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RESEARCH ARTICLE

Information and Communication Workforce Forecasting: Evidence from England

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ABSTRACT
The workforce plays a crucial role in the development of organizations and countries. Therefore, closely monitoring the status of the existing workforce and issues related to individuals entering the workforce is essential. Information and communication technologies (ICT) have resulted in significant consequences in the shift of production and service industries to different areas. This situation implies that advancements in the field of ICT necessitate the development of appropriate skills. Therefore, assessing the current workforce situation and determining future workforce trends are necessary in order to develop the skills required in the ICT field. To achieve this, the article analyzes data from the ICT labor market in England between 1996-2022 and proposes a model to predict the state of the ICT workforce for the upcoming five-year period. As a result, the study predicts the workforce numbers in the ICT field until 2027 and provides a forecast regarding the expected future. According to the findings, this study projects that the workforce in the IT sector will increase during each three-month period until 2027. The increase is expected to occur at a rate of 9.5% during the period of 2023-2027. This result is highly important as it provides a basis of a scenario analysis for different stakeholders on how to plan regarding job loss risks, wages, and education-related matters.

Keywords: Information and Communication, Workforce, England, Time Series, Forecasting

1. Introduction

Creating employment is the most important agenda item for countries worldwide (Bakule, Czesana, Havlickova, 2016, p. 5). Employment is a two-sided phenomenon. On one hand, it involves a workforce with specific skills, and on the other hand, it involves an employment market that aims to utilize these skills to generate benefits. The lack of individuals possessing the necessary skills the employment market requires has always been a significant problem for countries. One of the main reasons for this problem has been countries' failure to determine future workforce trends and to accordingly build a suitable workforce (Alyahya and Hadwan, 2022, p. 1).

Technology has a decisive impact on workforces and employment markets (Alyahya and Hadwan, 2022, p. 1). Technology has a broad range of applications in both work and social life, and information and communication technologies (ICT) play a crucial role in this regard. ICT refers to technologies that process data electronically to provide benefits. Computers, the Internet, mobile devices, and production automation form the foundations of ICT (United State Bureau of Labor Statistics, 2023). The ICT workforce can be defined as the individuals and groups responsible for obtaining, analyzing, and transforming data into information, for contributing to decision-making and process development, and for creating value propositions in goods and services (Economic Commission for Latin America and the Caribbean, 2021, p. 11).

Digitalization and automation lead to significant transformations in the business world. These transformations can create new job opportunities while also causing job losses. Therefore, importance is had in having the workforce adapt to these changes and develop the necessary skills (Eurostat, 2023). With the advancement of IT technologies has come an increased demand for a skilled workforce that requires more education and abilities. Throughout history, new technologies have tended to reduce or eliminate certain jobs. However, these technologies have also enabled the emergence of new tasks and occupations due to the new functions they provide (United State Bureau of Labor Statistics, 2023).

One of the best examples demonstrating the impact of technological advancements on the workforce and the need for decision-makers to develop a scenario for this situation is the invention of the knitting machine by William Lee in 1589. This invention

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foresaw workers producing socks using the machine instead of by hand knitting. However, Queen Elizabeth I did not show a positive approach toward granting a patent for the invention, as she believed it would eliminate the need for labor and negatively affect employment (Frey and Osborne, 2017, p. 250).

In the second half of the 19^{th} century, typewriters were first used as ICT in organizations. Later, other technologies were also introduced, such as dictation devices, calculators, matrix printers, address machines, and punch card machines as the precursor to computers. This situation led to a reduction in information processing costs while increasing the demand for the necessary skills (Goldin and Katz, 1995, p. 9, Frey and Osborne, 2017, p. 250).

The advancements in ICT facilitated access to distant geographies and different markets. This resulted in the expansion of industries and the growth of organizations. Growing organizations have placed greater importance on having a skilled workforce to perform diverse and complex tasks (Frey and Osborne, 2017, p. 257). Countries have prioritized an ICT workforce due to the advantages of creating new job opportunities, enhancing productivity, and achieving efficiency (Eurostat, 2023).

