector's transition to digitalisation and sustainability.

Lastly, paper [8] provided valuable methodological insights for the application of Latent Dirichlet Allocation (LDA) in this research. LDA model has already proved its effectiveness for the analysis of the large datasets in previous research (for instance, [9]). In this paper the LDA analysis allowed to identify and categorise professional skills and job trends along the transition to the renewable energy.

By integrating and adapting approaches and methods from this literature, this paper develops a comprehensive and robust methodology for deep analysis and provides actionable insights into the evolving professional landscape of the renewable energy sector.

The further theoretical and methodological application of the obtained information about the current market skill demand aligns with the studies of the relationship between a broader interpretation of the impact of skills on innovation and technological change.

For instance, study [4] shows a strong, significantly positive relationship between the innovation intensity and the proportion of high-skill workers in information and communications technology. The findings in [10] also confirm that an insufficient supply of skills restricts innovation.

The model in study [11] divides the labour force into high-skilled labour (*Lh*) and low-skilled labour (*Ll*), assuming that Research and Development (R&D) activities are undertaken by high-skilled labour while production activities for the final product are undertaken by low-skilled labour only. Their findings suggest that the skill-biased technological change setting marks the correlation between technological change and labour demand. Additionally, the findings of [12] confirm the falling trend in the elasticity of substitution between skilled and unskilled labour. However, to our knowledge, there is a lack of evidence of the impact of skills in a specific profession on the national innovation output.

## III. Methodology and Data

### A. Data used for this research paper

As identified in Section II, the research in renewable energy labour market faces a significant data gap because of insufficient availability and relevance of data. Major hiring platforms and social networks with recruitment functionalities, such as Indeed, LinkedIn and others, do not provide access to historical or detailed statistical data, often conducting their own research instead [13]. Commercial projects that aggregate job position data typically offer access on a subscription basis [14], which can limit access for academics. Furthermore, global research companies generally publish only statistical summaries [2], where the data is aggregated and inaccessible for detailed analysis. This lack of open and detailed data poses challenges for conducting comprehensive research in this critical area.

For investigation purposes, this paper utilises, as a raw input, an open-access dataset, provided by Techmap.io [14] and available on Kaggle [15]. This dataset contains job vacancy data sourced from 29 job boards, including 174 country-specific portals, with September 2021 data. The initial JSON file was preprocessed and had a substantial size of 50.4 GB, containing a total records count of 3,470,305 items.

Subsequently, data specific to the US and the UK was extracted from the dataset and the research was then further narrowed to focus exclusively on job positions directly relevant to the energy market, ensuring a targeted analysis of electrical engineering workforce trends in the sector. The overall amount of data taken into account is 9,000 job positions in the US and 8,000 in the UK, representing different types of electrical specialists in the energy industry, e.g. electrical engineers, technicians, designers, experts etc. This extensive amount of data provided a sample dataset for this study, enabling a detailed analysis of employment trends in the transforming energy sector.

For further empirical testing the impact of skills on innovation output, we obtained data from the International Energy Agency (IEA) (Total Energy Technology RD&D Expenditures, Share of renewables in energy consumption), Climate Policy Lab of the Center for International Environment and Resource Policy (CIERP) (Share of renewables in energy consumption), The World Intellectual Property Organization (WIPO) (Number of Patent Applications), the World Bank (Labour Force, GDP, Gross Capital Formation, Population).

### B. Methods used for this research paper

In this research, the Preprocess Text Data function from the MATLAB package [16] was employed to prepare textual data for analysis. The preprocessing involved word normalisation using lemmatisation, a technique that reduces words to their base or dictionary forms, which helps in grouping similar words and improving the quality of textual analysis. To maintain the relevance of the vocabulary, a minimum word length of 3 and a maximum word length of 14 were set. The text was tokenised in English, splitting into individual words or terms for subsequent analysis. Embedded HyperText Markup Language (HTML) features were cleaned to remove unnecessary formatting or code elements.

Subsequently, we utilised the LDA model [8] to identify topics present in the text data using Python programming language. The model employs a novel approach by integration of custom domain-specific skill preservation with LDA topic modelling, utilising NLTK library for basic Natural Language Processing tasks (preprocessing the text data, ensuring efficient tokenisation, removal of stop words, and preparation of the text for model training) [17] while adding specialised preprocessing to maintain engineering and technical terminology and analysis components for electrical engineer job requirements.

