RESEARCH ARTICLE

A Multilingual Approach to Analyzing Talent Demand in a Specific Domain: Insights From Global Perspectives on Artificial Intelligence Talent Demand

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ABSTRACT This paper introduces an innovative methodology for conducting demand analysis within various domains across multiple countries, presenting insights derived from a comprehensive analysis conducted in seven distinct nations. The proposed methodology provides a systematic process for gathering, processing, and analyzing textual data to discern global talent demand within specified domains. Three fundamental steps characterize the methodology: identification of areas of interest, calculation of relative demand, and execution of analysis and forecasting. Areas of interest within the job market are pinpointed through a combination of manual curation and automated techniques, ensuring the inclusion of only pertinent job postings. Relative demand for jobs within each specified domain is then computed for each country, furnishing a standardized metric for cross-country comparisons. Subsequently, analysis and forecasting unveil trends and patterns in job demand, enabling stakeholders to anticipate shifts in the job market landscape. Application of this methodology to scrutinize demand analysis across seven countries - the US, Canada, the UK, France, India, Singapore, and Australia - reveals substantial variations in demand across diverse regions, along with correlations and instances of skill shortages. These findings offer invaluable insights for policymakers, businesses, and researchers, facilitating informed decision-making and fostering growth and innovation within the specified domains.

INDEX TERMS Demand analysis, AI skills, job demand forecasting, skills shortage.

I. INTRODUCTION

A. AI JOB MARKET ANALYSIS, FORECAST, AND DEMAND

The rapid evolution of technology has led to an exponential growth in demand for professionals skilled in AI, resulting in a significant talent gap in many countries. Analyzing the job demand in specific countries, such as the US, Germany [1], China [2], and India [3], offers valuable insights for policymakers, local businesses, and researchers. This understanding can help identify industrial hubs of technology,

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map the evolution of skills, and assess the effects on the global innovation ecosystem [4], [5].

By leveraging data from online job portals, researchers can obtain a more accurate representation of labor market needs, helping to determine workforce trends, gaps, and opportunities in various industries impacted by Big Data and Artificial Intelligence (BD&AI) [6], [7]. Additionally, evaluating the curricula of BD&AI programs in colleges and universities plays a crucial role in bridging the gap between industry needs and academic training [7]. Novel methodologies have been proposed to analyze and predict the impact of AI on the US labor market by using online job

posting data to forecast occupational task-share demands and estimate the market value of various skills [8].

The increasing demand for AI skills has been observed from 2010-2019 in the US economy across most industries and occupations, with the highest demand in IT occupations, followed by architecture and engineering, scientific, and management occupations [9]. A rapid increase in demand for machine learning (ML) skills has been documented since 2016, especially in the IT, finance, and professional services industries [3]. As AI transforms various industries, it is expected to create millions of new jobs by 2025, with many new roles emerging due to the collaboration of humans, machines, and algorithms [10].

B. AI'S IMPACT ON THE WORKFORCE, ECONOMY, AND CORPORATE VALUE

Artificial intelligence (AI) has been a driving force behind significant transformations in various industries, including healthcare, finance, and transportation. The rise of large language models, such as ChatGPT and GPT4, within deep learning has revolutionized natural language processing, leading to numerous groundbreaking applications [5], [11]. As a result, AI and deep learning technologies have emerged as general-purpose technologies that influence not only their domain but also other sectors across the economy.

The rapid growth of AI adoption and investment, with worldwide expenditure projected to reach $79 billion by 2022, has significantly impacted how businesses operate [12]. This expansion has led to a global skills crisis and talent shortages, which could potentially hinder research, innovation, and development [10]. Understanding the potential effects of AI on firm growth, industry concentration, and the economy as a whole can help develop a comprehensive framework for navigating this rapidly changing landscape [4].

As the workforce gradually adapts to job transformations driven by AI, there is a growing need to learn new technical skills [8]. Managers embracing AI adoption will be key to unlocking its full potential and driving firm growth [13]. Technical talent has become a valuable asset for corporate employers, contributing to their market value [14]. However, a granular understanding of engineering talent's impact on market value is necessary, as aggregate data may not provide precise causal relationships.

Over the next decades, AI is expected to be a driving force behind significant changes in the labor market [9], and numerous trends affecting the future of work and IT, such as increased demand for hybrid jobs, work-life balance, and global environmental challenges, can provide valuable insights into potential pathways and strategies for promoting positive outcomes [15].

C. ADDRESSING SKILL GAPS, ASSESSING IN-DEMAND SKILLS, AND FUTURE DIRECTIONS

The rapid advancement of artificial intelligence (AI) has led to a growing need for a workforce with broader skills to integrate AI concepts into various industries [16]. To maximize the economic benefits of intelligent technology, addressing skill gaps in the workforce is of utmost importance, which requires innovative approaches to talent management and workforce development [12].

One effective strategy is to prioritize experience-based skills development through on-the-job training and apprenticeships, promoting lifelong learning across all age groups and skill levels [12]. Simultaneously, bridging the gap between industry needs and academic training necessitates evaluating and adjusting BD&AI programs in colleges and universities [7]. This is particularly relevant given the significant skills gap between labor market requirements and the current workforce's expertise in BD&AI [7].

Addressing the skill gaps also involves improving methods for assessing and forecasting in-demand skills in the labor market. Many current approaches rely on unrepresentative databases, leading to inaccuracies in identifying skill shortages and excesses [6]. Various factors contribute to these gaps, including rapidly evolving technology, changing corporate environments, and shortcomings in traditional education and training systems [12]. Advanced forecasting techniques, such as the multivariate and multi-step Long Short-Term Memory (LSTM) network architecture, have shown promise in predicting future task-shares with higher accuracy [8].

To ensure a balanced and competitive market, policymakers must consider the potential consequences of AI on firm growth and industry concentration when developing regulations and policies that promote competition and innovation [4]. By understanding the impact of AI on various aspects of the economy, informed decisions can be made to address skill gaps and guide the workforce towards a successful AI-enabled future.

D. SUMMARY AND MAIN CONTRIBUTION

This paper introduces a thorough examination of the demand for AI jobs in various countries, employing a unique methodology tailored specifically for this purpose. The primary innovation of this study lies in its methodological approach, which offers a systematic methodology for gathering, processing, and interpreting textual data to gauge the global demand for talent in the AI domain.

The methodology consists of three pivotal steps: delineating areas of interest, quantifying relative demand, and conducting comprehensive analysis and projections. Initially, areas of interest within the job market are pinpointed through a combination of manual curation and automated techniques, ensuring that only relevant job postings are considered for analysis. Subsequently, the relative demand for AI jobs in each country is quantified, providing a standardized metric that facilitates comparisons across nations. Finally, a thorough analysis and forecast are undertaken to glean insights into the trends and patterns of AI demand, enabling stakeholders to anticipate shifts in the job market and devise informed strategies.