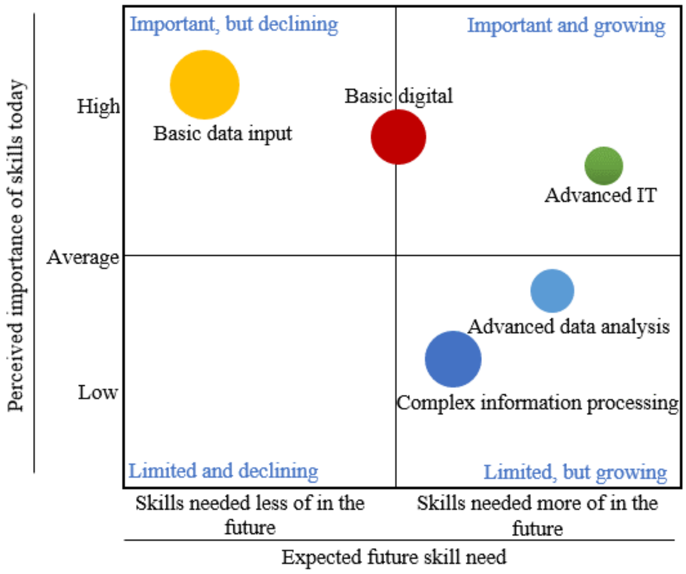

Figure 1. A chart based on the survey results from 3,031 business leaders in Canada, France, Germany, Italy, Spain, England, and the United States in March 2018 and organized specifically to show ICT skills (Source: Bughin, Hazan, Lund, Dahlström, Wiesinger and Subramaniam, 2018).

Industries can face challenges when they lose a skilled and experienced workforce. While new technologies can have positive outcomes on certain skills, they can also have negative consequences on others. The ability to communicate information is the primary skill that has been both positively and negatively affected by technological advancements (Dachs, 2018, p. 4). As the changes in the ICT field increase, the need exists to adapt to these changes in terms of technical skills. The need for changes regarding technical skills necessitates the implementation of measures for skill development (Böckerman, Laaksonen and Vainiomäki, 2016, p. 2).

Employers emphasize that individuals with high cognitive and technological skills will be of critical importance for organizations. Figure 1 has great importance for revealing the current and future state of ICT skills, with four skill clusters standing out. The top-right quadrant represents skills that are important today and will remain important in the future. The bottom-right quadrant represents the skills that currently have a lower level of importance but will become crucial in the future. The top-left quadrant represents skills that are important today but will decrease in importance in the future. The bottom-left quadrant represents skills that are of lower importance today and will decrease in importance in the future (Bughin et al., 2018, 18–19).

In the last 40 years, various research studies have been conducted on labor markets (Alyahya and Hadwan, 2022, p. 1). Several reasons are found as to why this topic has drawn the attention of researchers. ICT plays a determinant role in the growth of advanced regions around the world (Radda and Rydhem, 2022, p. 5). ICT finds application in every aspect of life, including production, healthcare, security, and education, and focusing on these technologies with such broad coverage has become critical for countries (Gates, 2023). Additionally, ICT is a crucial indicator of human capital in countries' development (Eurostat, 2023). Between 1995-2015, ICT service levels per hour increased by just over 150% in Japan, while Germany experienced an increase of over 300%, and the United States and the United Kingdom saw an increase of over 350% (Organisation for Economic Co-operation and Development [OECD], 2019, p. 41). Therefore, both public and private sector organizations invest in ICT to enhance service delivery. The decreasing percentage of youths in the total population highlights the increasing importance of ICT. While this declining trend in the younger population is more pronounced in countries like China, Italy, Japan, Korea, and Spain (OECD, 2019, p. 43), it also poses a significant potential problem for the United Kingdom. Therefore, the rapid changes in the ICT field has made investigating the future state of work and employment crucial (Alyahya and Hadwan, 2022, p. 1). The existence of these circumstances also encourages researchers and policymakers involved in ICT and its related topics to focus on this area.