The model integrates hierarchical skill categorisation across multiple domains and provides a skill-centric analysis framework based on a multi-layered examination of skill relationships. It preserves skill variations and contextual relationships through the automated identification of skill connections, as well as the tracking of skill co-occurrences and dependencies. Additionally, we conducted statistical analysis through probability distributions in topic modelling. A similar approach can be utilised for the analysis of employment trends in other professions, but it will require initial skills customisation beforehand.

For further modelling of the impact of skills on innovation output, the Bayesian regression analysis was employed. The effectiveness of this method has been widely proven for small datasets [18], and in our case, it can provide more stable estimates compared with classical regression.

## IV. Empirical Results

Based on the findings of the research [6], we utilise the list of current and future skill requirements for the renewable energy sector, which is then refined using the methodology proposed by [2]. This allows us to develop search strings and identify skills from the job descriptions for further analysis (Table I).

TABLE I. Representation of the Optimised Text Correlation for the Analysis

| # | Search string | Job skill description |
|---|---|---|
| 1 | experience | Personal experience |
| 2 | system | Cyber-physical systems; enterprise resource planning systems; online inspection and monitoring systems |
| … | … | … |
| 67 | entrepreneur | Entrepreneurship and initiative taking |
| 68 | machine | Machine learning |

The simple comparison of the future skill requirements dictionary for the renewable energy sector and the current market demand for electrical engineering specialists in the UK and US confirms that personal experience is equally emphasised in both the UK and the US markets, indicating the universal importance of practical, hands-on experience in the field. Skills like reverse engineering, Enterprise Resource Planning (ERP) systems, and platforms for energy management are similarly prioritised, suggesting a shared focus on technical and managerial competencies.

Several skills, such as Big Data, adaptability, negotiation skills, and cybersecurity, are barely mentioned in both markets. This could indicate an underrepresentation in job descriptions, despite their increasing relevance in modern engineering. There is the same trend for both markets with limited emphasis on innovative technologies, such as Artificial Intelligence (AI), cybersecurity, and blockchain, which could signal gaps in skill requirements or outdated job descriptions.

Also, both markets value customer relationship management, with slightly greater emphasis in the US. Environmental and energy efficiency skills are equally emphasised, highlighting the global importance of sustainability in engineering.

However, there are some notable differences between the US and the UK labour markets. Predictive and proactive maintenance sees greater emphasis in the UK, likely reflecting a stronger push towards condition-based maintenance and proactive engineering practices. Also, the UK employers place more emphasis on compliance and standards, potentially due to stricter regulations. In addition, skills such as teaching and training others, as well as leadership and managing others, are slightly more prevalent in the UK job descriptions, compared to the US.

As for the US, we can conclude that cyber-physical, ERP and online inspection and monitoring systems are prioritised due to the integration of digital and physical systems, reflecting advancements in Industry 4.0. In addition, a greater focus on cloud computing in the US suggests a stronger emphasis on cloud-based solutions and related infrastructure. Also, the US emphasises lifelong learning, which may indicate a more dynamic, skill-updating culture in response to rapid technological changes.

Ultimately, there is strong evidence that while the UK tends to have a greater focus on traditional engineering competencies and compliance-related skills, the US demonstrates a stronger emphasis on digital transformation.

To further structure the pre-processed dataset and explore more refined skills demand trends, we utilise the LDA model, which helps to reduce the complexity of the unstructured dataset by organising it into a manageable number of topics. In our case, we employed an LDA model enhanced with domain-specific skill preservation while adding specialised preprocessing and multi-layered analysis of skill relationships, along with the tracking of skill co-occurrences and dependencies, which eliminates the need to analyse every job description individually and provides data-driven insights from job analysis.

Specifically, for a topic $t$ and a word $w$, LDA provides probability $P(w|t)$, and then for each skill word $w$ and category $c$, we define an indicator function $I(w, c)$. As a result, we get the probability mass of category $c$ in topic $t$:

$$P(c,t) = \sum_{w \in vocabulary} P(w|t) \times I(w,c), \quad (1)$$

Based on the extracted topics and considering their interconnectedness, a statistical analysis was conducted using probability distributions within the topic modelling framework by pre-defined categories – analytical, management, technical, domain knowledge, and soft skills. The results of the analysis reveal the distribution of skills by importance within each category (Fig.4).