The primary contribution of this study lies in its innovative methodology and its application to scrutinize AI job demand across seven countries: the US, Canada, the UK, France, India, Singapore, and Australia. The findings reveal notable disparities in AI demand among different countries, with some experiencing rapid growth while others exhibit more stable trajectories. Furthermore, the analysis identifies correlations between countries and highlights regions where skill shortages are particularly acute, offering valuable insights for policymakers, businesses, and researchers alike.

II. RELATED WORK

A. AI JOB MARKET, WORKFORCE DEVELOPMENT, AND IMPACT ON INDUSTRIES

The rapid rise of deep neural networks in recent decades has caused significant disruption in numerous domains, including autonomous vehicles, translation services, and fraud detection [14]. This technological revolution has led to an increased demand for AI skills, with companies investing heavily in R&D and human capital to remain competitive [9].

A key concern in the AI job market is the geographical and demographic concentration of demand for AI skills [3]. Studies have shown a wage premium for job postings requiring AI skills, with managerial occupations exhibiting the highest wage premium [9]. Machine learning (ML) skill requirements have been associated with higher wages and more education [3].

Firm-level AI adoption has been positively associated with growth in size, Capex, R&D, and total investments, particularly when AI adoption occurs among managers [13]. However, productivity measures have not shown a robust relationship with AI adoption [13]. The primary mechanism responsible for the market valuation increases of AI adopters appears to be a revaluation of existing firm-specific technology-exposed assets [14].

The relationship between AI and industry concentration is an important consideration. AI technology can create a winner-takes-all market, in which a few dominant firms capture a large share of the market [4]. This concentration of market power can lead to reduced innovation and increased inequality [4]. The technological lead of top AI innovators has increased due to the accumulation of internal competences and an expanding knowledge base, contributing to the concentration process of the world's data market [17].

AI systems, including artificial learning, deep learning, and machine learning, have the potential to help organizations self-learn and implement skill-based operation systems, addressing skill gaps more effectively [12]. To leverage these technologies, companies should invest in skill development that combines learning sciences, digital applications, and experiential approaches, cultivating a range of skills such as creativity, analytical, and digital capabilities [12].

In conclusion, the adoption of AI technologies has had a profound impact on the job market, workforce development, and firm performance across industries. Understanding these effects and the market value of AI skills is essential for navigating the changing landscape of the global economy. Policymakers, educators, and business leaders must work together to address the challenges and opportunities presented by AI adoption, ensuring a more inclusive and innovative future.

B. CROSS-LINGUAL ANALYSIS AND NATURAL LANGUAGE PROCESSING

Natural language processing (NLP) has made significant strides in recent years, developing techniques and tools for understanding and processing human language. One of the main challenges in NLP is the variability and complexity of language, which can manifest in different forms such as multilinguality, cross-linguality, dialects, and jargon. To address this challenge, resources like multilingual knowledge bases can be employed, providing a unified representation of concepts across multiple languages [18].

Semantic annotation based on Wikipedia concepts, also known as wikification, is a prominent approach to addressing multilinguality [19]. Wikification typically involves two steps: (1) identifying mentions of entities in the document to be annotated, and (2) determining which (if any) of several candidate entities the mention refers to [20] and [21]. More recent work uses deep neural models to obtain vector representations of mentions and entities, while some studies emphasize simple and fast-to-compute methods suitable for large-scale wikification [22].

Wikifier.org is a resource for semantic annotation that uses Wikipedia as a multilingual knowledge base, annotating and linking text to Wikipedia concepts in multiple languages [23]. It has been applied to various tasks, such as cross-lingual information retrieval, named entity recognition, and machine translation, demonstrating the importance of addressing multilingual challenges to improve understanding and processing of human language across various applications.

C. SKILL EXTRACTION, ANALYSIS, AND TALENT DEMAND FORECASTING

Various methods have been employed to identify the domain of job postings and extract the required skills. Babina et al. [4] utilized a keyword-based method for selecting key AI-related skills, while Sibarani and Scerri [24] employed an Ontology-based Information Extraction (OBIE) method, building on their previous work [25], which used the Skills and Recruitment Ontology (SARO) designed for representing job postings in the context of skills and competencies. The latter method identifies skills requested by employers through co-word analysis based on skill keywords and their co-occurrences in job posts.

Revealed Comparative Advantage (RCA) has been used to measure skill importance for each occupation in different countries [26]. Rock and Shotts [14] utilized over 180 million position records and 52 million skill records from LinkedIn to measure the market value of exposure to newly available

deep learning talent. Technology skills, such as deep learning, are well-suited for these analyses due to high online coverage of tech workers, easily captured and explicitly named skills, and the rapid rise and fall of certain skills [14].

Sibarani and Scerri [24] used a graph-based approach to analyze skills from job postings, constructing the graph based on skill co-occurrences to analyze skill evolution and identify in-demand skills. Graph clustering and traditional statistical methods were employed to forecast in-demand skillsets. Squicciarini and Nachtigall [27] investigated the growth of AI-related job opportunities in Canada, Singapore, the UK, and the US, and found an increase in the total number of AI-related jobs, with a growing demand for multiple AI-related skills.

Essential skills include communication, problem-solving, creativity, and teamwork, along with complementary software-related and AI-specific competencies [27]. AI-related jobs are primarily found in categories such as professionals and technicians, but are in demand across almost all economic sectors, with the most AI job-intensive sectors being information and communication, financial and insurance activities, and professional, scientific, and technical activities in the countries examined [27]. Sun and Lu [2] discussed the growing demand for information service talents in China and highlighted the need for better relevance between talent demand analysis and industry planning, improved coordination in report preparation, and the application of scientific forecasting models for information service personnel demand. Das et al. [8] proposed novel methodologies for analyzing and predicting the impact of AI on the US labor market by using online job posting data to forecast occupational task-share demands and estimate the market value of various skills.

D. FORECASTING TECHNIQUES, APPLICATIONS, AND AI'S IMPACT ON THE LABOR MARKET

The rapid growth of Artificial Intelligence (AI) has reshaped the labor market, driving demand for a range of skills and requiring more accurate forecasting methods for talent acquisition. This section reviews various studies that focus on predicting talent demand, AI's impact on the labor market, and novel forecasting techniques and applications that address the challenges posed by this evolving landscape.