Countries use a three-stage process to develop strategic workforce plans. This process includes analyzing the current situation, making future predictions, and developing different scenarios. The first two stages are primarily quantitative data-driven decision-making processes, while the third stage involves qualitatively evaluating the information obtained from the previous stages. When assessing the current situation, the analysis focuses on the historical development and trends of internal capacity and capabilities from past to present. In the second stage, statistical tools suitable for this trend analysis are utilized to make predictions. Lastly, scenarios that align with the findings are determined based on the obtained statistical analysis (Queensland Government, 2020, p. 6).

This study was conducted to provide insights into the developments regarding the ICT workforce in the England. The research aims to create an appropriate model for predicting the number of ICT workers in the England. The study seeks to answer questions about the current state of the ICT workforce in the England and how the ICT workforce trend will shape up. The study uses the ARIMA model, a time series analysis, as the analysis method utilizing ICT workforce data from 1996-2022.

Literature

Various approaches are utilized for forecasting labor market needs. When examining previous studies, research focused on employment predictions can be observed to have maintained its significance and relevance.

Navarro-Espigares, Martín-Segura and Hernández-Torres (2012), examined the impact of economic crises on how the factors of gross value added and employment respond in the service sector in the Spanish autonomous regions using the autoregressive integrated moving average (ARIMA) method. Time series data were used to forecast gross value added and employment during the period of 1986-2009. They found that regions with a larger service sector were less affected in terms of the factors of gross value added and employment during the 1992 and 2008 crises.

Vicente, López-Menéndez and Pérez (2015), analyzed unemployment rates in Spain using the ARIMA method based on Google Trends data from 2004-2013. The analysis specifically covered the period from January 2004-June 2013. The study utilized the Employment Confidence Indicator (ECI) statistics published by the Spanish Ministry of Industry, Energy, and Tourism for demand data, while Google Trends indicators were used for labor supply data. The use of these data sources enabled the researchers to obtain meaningful results for explaining unemployment.

Pantea, Sabadash and Biagi (2017) examined the increase in productivity through the replacement of labor by ICT usage in Europe in relation to different output factors. For this purpose, they utilized internationally comparable data based on production statistics and new ICT usage indicators for the period of 2007-2010 in seven countries (i.e., UK, France, the Netherlands, Finland, Norway, Sweden, and Poland). The obtained results demonstrated ICT usage intensity to have had no negative impact on the workforce.

Frey and Osborne's (2017) study examined the potential spread of computer usage in various job processes in the United States. A total of 702 different occupations were analyzed using the Gaussian process classification method to predict the probability of computerization. The results provided estimations regarding the likelihood of computerization for each occupation, the risk of job elimination, and the relationship between education level and wages. The findings indicated approximately half of the total employment in the United States to be at risk. Another notable observation was that education and wage levels tended to decrease as job processes became computerized.

Herman's (2019) study compared the level of digitalization in Romania's economy to that of other EU countries, along with employment and skill levels in the ICT sector. The study found the average contribution from the ICT sector to employment and GDP, the proportion of employed ICT specialists, and their competencies to be significantly higher in EU countries compared to Romania.

Voumik, Hossain, Dewan, Rahman and Rahman (2020) utilized the ARIMA method to forecast the growth rate of the service sector in Bangladesh for the period of 2019-2028. According to their findings, if the current trend continues, the estimated employment rate in the service sector is projected to reach between 43.33% and 47.28% in 2028. The study also indicated that the employment growth rate will continue to persist in the service sector in the future.

Alisjahbana, Setiawan, Effendi, Santoso, Hadibrata (2020) examined the impact that adopting digital technology has on labor demand in the Indonesian banking sector using panel data analysis method with the data obtained from the Indonesia Financial

Service Authority (OJK) for the period of 2010-2017. Their study findings indicated adopting technology to have a significant effect on all the business activities of commercial banks.

Fukao, Miyagawa, Kil Pyo, Rhee and Takizawa (2020) examined skill-biased technological change in Japan and Korea. For this purpose, they analyzed the impact of ICT investments on the workforce for the period of 1979-2000 and found the intensity of ICT components in total capital to have had a positive effect on highly skilled workers' wages in both Japan and Korea.