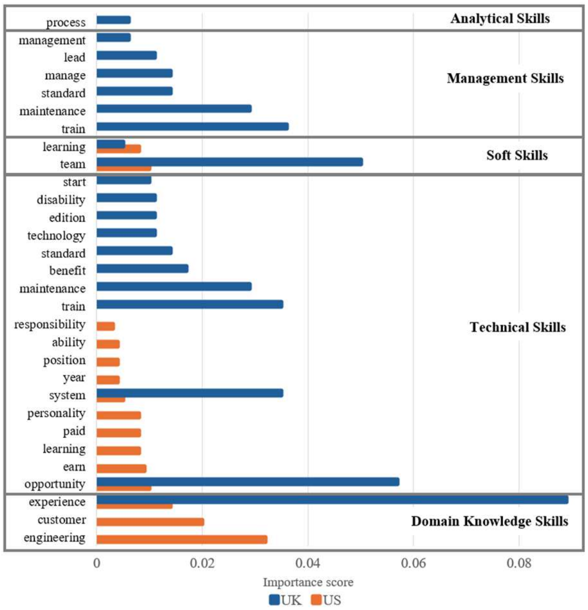


Fig.4. The comparison of skills importance by categories for the US and the UK

Domain knowledge skills for both the UK and the US markets are mainly represented by experience, but while practical expertise is highly valued for the UK (0.09) and contains a "*customer*" oriented signal, it is less emphasised in the US (0.014).

Among technical skills in the UK the most dominant are such signals as "*opportunity*" and "*train*", suggesting a focus on growth and continuous technical development, while the US along with "*opportunity*" contain "*earn*", which suggests a stronger financial or benefit-oriented perspective in technical roles compared to the UK.

As for soft skills, both markets have similar signals represented by "*team*" and "*learning*", with "*team*" having a notably higher importance score in the UK (0.05), suggesting a strong emphasis on collaboration, while it is much lower in the US (0.01). This indicates a weaker emphasis on soft skills.

Management and analytical skills are represented only in the UK and while the importance scores of management skills are relatively balanced, with "*train*" and "*maintenance*" signals having the highest scores, the importance score of the analytical signal "*process*" is low (0.006), which indicates limited emphasis on analytical skills in this labour market.

The results of the analysis confirm that the labour markets of both the US and the UK exhibit significant similarities, primarily emphasising work experience and core engineering skills, and showing a global trend toward growth and continuous development. However, notable differences are evident, aligning with previously identified trends, particularly in areas related to data orientation, customer focus, and learning and training priorities. This demonstrates that the current renewable energy labour market demand is not significantly aligned with the future skill requirements for electrical engineers, the list of which was identified by [6].

Therefore, it is crucial to examine whether the acquisition of future-oriented skills by a specific occupational group in energy industry, is vital for the advancement of the industry, and to what extent this skill development influences the broader national innovation output.

In our study, we found evidence that there are differences in the skill requirements within this job category and would like to find out how likely these differences in the skill demands influence national innovation performance.

For each region $r$ (US or UK), a skill distribution function can be defined as:

$$S_r(k) = \{S_{r_1}, S_{r_2}, \dots S_{r_n}\}, (2)$$

where $S_r(k)$ – the skill importance distribution in region $r$,
$k$ – the skill category from topic modelling,
$S_{r,i}$ – the importance weight of skill $i$ in region $r$

Based on [11], the R&D innovation and industrial evolution can be modelled by the following regression equation:

$$lnINNOV = \beta_0 + \beta_1 lnRE + \beta_2 lnRND + \beta_3 lnPAT + \beta_4 lnTFP + \beta_5 lnQ + \beta_6 ln\frac{K}{L} + \varepsilon, (3)$$

where $\beta$ – coefficients,
RE – renewable energy market share,
RND – R&D expenditure in the energy sector,
PAT – number of effective patents,
TFP– Total factor productivity,
Q – output (GDP) in the energy sector,
K/L – Capital-labour ratio,
$\varepsilon$ – random error