To predict information service talent demand, Sun and Lu [2] proposed a combined GM (1, 1)-BP neural network prediction model using gray system theory, resulting in satisfactory prediction outcomes for government decision-making and personnel training. Zhang et al. [28] introduced the Talent Demand Attention Network (TDAN) for fine-grained talent demand forecasting, which augments univariate time series and extracts intrinsic attributes of companies and job positions using matrix factorization techniques. TDAN also addresses the challenges of sparse fine-grained talent demand and complex temporal correlations.

In parallel, Giabelli et al. [26] developed Skills2Job, a recommender system identifying suitable jobs based on users' skills from millions of Online Job Vacancies (OJVs). The data-driven approach used in Skills2Job allows for adaptation to different countries and industries and easy updates over time. Baral et al. [12] emphasized the importance of developing both technical and fundamentally human skills like empathy and critical thinking.

Johnson et al. [7] investigated the increasing demand for Big Data and Artificial Intelligence (BD&AI) practitioners and the existing talent shortage and skills gap in the workforce. Das et al. [8] found that job transformation is happening slowly, allowing the workforce time to learn new technical skills and adapt to the changing job market, and highlighted the importance of understanding and predicting the impact of AI and automation on the labor market.

Several studies have proposed novel forecasting techniques, such as Borges and Nascimento [29] proposing a two-stage integration of Prophet and LSTM models for predicting COVID-19 ICU demand, and Du et al. [30] introducing a hybrid KDE-PSO-LSTM model for interval forecasting of urban water demand. Criado-Ramón et al. [31] combined LSTM with symbolization techniques like SAX and aSAX to improve demand forecasting and train neural networks faster while maintaining similar results to traditional methods.

Lastly, Tsilingeridis et al. [32] developed the MULTIFOR framework, which combines PESTEL analysis, open time-series data, and LSTM networks, improving forecasting performance by around 30% compared to traditional LSTM and ARIMA models.

III. DATA

To assess the effectiveness of the proposed methodology, we first gathered relevant talent demand data. Utilizing Adzuna.com [33], a comprehensive job search engine, we collected job postings pertaining to AI. Adzuna's coverage extends to numerous countries including Austria, Australia, Brazil, Canada, France, Germany, India, Italy, Netherlands, New Zealand, Poland, Singapore, United Kingdom, USA, and South Africa. These job advertisements are available in multiple languages, including English, German, Portuguese, French, Hindi, Italian, Dutch, and Polish.

Adzuna categorizes each job posting into various fields such as Consultancy, Charity & Voluntary, IT, Legal, Customer Services, Teaching, and many others. The dataset, obtained through a collaboration between OECD and Adzuna, is analyzed by JSI, serving as the primary technical partner for OECD.

Each job posting within the dataset is characterized by several attributes, including the job description text, posting timestamp, language, origin country, and category. The dataset encompasses job postings dating back to 2018, with our study focusing specifically on postings from seven countries: USA, Canada, United Kingdom, France, India,
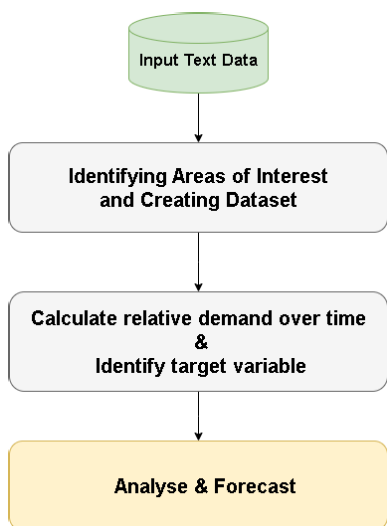
FIGURE 1. Overview of the proposed methodology.

Singapore, and Australia, spanning from January 1, 2018, to December 31, 2022.

To determine the areas of interest as depicted in Figure 1, we must first distinguish which job postings pertain to AI. We established a criterion mandating the inclusion of at least three terms from a predefined set, which includes "machine learning," "big data," "data science," "artificial intelligence," "deep learning," "natural language processing," "tensorflow," "pytorch," "computer vision," "unsupervised learning," or "supervised learning." This stringent criterion ensures a cautious approach, filtering out job postings that merely mention these terms as buzzwords or preferences, and instead prioritizes positions where AI plays a substantial role.

IV. PROPOSED METHODOLOGY

In this section, we outline the proposed methodology for analyzing talent demand for a specific area of interest across multiple countries. The methodology encompasses three main steps: identifying areas of interest, calculating relative demand, and conducting analysis and forecasting. The methodology is outlined in Figure 1.

A. IDENTIFYING AREAS OF INTEREST AND CREATING DATASET

The first step in our methodology involves identifying areas of interest which in our case is within the job market to focus our analysis on. This could be any specific field, industry, or skill set that is of interest for research or policy purposes. For example, areas of interest could include artificial intelligence, cybersecurity, renewable energy, healthcare, or digital marketing.

To identify these areas of interest, we employ a combination of manual curation and automated techniques. Manual curation involves reviewing existing job classifications, industry reports, and expert knowledge to identify relevant

job categories or skill sets. Automated techniques, such as keyword extraction and natural language processing, can further refine this process by identifying job postings that explicitly mention terms related to the area of interest.

Once the areas of interest are identified, we proceed to collect job posting data from various sources, including online job boards, company websites, and professional networking platforms. This data collection process ensures that we have a comprehensive dataset that represents the job market landscape accurately.

B. CALCULATING RELATIVE DEMAND OVER TIME

With the relevant job posting data collected, the next step is to calculate the relative demand for the identified area of interest in each country. Relative demand refers to the proportion of job postings within a specific category, relative to the total number of job postings in that country.

To calculate relative demand, we first categorize job postings based on predefined criteria related to the identified area of interest. This categorization process ensures that we only include job postings that are relevant to our analysis. Once categorized, we count the number of job postings related to the area of interest in each country, as well as the total number of job postings across all categories.

Using this information, we calculate the relative demand for the identified area of interest by dividing the number of relevant job postings by the total number of job postings in each country. This provides us with a standardized measure of demand that can be compared across different countries and time periods.

C. ANALYSIS AND FORECASTING

The final step in our methodology involves conducting analysis and forecasting to gain insights into the trends and patterns of demand for the identified area of interest. This includes analyzing historical data to identify trends, correlations, and patterns in demand across different countries.

To conduct this analysis, we employ a variety of statistical and machine learning techniques. These may include time series analysis, correlation analysis, and predictive modeling. By leveraging these techniques, we can identify factors influencing demand, such as economic conditions, technological advancements, and regulatory changes.

Additionally, we use forecasting models to predict future trends in demand for the identified area of interest. These models utilize historical data to make predictions about future demand levels, allowing stakeholders to anticipate changes in the job market and plan accordingly.