Alyahya and Hadwan (2022) utilized the Government Job Advertisements (GJA) dataset owned by the Ministry of Human Resources and Social Development (MHRSD) to predict future technical jobs in the information technology industry in Saudi Arabia. The study employed the ARIMA method for a time series analysis. Accordingly, their findings predicted that high school-level computer teachers, senior software developers, system analysts, and software developers will be the most desirable jobs in the ICT field in Saudi Arabia in the future.

Zatonatska, Klapkiv, Dluhopolskyi and Fedirko (2022) used the Markov chain method to predict the employment rate of IT personnel with different educational levels in the IT industry until 2025. The analysis was based on data from 2005-2019. The study's findings suggested that the employment rate of IT personnel is projected to increase by 64% over a seven-year period. Furthermore, they determined that the growth in IT personnel employment will start to decline after 2023.

Hüsnüoğlu and Oda's (2022) study examined the impact of mobile phone and Internet usage rates, fixed capital and R&D investment amounts, and workforce participation rate on economic growth in Türkiye between 1996-2018, using artificial neural networks (ANNs) and the ARIMA method to compare the results. According to their findings, ICT factors such as mobile phone usage rate, Internet usage rate, fixed capital investments, workforce participation rate, and R&D investments rank as the most influential factors on economic growth. When comparing the data modeling techniques, the ANN method was observed to yield better results.

Dataset and Method

Individuals, organizations, and countries develop, implement, and evaluate decisions and policies. Predictability is a key criterion in determining priority decisions and policies and is achieved through the use of various prediction models. These models provide information based on the potential outcomes current decisions will have in the future. Such information enables the assessment of whether the resources allocated for the implemented decisions and policies will be effectively and efficiently utilized. Developing an accurate prediction model is crucial for analyzing future scenarios. In order for prediction models to be valuable and meaningful, obtain relevant and accurate data is important. Appropriate models should be selected based on the obtained data. Furthermore, the obtained results need to be interpreted correctly. Ignoring these aspects can lead to inaccurate predictions and hinder the implementation of the correct policies and decisions. This situation results in wasted resources, time, and missed alternative opportunities.

This study will use the time series analysis method. Time series analysis is a widely used method in various fields that allows the behavior of events to be modeled based on data related to events that occur within a specific time period. The data used in a time series analysis can vary over time. To predict future values, trends in the available data are used to make predictions. This analysis gives more importance to the most recent data, with less importance being attributed to previous data. Different models can be used in time series analysis, but one of the most commonly used models is the ARIMA model. This study has preferred the ARIMA model because of its flexible structure, which enables it to quickly and accurately respond to changes (Köppelová and Jindrová, 2019, p. 76).

The ARIMA model is a time series analysis method that utilizes data from a specific time period to make future predictions that include an error term. These predictions are obtained by integrating the autoregressive (AR) and moving average (MA) models (Bajracharya, 2010, p. 13). In the ARIMA model, the lags of a stationary series are represented by AR terms, the lags of prediction errors are represented by MA terms, and differencing is used to make the series stationary, which is indicated by the I term (Nau, 2014, p. 2).

In a general approach to ARIMA modeling, the following steps are typically followed. However, the order of these steps and the use of certain steps can vary depending on the specific problem:

1. Examine the trend of the series.
2. Analyze the autocorrelation and partial autocorrelation patterns of the series to determine the values that need to be included in the prediction equation.
3. If the series is non-stationary, apply methods such as differencing, logarithmic transformation, or deflation to make it stationary.
4. Examine the patterns of lagged values in the differenced series.

5. Examine the patterns of lagged values in the prediction errors.
6. Apply the proposed model.
7. Perform diagnostic checks such as ACF and PACF plots to assess the residuals.
8. Evaluate the significance of all coefficients and the overall goodness-of-fit of the model.