For the investigation of the relationship between skills and innovation output, we incorporate skills index (S) as an independent variable, which was measured as:

$$S = \sum(w_k \times i_k), (4)$$

where $w_k$ – theoretical weight assigned to skill category $k$ *(0,2 for each category to avoid subjective bias)*,
$i_k$ – importance intensity for skill category $k$

Given the limitations in the availability of skill-related data, we employ a 10-year observation window (2014 –2023) to enhance the statistical power of our estimations. This extended period of observation necessitates a parsimonious model specification, with a restricted number of independent variables, to ensure the robustness and reliability of the results.

To ensure cross-country comparability, we normalised such variables as the number of effective patents (PAT_pc), R&D expenditure in the energy sector (RND_pc), and output in the energy sector (Q_pc) by population size.

To guide our selection of explanatory variables, we conducted a correlation analysis with innovation output, the results of which are presented in Table II.

TABLE II. THE RESULTS OF THE CORRELATION ANALYSIS OF INDEPENDENT VARIABLES WITH THE INNOVATION OUTPUT DEPENDENT VARIABLE

| Variable | UK | US |
|---|---|---|
| Q_pc | 0.9967 | 0.9995 |
| K/L | 0.9691 | 0.9975 |
| RND_pc | 0.8586 | 0.6392 |
| PAT_pc | 0.8233 | 0.6448 |
| RE | 0.5019 | 0.5733 |
| TFP | 0.4854 | 0.9635 |

The correlation analysis reveals extremely high correlation among variables Q_pc and K/L, so they were excluded due to potential endogeneity or collinearity. Similarities of the correlation with RND_pc and PAT_pc suggest that we can use one of these variables for the final model.

To enhance the methodological choice of variables while maintaining theoretical rigor, we refer to the latest findings in the literature [4, 10, 12] to guide our final model specification. This literature consistently identifies total factor productivity (TFP) and R&D expenditure (RND_pc) as critical innovation determinants. Additionally, we include renewable energy market share (RE) given its specific relevance to our research focus on the electrical engineering sector.

The final model explaining the effect of skills on the innovation output in the *r* country can be defined as follows:

$$lnINNOV_r = \beta_0 + \beta_1 S_r + \beta_2 lnTFP_r + \beta_3 lnRND\_pc_r + \beta_4 lnRE_r + \varepsilon, (5)$$

For the estimation of the skills impact on innovation output according to our model, we employ Bayesian regression using a direct sampling approach, assuming that variable S is constant during the observation period of time (2014–2023).

The model equation for the UK and descriptive statistics (Table III) is presented below:

$$\ln INNOV_{UK} = 0.7424 + 0.3678 \times S + 0.6273 \times TFP + 0.1772 \times RND\_pc + 0.1997 \times RE\ , (6)$$

TABLE III. THE DESCRIPTIVE STATISTICS FOR THE UK INNOVATION OUTPUT MODEL

| UK | mean | median | st. dev. | ci_95%_lower | ci_95%_upper | prob_positive | prob_negative |
|---|---|---|---|---|---|---|---|
| Intercept ($\beta_0$) | 0.7424 | 0.8173 | 1.6239 | -2.2013 | 3.6614 | 0.6518 | 0.3482 |
| Skills ($\beta_1$) | 0.3678 | 0.3392 | 0.9885 | -1.4803 | 2.3264 | 0.6346 | 0.3654 |
| TFP ($\beta_2$) | 0.6273 | 0.6408 | 0.5306 | -0.3801 | 1.6739 | 0.8876 | 0.1124 |
| RND_pc ($\beta_3$) | 0.1772 | 0.1601 | 0.6072 | -0.9355 | 1.4990 | 0.5904 | 0.4096 |
| RE ($\beta_4$) | 0.1997 | 0.2553 | 0.7669 | -1.5007 | 1.7435 | 0.6338 | 0.3662 |

The estimated model equation for the US and descriptive statistics (Table IV) is presented below:

$$\ln INNOV_{US} = 1.0336 + 0.3181 \times S + 0.0255 \times TFP + 0.7686 \times RND\_pc + 0.4725 \times RE, (7)$$