V. APPLIED METHODOLOGY

In this section, we present a practical application of our methodology for gathering relevant job posting data and analyzing it to determine AI demand by country. The system architecture, depicted in Figure 2, illustrates the underlying methodology. Subsequently, we detail the primary steps
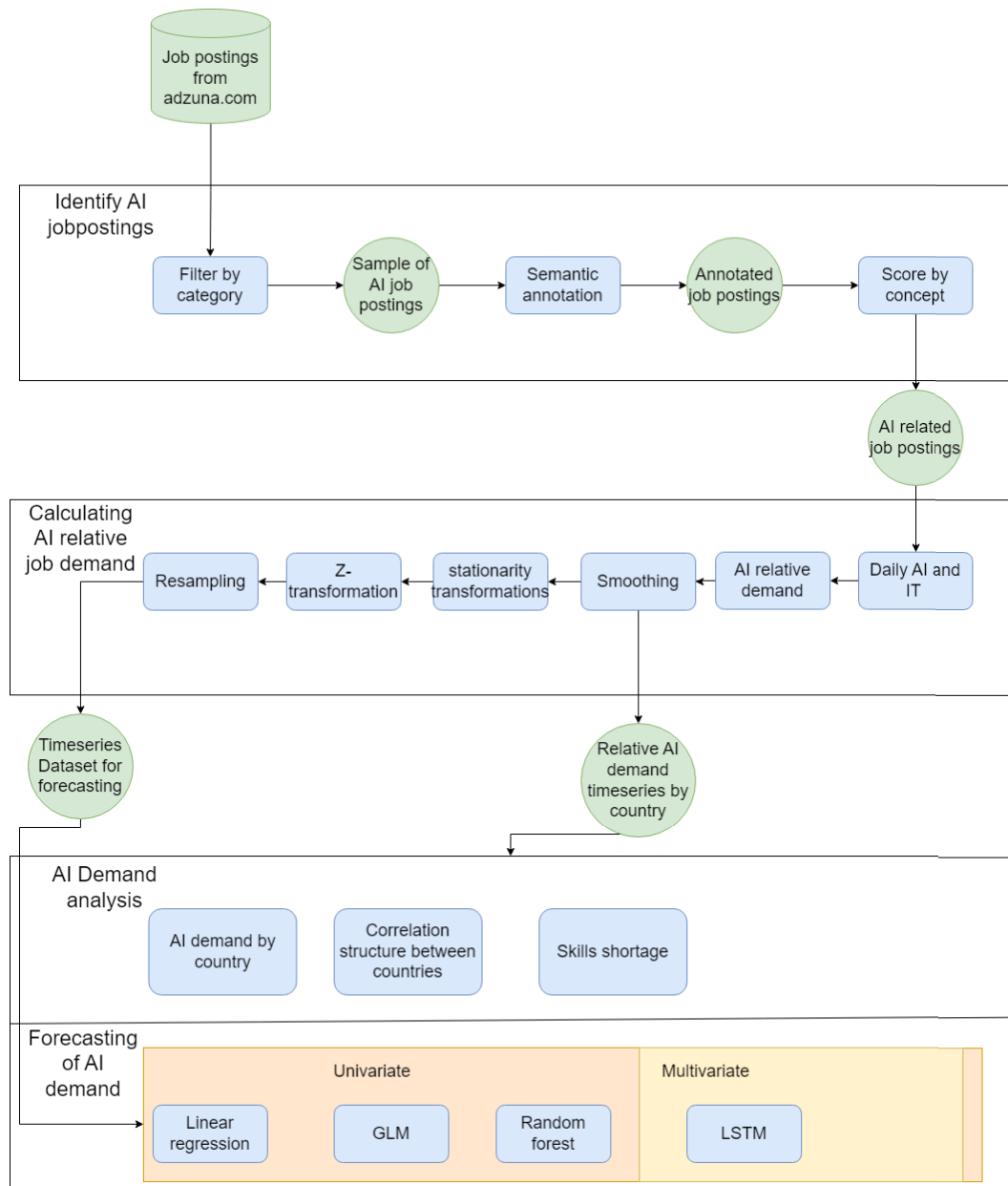
FIGURE 2. Architecture of a system applying the proposed methodology.

involved in preparing AI demand time series by country. Notably, the forecasting aspect is covered in Section VI-D.

Our focus in this paper is on the analysis of AI job demand across multiple countries. To accomplish this, we conducted an online collection of job postings, overcoming the challenge of multilinguality by leveraging Wikifier, a multilingual named entity recognition tool. Subsequently, we established criteria defining an AI job posting and proceeded to calculate the demand per country for seven different nations.

A. IDENTIFYING AI JOB POSTINGS

With the increasing demand for Artificial Intelligence (AI) talent in various industries, identifying and defining what constitutes an AI job posting has become a challenging task. Job postings that require AI skills and expertise can be ambiguous and heterogeneous, making it difficult to distinguish between them and non-AI related jobs. This is especially true for job postings in fields where AI skills are not necessarily required but can be beneficial. In this paper, we aim to provide a clear and consistent definition of AI job postings by analyzing a diverse set of job postings from 16 different countries. By defining what constitutes an AI job posting, we can better understand the trends and demand for AI talent, and provide insights into the skills and qualifications required for AI-related jobs.

1) **Filter for category**: At first, we utilize the Adzuna categorization to filter for IT-related job posting. It worth noting that this categorization is role-based not

industry based. For example, a software engineering job in healthcare company is still considered IT. Hence by filter to IT category, we ensure the filtering for the relevant roles, while being cross-industry.

2) **Select a representative sample**: From the IT job postings, we select a random sample of 20 million job posting to perform the analysis.

3) **Semantic annotation**: For each selected job posting, we semantically annotate the description with Wikipedia concept, using wikifier [23]. wikification enables identifying related concepts from the job posting in different countries/languages and map them to the English Wikipedia concepts/articles.

4) **Selecting AI related job postings**: following the methodology used in [4], but adapting it to concepts instead of keywords. A job posting is considered AI if it's tagged at least 3 of the following concepts: "machine learning", "big data", "data science", "artificial intelligence", "deep learning", "natural language processing," "tensorflow", "pytorch", "computer vision", "unsupervised learning", "supervised learning". The reason to of selecting at least 3 is to be on the conservative side and avoid job postings that just mention the names as buzz words or preferred to have, and focusing on job postings that involves AI for substantial part of the work.

B. CALCULATING AI RELATIVE JOB DEMAND

To analyze the AI demand across countries, we calculate the AI demand timeseries by country. To do that we apply the following steps:

1) **Calculating daily AI and IT job posting by country**: we count the number of AI and IT job posting daily for each country

2) **Calculate AI relative demand**: We calculated the ratio of how many of IT jobs are AI related as percentage (1% means that 10 of 1000 IT jobs were AI).