A non-seasonal ARIMA model is expressed as ARIMA (*p,d,q*), where *p* represents the number of autoregressive terms, *d* represents the number of non-seasonal differences, and *q* represents the number of moving average terms. The model may also include a white noise or error term. (Nau, 2014, p. 3).

The prediction equation in an ARIMA model is typically expressed as follows:

$$\hat{y} = \overbrace{\mu}^{\text{Constant}} + \overbrace{\emptyset_1 y_{t-1} + \cdots + \emptyset_p y_{t-p}}^{\text{AR terms (lagged values of y)}} \underbrace{-\emptyset_1 e_{t-1} + \cdots + \emptyset_q e_{t-q}}_{\text{MA terms (lagged errors)}} \qquad (1)$$

By convention, the AR terms are (+) and the MA terms are (-

Source: (Quinn, 2023)

The current study utilizes quarterly data on ICT workforce from the United Kingdom Office for National Statistics covering the period 1996-2022. The study specifically focuses on ICT sector workforce in the England. The workforce data involve information on employed workers measured through employer surveys, self-employed jobs obtained from workforce surveys, government-supported interns derived from UK regional data and administrative sources, and ICT workforce data obtained from the Ministry of Defense records (Nomisweb, 2023).

Figure 2 illustrates the changes in ICT employment between 1996-2022, focusing on the quarterly data from each March, June, September, and December. The y-axis represents the number of employed individuals in the ICT sector, while the x-axis denotes the years. The line on the graph showcases the fluctuations in ICT employment levels throughout the specified timeframe. The graph starts with the ICT employment value for the first quarter of 1996, specifically in the month of March, while the last value on the graph line represents the ICT employment statistics for the last quarter of 2022 in December.

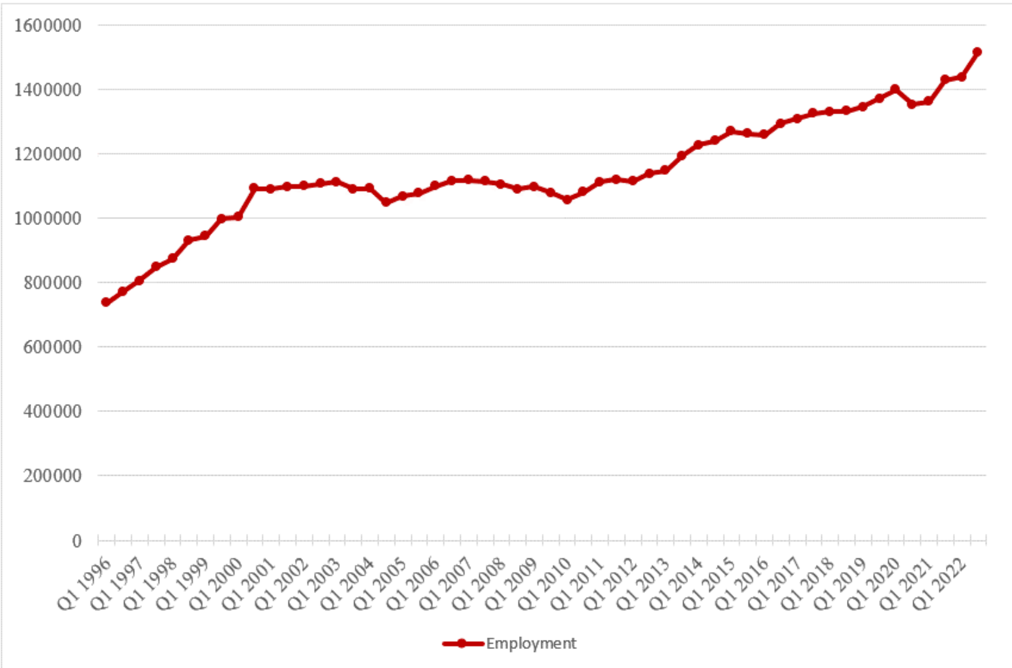

Figure 2. The timeline graph of ICT employment.