TABLE IV. THE DESCRIPTIVE STATISTICS FOR THE US INNOVATION OUTPUT MODEL

| US | mean | median | st. dev. | ci_95%_lower | ci_95%_upper | prob_positive | prob_negative |
|---|---|---|---|---|---|---|---|
| Intercept ($\beta_0$) | 1.0336 | 1.1815 | 1.5170 | -2.4127 | 3.8389 | 0.785 | 0.2150 |
| Skills ($\beta_1$) | 0.3181 | 0.3206 | 1.0181 | -1.6479 | 2.3088 | 0.621 | 0.3794 |
| TFP ($\beta_2$) | 0.0255 | -0.005 | 0.4654 | -0.8258 | 1.113 | 0.497 | 0.5030 |
| RND_pc ($\beta_3$) | 0.7686 | 0.7019 | 0.7357 | -0.6381 | 2.1615 | 0.856 | 0.1438 |
| RE ($\beta_4$) | 0.4725 | 0.4067 | 0.9305 | -1.1648 | 2.7999 | 0.691 | 0.3086 |

The Bayesian R-squared values reflect modest explanatory power (UK: 0.2685, US: 0.2216), with wide confidence intervals reflecting uncertainty given our data constraints. These values indicate that while our model captures meaningful variation in innovation, substantial innovation determinants exist beyond our measured variables.

The skills coefficient ($\beta_1$) demonstrates remarkable consistency across both countries (UK: 0.3678, US: 0.3181), with similar probabilities of positive effect (UK: 63%, US: 62%). This consistency suggests a universal relationship between skills and innovation that transcends national contexts. While the wide confidence intervals (-1.48 to 2.33 for UK, -1.65 to 2.31 for US) reflect our data limitations, the consistent positive mean effect and probability values above 60% suggest a likely positive relationship between skills and innovation outputs.

Despite similar skills effects, our results reveal distinct innovation patterns between countries. The UK innovation system shows stronger responsiveness to productivity factors, with TFP having the highest coefficient (0.6273) and probability of positive effect (88.8%) among all variables.

The US innovation system demonstrates a stronger investment orientation with RND_pc having the highest coefficient (0.7686) and probability of positive effect (85.6%) among all variables.

Notably, RE demonstrates considerably stronger effects in the US ($\beta_4$ = 0.4725, 69% positive) compared to the UK ($\beta_4$ = 0.1997, 63.4% positive). This suggests that renewable energy initiatives may be more effectively integrated into broader innovation systems in the US electrical engineering sector.

The comparison of estimated coefficients for two countries is presented in Fig.5.

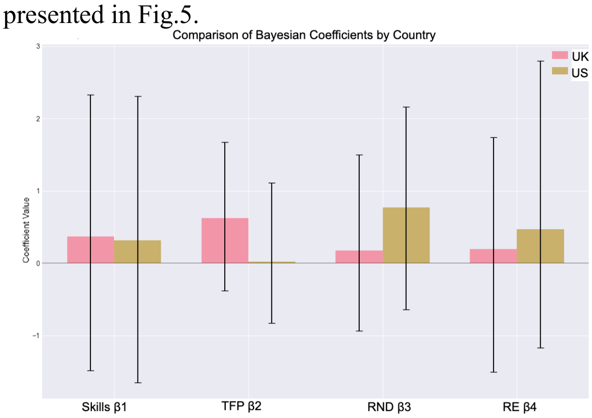


Fig.5. The comparison of coefficients for the UK and the US innovation output models

To address the limitation of the Skills data and its impact on the final model, we conducted a sensitivity test, constructing a time series for the Skills variable. This time series is developed using two alternative theoretical approaches: one assumes a 2% annual rate of change, and the other assumes a 2% change every two years, projected both forward and backward from the 2021 baseline.

The results of both tests are presented in Table V.