3) **Apply smoothing**: using 90-days moving average

4) **Differentiate timeseries**: to make it stationary

5) **Apply z-transformation** to normalize timeseries

6) **Re-sampling timeseries** to quarter time steps with one week offset between each step

VI. AI DEMAND ANALYSIS

A. AI DEMAND BY COUNTRY

In recent years, the global market for artificial intelligence (AI) has experienced rapid growth, with increasing demand for AI products and services across different sectors and industries. Understanding the patterns and trends in this demand is essential for policymakers, businesses, and researchers seeking to develop strategies for innovation and growth. In this subsection, we present the demand for AI across seven countries: the US, Canada, the UK, France, India, Singapore, and Australia. The visualizations provide an overview of the trends in demand for AI over a period
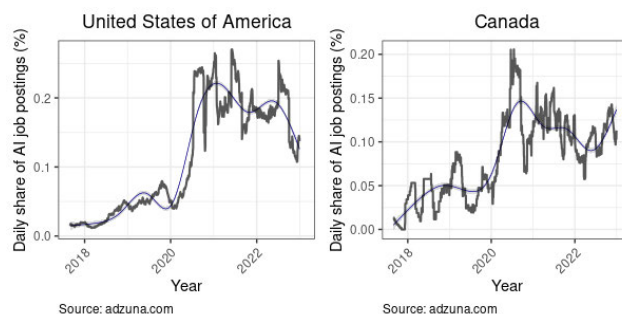

FIGURE 3. Comparison between relative AI demand between united states and canada.

of five years, from 2017 to 2021. By examining the chart, we can observe how the demand for AI has changed over time in each country and how it compares to other countries in the dataset. The insights gained from this analysis can inform decision-making and help stakeholders identify opportunities for collaboration and growth in the global AI market.

Figure 3 displays the trend of AI demand over the years from 2018 to 2023. The graph indicates a significant increase in demand for AI in recent years, with a noticeable surge in 2020 due to the COVID-19 pandemic, followed by a normalization. The trend is projected to continue its upward trajectory, with a substantial spike observed in late 2022. The findings suggest that AI is rapidly becoming an integral part of various industries and sectors, with businesses seeking to leverage the technology's benefits to enhance efficiency, productivity, and profitability. Moreover, the rise in AI demand is expected to have significant implications for policymakers, who must ensure that the appropriate regulations and policies are put in place to govern AI's ethical use and prevent potential harm to society. Overall, the trends indicate that AI demand is set to increase significantly in the coming years, creating vast opportunities for individuals and organizations to develop innovative solutions that harness the full potential of AI technology.

Figure 4 shows the demand for AI in Europe, specifically in the United Kingdom and France. Both countries show a gradual increase in demand from 2018 to early 2023, with some minor fluctuations. The trend appears to be relatively flat compared to the sharp increase seen in the US and India 6. However, it is worth noting that the demand for AI in Europe may not necessarily reflect the actual investment and progress being made in the field, as there may be other factors at play such as regulatory challenges and cultural differences. Nevertheless, the steady increase in AI demand in Europe suggests that there is a growing interest and awareness of the potential benefits that AI can bring, and policymakers should take note of this trend and continue to support and invest in the field.

Figure 5 shows the demand for AI in Australia and Singapore over the past few years. Unlike the other countries, the trend for both countries appears to be more or less flat,
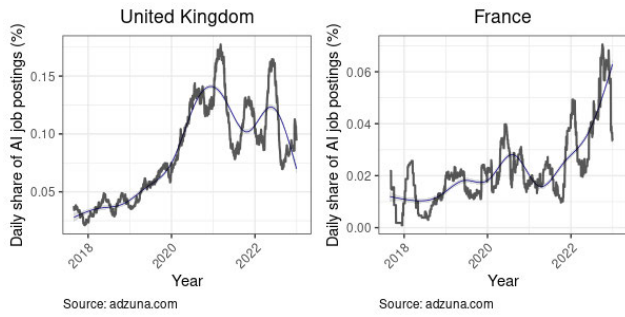
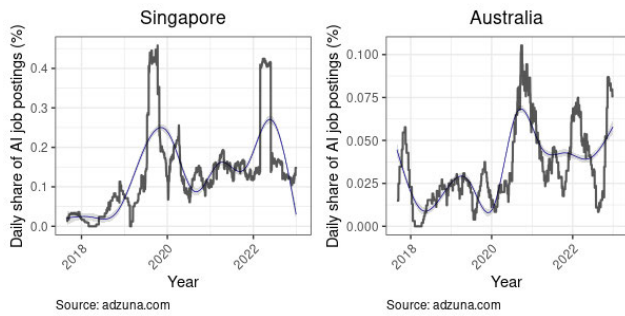**FIGURE 4.** Comparison between relative AI demand between united kingdom and france.

FIGURE 5. Comparison between relative AI demand between singapore and australia.

FIGURE 6. Relative AI demand India.

TABLE 1. Correlation of demand between countries.

	US	CA	UK	FR	IN	SG	AU
US	1.00	0.87	0.81	0.33	0.83	0.31	0.66
CA	0.87	1.00	0.82	0.38	0.83	0.22	0.65
UK	0.81	0.82	1.00	0.30	0.77	0.34	0.61
FR	0.33	0.38	0.30	1.00	0.54	0.08	0.17
IN	0.83	0.83	0.77	0.54	1.00	0.40	0.51
SG	0.31	0.22	0.34	0.08	0.40	1.00	0.07
AU	0.66	0.65	0.61	0.17	0.51	0.07	1.00

with no clear increase or decrease in demand. This lack of growth in AI demand in these countries is concerning, as AI is becoming an increasingly important technology in the world, and countries that do not keep up with this trend may fall behind in terms of innovation and competitiveness. It is possible that this lack of growth is due to a number of factors, such as limited investment in AI research and development, a lack of skilled AI professionals, or a lack of policy support for AI adoption. Further investigation is needed to determine the reasons for this trend and to identify potential strategies for stimulating AI growth in these countries.