Findings

In line with the steps outlined in the methodology section, the autocorrelation and partial autocorrelation models in the series were analyzed and the autocorrelation function (ACF) and partial autocorrelation function (PACF) patterns were examined to assess the stationarity and the presence of autocorrelations in the series. ACF is used to determine the relationship between the current value of the series and its past values through a comparison, while PACF is used to de-correlate the current value of the series from its past values in order to show any direct relationship between associated lags. The blue bars in a graph represent the relationship between the current value and the previous values (www.sv-europe.com), and PACF examines the relationship between errors and the current time point, which allows one to check the relationships for all points in time (Köppelová and Jindrová, 2019, p. 7).

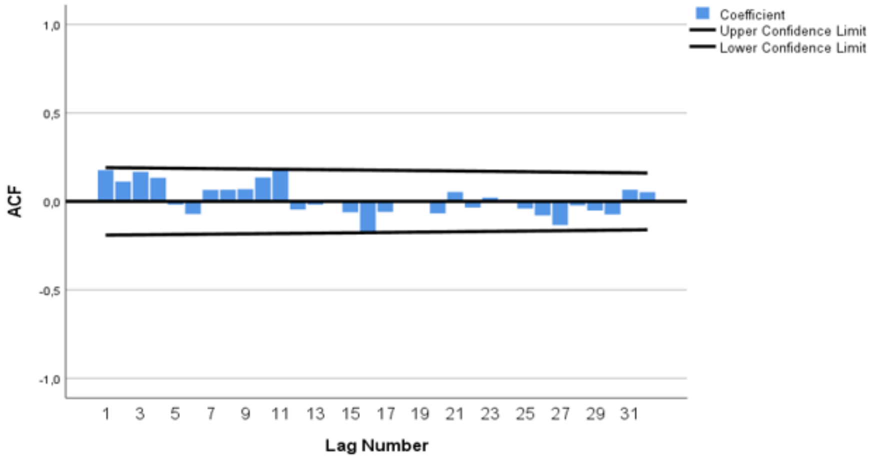

Figure 3. Autocorrelation function (ACF) of the differenced series.

Upon examining the ACF and PACF graphs (Figures 3 and 4, respectively), the series is determined to have a trend. Therefore, the first difference of the series has been taken to stationarize the series and remove the trend. As a result of taking the first difference of the series, the ACF graph in Figure 3 and PACF graph in Figure 4 have been obtained.

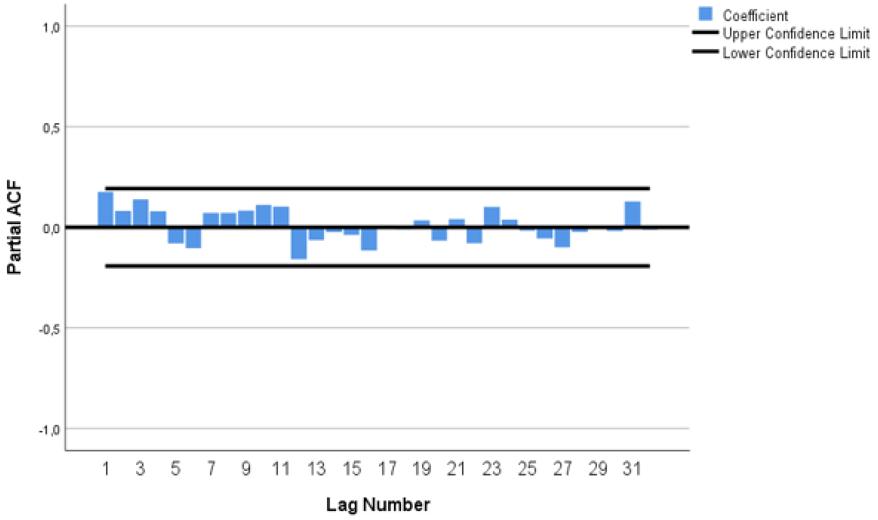

Figure 4. Partial autocorrelation function (PACF) of the differenced series.