TABLE V. THE RESULTS OF THE TIME SERIES APPLICATION TO THE INNOVATION OUTPUT MODELS

| | 2% annual change | | 2% two years change | |
|---|---|---|---|---|
| | UK | US | UK | US |
| Intercept ($\beta_0$) | -0.2393 | -0.0253 | 0.7307 | 0.8196 |
| Skills ($\beta_1$) | 0.3669 | 0.2882 | 0.3320 | 0.3126 |
| TFP ($\beta_2$) | 0.8913 | 0.4807 | 0.6034 | 0.5391 |
| RND_pc ($\beta_3$) | 0.3874 | 0.6591 | 0.1167 | 0.2530 |
| RE ($\beta_4$) | -0.0990 | 0.2044 | 0.3271 | 0.3184 |

The explanatory power of the models remained relatively consistent overall. However, for the UK, the original model demonstrated the strongest explanatory power, as test results revealed slightly lower values (0.2525 and 0.2490). In contrast, for the US, the highest explanatory power was observed in the second test, which assumed a 2% change every two years (0.1920 and 0.2239), shows nearly identical model fit for both countries.

Both tests showed a relatively stable skills-innovation relationship under different assumptions, which strengthens confidence in our core finding despite small samples. Skills coefficient remained consistently positive with around 60% probability across both countries and models, confirming robust positive relationship.

The innovation patterns in the TFP and RND_pc ratio remained similar to the original model for both countries during the testing of the first assumption. Although the TFP coefficient for the US increased significantly, and during the testing of the second assumption, the importance of TFP for the US changed ($\beta_3$=0.5391 with a probability of a positive effect of 76%). This change suggests that TFP can have a considerably high impact on the US innovation system, even if it is lower than the impact of RND_pc and confirms the right choice of the main variables for the model.

Additionally, there is a dynamics in the RE variable, but the proportion of its impact compared to other variables remains similar to the original model.

Overall, the results of testing the assumption of a 2% change in skills every two years show more stable results, producing convergent estimates that align with more realistic expectations for the innovation output model.

Our results, supported by the model construction and robustness testing under varying time series assumptions, highlight the potential benefits of skill growth for innovation. These findings confirm the innovation-related impacts of skill development initiatives and contribute to an understanding of how educational and labour policies can influence innovation outcomes, offering a forward-looking perspective to policymakers.

## CONCLUSIONS

This study analyses the current market demand for electrical engineering specialists in the energy sector of the US and UK, on the transition path towards renewable energy. Using text data from job descriptions, we applied an advanced text preprocessing technique, utilising an enhanced LDA model that incorporates hierarchical skill relationships and automated variation handling, to analyse the patterns and dynamics in skill interactions. The findings reveal the similarities of the UK and the US labour markets in terms of a shared global emphasis on practical experience and technical skills, but also indicate regional priorities and differences, which highlight how regional focus areas shape the skillsets demanded by local renewable energy industry.

In this context, evidence remains limited regarding how skills in the specific occupational group in energy industry can influence a country's competitiveness through its impact on innovation. To address this question, we suggested a parsimonious specification of the county's innovation output model and employed Bayesian regression analysis for the available small dataset.

The results indicate that skills contribute comparably to innovation across both countries, with a one-unit increase in the skills index corresponding to an approximate 30% increase in innovation output. However, the broader innovation ecosystems exhibit varying degrees of responsiveness to other influencing factors. These findings contribute to understanding how skills development initiatives might impact innovation outcomes. Although innovation remains a complex phenomenon influenced by many factors beyond our model, the consistency of skills effects across specifications provides preliminary evidence for the importance of skills in driving innovation in the electrical engineering sector.

The results of the sensitivity analysis of the model revealed that while the specific magnitude of effects varies with methodological choices, the fundamental relationship between skills and innovation remains robust. Across all specifications, skills coefficients range from 0.29 to 0.37, consistently showing positive effects on innovation in both countries. The similar coefficients between the UK and US suggest that skills in one profession contribute comparably to innovation across different national contexts, even as other innovation drivers may vary.

The proposed enhanced methodology can be further applied in practical contexts such as curriculum development, the design of targeted training and experience exchange programs, and the improvement of market analysis through the tracking of emerging skill trends. Additionally, it can support a better understanding of industry-specific skill requirements, the identification of gaps in current workforce competencies, and the study of best practices, as well as contribute to the development of employment-related policies.

Future research should aim to refine the proposed analytical methodology by incorporating advanced data scraping techniques to obtain historical data, enabling a deeper exploration of the emergence and decline of specific skills over time.

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