Figure 6 shows the trend of AI demand in India from 2018 to early 2023. The figure shows a steady and consistent increase in AI demand over time, with a nearly triple increase in demand observed in early 2023 compared to demand in 2018. This trend suggests that India is investing heavily in AI and that this investment is likely to continue in the future. As one of the fastest-growing economies in the world, India has a vast potential for growth in AI, which can contribute to economic development, job creation, and the overall progress of the country. The findings of this study can inform policymakers and stakeholders in India to better understand the growing importance of AI and to develop strategies to harness the potential of AI to foster economic growth and innovation

B. CORRELATION STRUCTURE BETWEEN COUNTRIES
The table presents the correlation of demand for artificial intelligence (AI) between seven countries, namely the US,
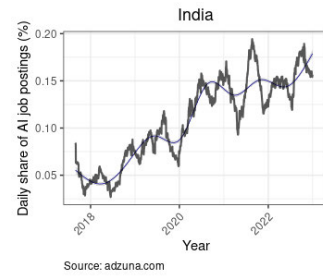
Canada, the UK, France, India, Singapore, and Australia. The correlations are measured on a scale from −1 to 1, where 1 indicates a perfect positive correlation, 0 indicates no correlation, and −1 indicates a perfect negative correlation. The results show that the demand for AI is highly correlated between the US and Canada, with a correlation coefficient of 0.87, and moderately correlated between the US and the UK (0.81) and Canada and the UK (0.82). The demand for AI between France and other countries shows a lower correlation, ranging from 0.08 to 0.54. Interestingly, the correlation between Singapore and Australia is the lowest among all pairs, with a coefficient of only 0.07. The results of this study can be useful for policymakers and businesses in identifying potential markets for AI products and services and developing strategies for international expansion. Further research could investigate the factors that contribute to the observed correlations and their implications for the global AI market.

C. SKILLS SHORTAGE
One of the benefits of the semantic annotation process is that it allows for the extraction of skills related to the job posting. The extracted concepts help us understand the skills landscape in AI jobs, as well as identify any shortages in skills related to AI jobs in each country. In this context, we define skills as Wikipedia concepts extracted from job postings.

Figure 7 below shows the landscape of skills in jobs, highlighting the top 100 skills by relevance. The top concepts include the ones that match the filter, namely artificial intelligence, machine learning, and data science, but also others like python, and c++. Other concepts include skills and roles around data science, like data visualizations and data mining, and MLOps. Tools and databases like Apache Hadoop, Kubernetes, MongoDB, and Elasticsearch, indicates

the need for having engineering skills for doing AI in the industry. Career-related skills like higher education and academic degrees highlight the yet required higher educational degrees to do most of the AI and machine learning work.

While the skills landscape provides meaningful but obvious results, a more useful analysis of skills is to identify for each country, what are the most needed skills required, as this helps policymakers develop programs for handling shortages. The intuition behind identifying skill shortages is the inverse correlation between jobs in demand and skills supply (i.e. supply and demand). That is, if a skill is associated with a lot of job postings that take a long to fill, that means the skill is in demand but there isn't enough supply of people to fill it, hence a skill shortage.

More concretely, we utilize a process that involves observing the duration of job postings on Adzuna. First, We define J_i as the set of job postings that closed within the i_{th} week of its posting. Second, we identify two points of interest; $J_{t0} = J_1$ as being the set of in-demand jobs and $J_t = J_9$ as being the set of jobs filled within the 9th week. Due to the distribution of jobs, $J_9 \approx \sum_{i>=9} J_i$, hence it represents the jobs that are in demand but not filled for more than two months approximately due to not enough supply.

Now for these two timestamps, we count the distribution of the skills, to calculate the decline in demand for each skill, we can define a skill shortage if its decline (first derivative) is larger than the average of all skills, i.e. takes longer than average to get filled. More concretely:

Then we define the skill decline D_s as follows

$$D_s = \frac{\sum_{\forall j \in J_t} P_{j,s} - \sum_{\forall j \in J_{t0}} P_{j,s}}{t - t0} \quad (1)$$

where $P_{j,s}$ is 1 if job posting j is tagged with skill s, and 0 otherwise

We calculate the Demand score by the country for each of the 100 most common concepts. The demand allows us to gain insights into the skill sets that are sought after by employers (high in-demand score) and the ones that are not (low on-demand score). A high-demand skill will have more occurrences in in-demand jobs than in not-in-demand ones.

Then the skill shortage score for each skill is defined as the demand score of the skill divided by the average demand of the skills minus one:

$$SS_s = \frac{D_s}{\frac{1}{|S|} \sum_{s \in S} D_s} - 1 \quad (2)$$

A positive score (ratio above 1) indicates that jobs with this skill remained online longer than average, indicating a shortage of this skill. Conversely, a negative score (ratios below 1) indicates that jobs with this skill were filled quickly, suggesting an abundance of that skill.

Looking at the shortage of skills in the US in Figure 8, we observe that skills with the most shortage (the right most skills in the barchart) are ''Unstructured data'', ''Artificial intelligence'', ''Deep learning'', ''Master's degree'', whereas

some of the top skills with no shortage of supply (the left most skills in the barchart) are ''JavaScript'', ''Scrum and agile development'', ''Information technologies'', ''Kubernetes''.

Singapore and France provide similar skills with the exception of the top skill in shortage in Singapore being ''Virtual reality'' and in France being ''AutoCAD'', as seen in Figure 9 and in Figure 10. Virtual reality is correlated with the rise of virtual reality and the meta-verse, while AutoCAD is due to the fact that a lot of the AI designer jobs require design experience in programs like AutoCAD.

India's list of skill shortages in Figure 11 is drastically different and focuses on web-related technologies.

We assume that other factors, such as pay and remote work, are canceled out by the law of large numbers, assuming a normal distribution. This information can help job seekers better understand which skills to focus on developing and employers understand which skills are needed in their industry.

D. FORECASTING OF AI DEMAND

In this chapter, our objective is to offer a practical demonstration of various model families–specifically regression, decision trees, and deep learning–rather than introducing groundbreaking model architectures. We aim to showcase how these widely employed methodologies can be effectively utilized to forecast demand in an AI job market across seven countries. It's essential to recognize that while the models we showcase serve as valuable examples, more sophisticated approaches may be required for real-world applications. The models will be evaluated with mean squared error (MSE) due to simple but effective comparison between different nature of models.

Following an examination of artificial intelligence (AI) demand across seven countries, our attention shifted to modeling this demand using diverse methods. Our analysis spanned from 2022 onwards for test data, covering a one-year period. To prevent data leakage during the smoothing step, we excluded timesteps that only partially overlapped with 2022 from the training data. Our primary focus was on predicting AI demand for the upcoming quarter–a crucial aspect for businesses and policymakers in planning resource allocation, staffing, and budgeting. We employed both univariate and multivariate models, with detailed results provided below.

To achieve this, we first outline our methodology for modeling AI job demand, detailing the steps taken and the data utilized. Subsequently, we delve into the specifics of three model families: regression, decision trees, and deep learning. For each model family, we offer a practical example demonstrating its application in forecasting AI job demand.