As a result of taking the first difference, the information obtained from the ACF graph in Figure 3 and PACF graph n Figure 4 have led to the decision that an ARIMA (0,1,1) model is suitable for the series. After applying the model, the curve pattern of the ICT series and the corresponding forecast are obtained in Figure 5, in which the red curve represents the actual employment data, and the blue curve represents the simulated training data, which closely align with actual production data. Upon examining the curves, the training data is evidenced to effectively represent the real data.

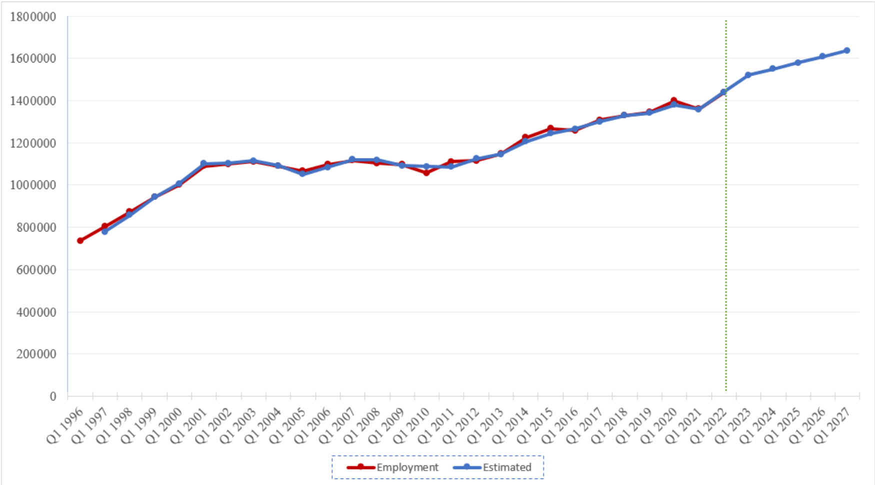

Figure 5. Curve pattern of the ICT series and the corresponding forecast.

Estimates for employment statistics are made for different countries and employment offices and cover periods of 2, 5, and 10 years (Peinecke, Forland, Wheeler, Roubinchtein and Nimmo, 2017, p. 2). Therefore, this study develops and implements a prediction model for a 5-year time frame.

Upon analyzing the prediction results, the total ICT workforce in the England was found to be comprised of 1,513,763 individuals as of December 2022. This workforce has been estimated to reach 1,542,333 people in 2023, 1,571,411 by the end of 2024, 1,600,489 by the end of 2025, 1,629,566 by the end of 2026, and 1,658,644 by the end of 2027. A 9.6% increase in the ICT workforce is expected by the end of 2027. The statistical findings demonstrate that the growth of the ICT workforce in the England will continue at an upward trend in the future.

A portion of the values for the ICT workforce for the first quarter of 2021 and beyond, along with the predicted values from the model, are also provided in Table 1.

Table 1. *Model Forecasting Results*

Date	ICT Workforce	Forecasting
Q1 2021	1,360,895	1,357,549
Q2 2021	1,343,294	1,368,683
Q3 2021	1,380,007	1,346,624
Q4 2021	1,427,543	1,392,455
Q1 2022	1,437,349	1,440,255
Q2 2022	1,481,710	1,444,167
Q3 2022	1,507,754	1,494,803
Q4 2022	1,513,763	1,517,032
Q1 2023	-	1,520,525
Q2 2023	-	1,527,794
Q3 2023	-	1,535,064
Q4 2023	-	1,542,333
Q1 2024	-	1,549,603
Q2 2024	-	1,556,872
Q3 2024	-	1,564,141
Q4 2024	-	1,571,411
Q1 2025	-	1,578,680
Q2 2025	-	1,585,950
Q3 2025	-	1,593,219
Q4 2025	-	1,600,489
Q1 2026	-	1,607,758
Q2 2026	-	1,615,028
Q3 2026	-	1,622,297
Q4 2026	-	1,629,566
Q1 2027	-	1,636,836
Q2 2027	-	1,644,105
Q3 2027	-	1,651,375
Q4 2027	-	1,658,644

The adequacy indices for the model are examined in Tables 2 and 3. Software programs for model fitness criteria typically generate R2, root mean square error (RMSE), mean absolute percentage error (MAPE), maximum absolute percentage error (MaxAPE), mean absolute error (MAE), max absolute error (MaxAE), and normalized Bayesian information criterion (BIC) values. Normalized BIC can be considered a fundamental criterion for evaluating model fitness. In particular, the expert model interface attempts to find models that yield the lowest normalized BIC values (www.sv-europe.com). A low value for the normalized BIC is considered an indicator of a simpler model with better fit.