Through this exploration, our aim is to highlight the adaptability of these modeling techniques and offer insights into their strengths and limitations when applied in practical scenarios. Although our focus lies on AI job demand, the methodologies discussed can be adapted and implemented in other domains with similar forecasting requirements.
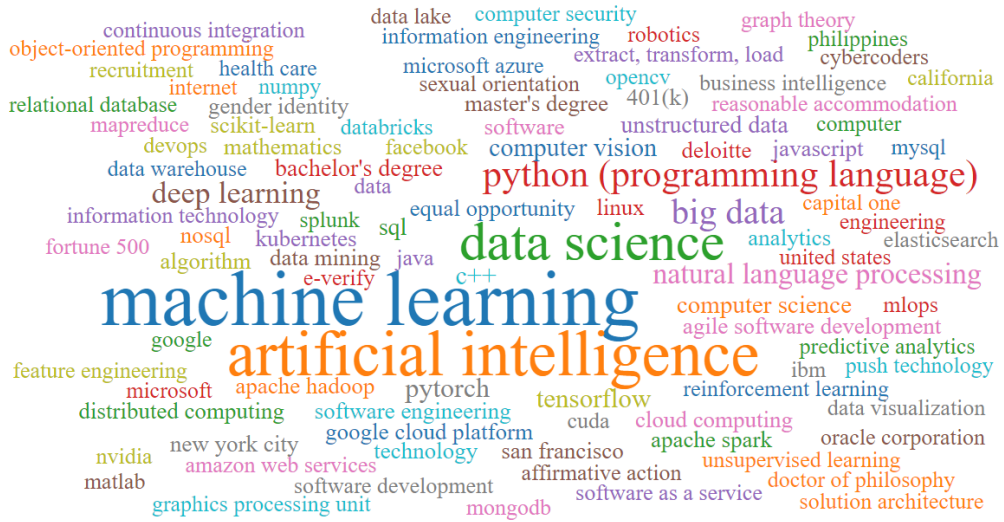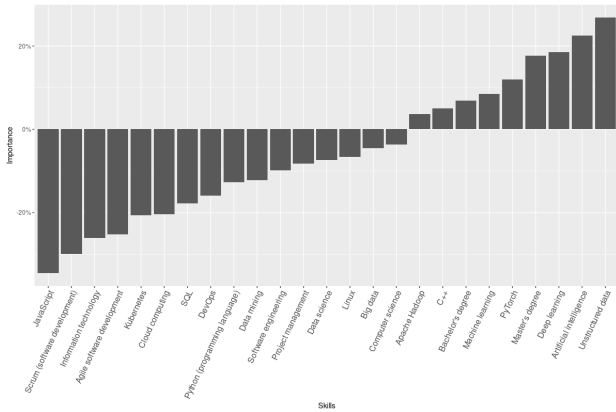
FIGURE 7. Top 100 skills by frequency.

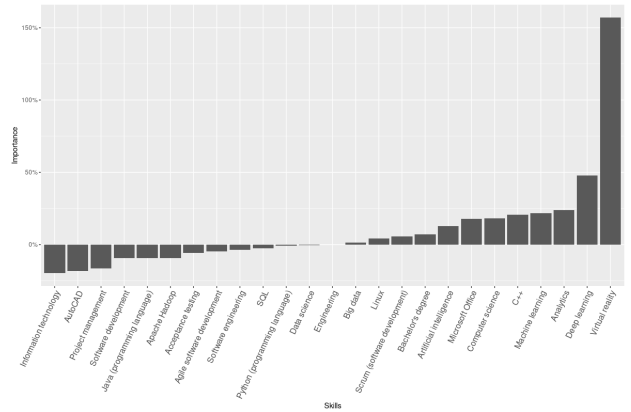**FIGURE 8. Skill shortage of US job postings.**

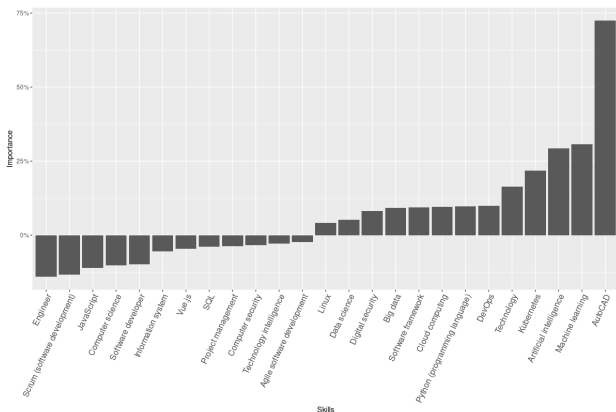**FIGURE 10. Skill shortages for singapore.**
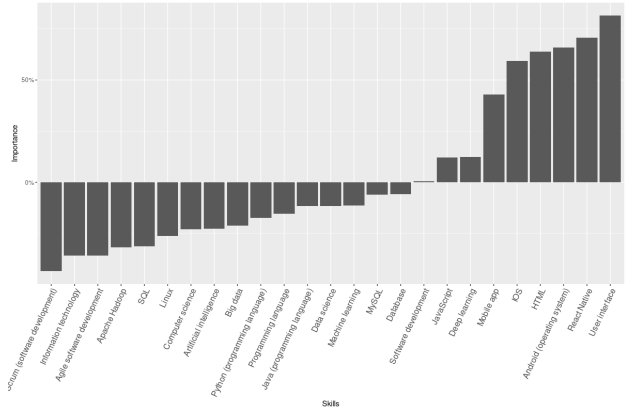

FIGURE 9. Skill shortages for france.

FIGURE 11. Skill shortage for India.

1) UNIVARIANT PREDICTIONS

For univariate modeling. We compared four different models: a baseline model (last known value), a generalized linear model (GLM), a random forest model, and a univariate long short-term memory model (LSTM). For LSTM, the

architecture consisted of 3 stacked LSTM layer, with 32 parameters each, we used the last 6 steps for the prediction of the next step.

The table above shows the mean squared errors (MSE) for each model and country. The baseline model, which simply

used the mean demand for each country, had MSEs ranging from 1.54 for India to 3.292 for the US. The GLM, random forest, and univariate LSTM models all performed better than the baseline, with MSEs ranging from 0.709 for random forest in Singapore to 1.768 for LSTM in Canada. The results suggest that these models can help improve the accuracy of AI demand forecasting, with different models performing better in different countries. In the following sections, we will delve deeper into the results of each model and discuss the implications for AI demand forecasting.

To further elaborate on our findings, we note that the GLM and random forest models outperformed the LSTM model in most countries. The GLM model achieved the lowest MSE in four out of seven countries, while the random forest model achieved the lowest MSE in two countries, including Singapore. However, the LSTM model performed better than the GLM and random forest models in France, indicating that the LSTM model may be better suited for countries with less predictable demand patterns. In general, our findings suggest that machine learning models, such as GLM and random forest, can help improve the accuracy of AI demand forecasting and should be considered by businesses and policymakers when planning for the future.

2) MULTIVARIATE PREDICTIONS
After obtaining promising results from univariate modeling of AI demand, we proceed to explore the effectiveness of multivariate modeling using LSTM. In this section, we compare the results of multivariate LSTM modeling to the previous univariate LSTM results. The table shows the mean squared errors for the multivariate LSTM model across all seven countries. Notably, the multivariate LSTM model outperforms the univariate LSTM model in five out of seven countries, with a lower mean squared error for the overall prediction. These results indicate that incorporating multiple variables into the LSTM model improves its accuracy in predicting AI demand, even when predicting just one quarter ahead.

VII. DISCUSSION
This paper offers a thorough examination of the demand for AI jobs across seven countries: the USA, Canada, the United Kingdom, France, India, Singapore, and Australia. By employing a systematic pipeline for collecting and processing relevant job posting data, we conducted a comprehensive analysis. Furthermore, we delved into the forecasting of AI job demand and explored the potential implications of AI skill shortages. In this section, we delve into the main findings of our study, outline its limitations, and propose avenues for future research.

A. MAIN FINDINGS
The application of the proposed methodology has led to several important discoveries.

The correlation analysis reveals robust connections in AI job demand between the US and Canada, with moderate correlations observed between the US and the UK, as well as Canada and the UK. These findings suggest a significant association among these countries, potentially attributed to shared industry structures, language, and cultural affinities. Conversely, the lower correlation observed in AI demand between France and other countries implies a distinct AI job market in France compared to the studied counterparts. Further exploration into the contributing factors behind these correlations could unveil fascinating insights into the dynamics of the global AI market landscape.

The burgeoning growth of AI job demand and the looming specter of skill shortages pose significant challenges for nations to navigate, with certain regions potentially facing more pronounced deficits than others. Additionally, the forecasting of AI job demand indicates a persistent upward trend in the years ahead. This carries crucial implications for policymakers, educators, and industry stakeholders, necessitating proactive measures to anticipate and mitigate these shortages to sustain the growth and competitiveness of their respective AI sectors. These efforts encompass strategies for talent attraction, retention, and training, alongside fostering diversity and inclusivity within the AI workforce.

An analysis of skills shortages across different countries unveiled both commonalities and disparities. For example, the US and France exhibited shortages in deep learning and artificial intelligence skills, while Singapore faced a deficit in virtual reality expertise, and India grappled with shortages in web-related technologies. These insights offer valuable guidance for individuals seeking to refine their skill sets and employers aiming to stay ahead of industry trends.

Moreover, the skill landscape in AI jobs underscores the significance of engineering prowess, data science acumen, and higher education credentials. Addressing skill shortages necessitates investments in education and training initiatives tailored to AI and its related technologies. This entails expanding existing computer science and engineering programs and developing specialized AI courses and degrees. Additionally, reskilling and upskilling programs for professionals already in the workforce can facilitate transitions into AI-related roles.

Furthermore, fostering diversity and inclusivity within the AI workforce emerges as a pivotal strategy. This entails advocating for gender diversity and ensuring equitable access to AI education and career pathways for underrepresented groups. By cultivating a diverse and inclusive talent pool, nations can harness a broader spectrum of expertise and drive innovation within the AI domain.

B. LIMITATIONS AND FUTURE DIRECTIONS
While our analysis yields valuable insights into AI job demand and potential skill shortages, several limitations warrant consideration. Firstly, our reliance on job postings from Adzuna.com may not fully represent the entirety of AI job opportunities across the studied countries, potentially resulting in an incomplete portrayal of the AI job market. Expanding data collection to include additional job search

TABLE 2. Comparison of mean squared errors for univariate AI demand models across seven countries.

	US	CA	UK	FR	IN	SG	AU	ALL
Baseline (last value)	3.292	2.770	2.173	2.196	1.540	2.378	1.691	2.291
GLM	1.378	**1.503**	1.217	1.228	1.254	1.468	0.978	1.289
Random forest	**1.310**	1.534	**1.129**	1.102	**1.047**	1.461	**0.709**	**1.185**
LSTM	1.631	1.768	1.285	**1.095**	1.193	**1.348**	0.811	1.304

TABLE 3. Comparison of mean squared errors between univariate and multivariate LSTM model predictions across seven countries.

	US	CA	UK	FR	IN	SG	AU	ALL
Univariate	**1.631**	1.768	1.285	1.095	1.193	1.348	0.811	1.304
Multivariate	1.659	**1.649**	**1.083**	**1.062**	**1.074**	**1.318**	**0.703**	**1.162**

engines and platforms could provide a more comprehensive perspective.

Secondly, our methodology for identifying AI job postings, though effective, may overlook postings that do not explicitly mention AI-related concepts. Refinements to our methodology could enhance accuracy, ensuring a more inclusive representation of AI job postings across diverse industries and roles.

Moreover, while our study forecasts AI demand using multivariate LSTM models with promising accuracy, future research could explore the integration of additional data sources, such as GDP indicators and software development trends from platforms like GitHub. Incorporating such data could enrich our understanding of the relationship between economic activity, technological innovation, and AI job demand.

Additionally, policymakers may benefit from considering regulations that address the potential impact of AI technology on job markets. Measures such as retraining programs could mitigate adverse effects on workers while harnessing the benefits of AI innovation.

Moving forward, leveraging new data sources and refining methodologies will be crucial for advancing our understanding of the dynamic AI job market and informing effective policy and business decisions.

VIII. CONCLUSION

Our study serves as a foundational exploration of the AI job market, offering insights into job demand and skill shortages across seven countries. By forecasting AI demand and identifying skill gaps, we provide valuable guidance for policymakers, educators, and industry stakeholders. However, our analysis also underscores the need for further research to deepen our understanding.

Future studies could expand the scope of analysis to encompass additional countries, industries, and job roles, facilitating a more comprehensive assessment of global AI talent demand. Exploring the drivers of AI job growth and its implications for labor markets, economic development, and policy-making represents an exciting avenue for future inquiry.

Moreover, incorporating an in-depth exploration of use cases, potential advancements, and a roadmap for AI in the job market would provide readers with a forward-looking perspective, helping them grasp the trajectory of AI employment and its potential impacts on various sectors. By addressing limitations, integrating new data sources, and refining methodologies, researchers can continue to elucidate the intricacies of the evolving AI job market, empowering decision-makers to navigate challenges and capitalize on opportunities in the AI-driven era.

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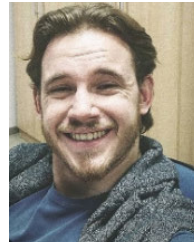
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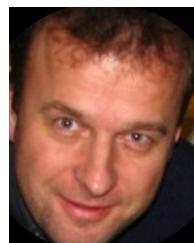
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