Table 2. *The Goodness-of-Fit Indices*

Fit Statistic	Mean
Stationary R^2	.027
R^2	.990
RMSE	16.330
MAPE	1.087
MaxAPE	3.836
MAE	12.456
MaxAE	37.542
Normalized BIC	19.489

Table 3 examines the significance level of the chi-square p-value for the residuals. The significance level was observed as $p > 0.05$ ($p = 0.510$), indicating that the evaluated model does not establish a significant correlation and thus meets the assumption that it adequately models the series (Minitab, 2023).

Table 3. *Ljung-Box Significance Levels*

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q (18)			Number of Outliers
		Stationary R^2	Statistics	*df*	Sig.	
Employmet-Model_1	0	.027	16.191	17	.510	0

Conclusion

This study has developed a forecasting model using the ARIMA method to predict the future of the information and communication technology (ICT) workforce in England. The study has preferred the ARIMA model due to its ability to provide fast and efficient results and its ability to contribute to operational planning (Ning, Kazemi and Tahmasebi, 2022, p. 7). The study produced its results based on the statistical model using the data that were obtained in order to understand the behavior of the ICT workforce. In this context, the expected workforce employment in the ICT sector in England for the coming years has been forecast. According to the forecasts, employment for ICT workforce is expected to show an increasing trend in England. In other words, the demand for professionals with ICT skills is estimated to increase in the ICT sector in the coming years.

A proper evaluation of the obtained evidence will guide the decision-making process at both the strategic and operational levels for sustainable growth in the ICT sector. These forecasts will play a guiding role in labor force planning and the formulation of education policies and will help shape the decisions of stakeholders in the sector. They will also enable priorities to be set to adapt to the future needs of the ICT workforce.

Systematic examinations of the workforce can contribute to sustaining competitiveness at every level. The rapid changes in technology indicate the need for more research regarding the workforce. The demand for skilled labor is particularly important in the ICT field. Thanks to workforce predictability, countries can set more effective development priorities and policies (Economic Commission for Latin America and the Caribbean, 2021, p. 164).

Demographic changes, data related to the findings of this study and the combined evaluation of the current talent situation represent an important strategic approach for workforce planning and management. Countries and organizations benefiting from such studies can gain an advantage in successfully planning and implementing policies and programs. Additionally, they can develop a better understanding of how skills and capabilities are distributed within the existing workforce and how these can be cultivated and managed to meet future needs.

The possibility of a potential skill shortage should be assessed by considering employment trends in ICT. In this context, policy changes in the education and training system and in the acquisition of skills at the global level should be discussed in order to prevent possible negative consequences. Practices for developing the workforce through skill courses and on-the-job training, especially in areas that require fundamental ICT skills, should be identified to facilitate transitioning to jobs in these areas. Additionally, policies should be established for transferring the part of the workforce that has been rendered obsolete due to the proliferation of jobs in the ICT field to new jobs within the ICT sector.

The outcomes of workforce-related policies are usually long term and influenced by many factors. The use of data in determining policies for identifying workforce needs, acquiring labor, and maintaining the existing talent pool increases the likelihood of success by enabling evidence-based decision making. For this reason, countries are recommended to closely follow trends, especially with regard to ICT, in order to formulate workforce-related policies.

In the wake of advancements in high technology, each skill area that is created may lead to the emergence of five different skills. In this case, how current jobs will transform and identify the skills that will replace these jobs need to be determined (OECD, 2016, p. 3).

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