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# COVID-19 Pandemic and Technological Change: Analysis of Patent Applications

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***ABSTRACT***
***Purpose:*** This study is aimed to measure COVID-19's impact on innovation and monitor technical change during the Pandemic through patent applications.
***Methodology:*** Patent application annual total number of European Patent Office patent applications data on 35 different technological disciplines separated into five key categories from 2012 to 2021 were utilized in the analysis. The Prophet forecasting model to forecast patent applications for 2020 and 2021 has been developed. The technological advancements and Pandemic impact on innovation were then analyzed using the actual and forecasted values.
***Findings:*** The study's findings indicate no apparent difference between actual numbers and forecasted values. It was found that in 2020 and 2021, more patent applications than expected were made in 15 and 16 technological areas, respectively. The study also found that semiconductors, audio-visual, and nanotechnology advancements have been notable during the Pandemic.
***Originality***: The originality of this study lies in the use of the Prophet forecasting model based on European Patent Office patent application values in the analysis of the effects of the pandemic on innovation and technological change for 35 different technological disciplines.
***Keywords:*** Technological Change, Innovation, Patent, Prophet Model, COVID-19.
***JEL Codes*:** O30, O33, C22.

## COVID-19 Salgını ve Teknolojik Değişim: Patent Başvurularının Analizi

***ÖZET***
***Amaç:*** Bu çalışmanın amacı, COVID-19'un inovasyon üzerindeki etkisinin ölçülmesi ve Pandemi sürecinde teknolojik değişimlerin izlenmesidir.
***Yöntem:*** Avrupa Patent Ofisi'ne yapılan 2012-2021 yılları arasındaki patent başvuruları araştırmanın temel veri kaynağını oluşturmaktadır. İlgili veri seti içinde beş ana kategori ve 35 farklı teknolojik disipline ait yıllık patent başvuru değerleri yer almaktadır. Zaman serisine dayanan Prophet tahmin modeli, 2020 ve 2021 yılları için patent başvurusu sayılarını tahmin edilmesi amacıyla oluşturulmuştur. Pandeminin neden olduğu krizin teknolojik değişimler ve inovasyon üzerindeki etkisinin izlenmesi amacıyla gerçekleşen ve öngörülen patent başvuru değerleri üzerinden analiz gerçekleştirilmiştir.
***Bulgular:*** Çalışmanın bulguları, 2020 ve 2021 yıllarında toplam patent başvuru değerinde önemli bir değişiklik olmadığını göstermektedir. 2020 ve 2021'de, sırasıyla 15 ve 16 teknolojik alanda tahmin edilenden daha fazla patent başvurusunun yapıldığı saptanmıştır. Yarı iletkenler, görsel-işitsel ve nanoteknoloji olmak üzere üç alanda Pandemi sırasında önemli ilerlemelerin kaydedilmiş olması çalışmanın ortaya koyduğu diğer önemli bulgulardan bir diğeridir.
***Özgünlük:*** Bu çalışmanın özgünlüğü, 35 farklı teknolojik disiplin için pandeminin inovasyon ve teknolojik değişim üzerindeki etkilerinin analizinde Avrupa Patent Ofisine yapılan patent başvurularının Prophet tahmin modeli ile kullanılmasında yatmaktadır.
***Anahtar Kelimeler:*** Teknolojik Değişim, İnovasyon, Patent, Prophet Modeli, COVID-19.
***JEL Kodları:*** O30, O33, C22.

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## 1. INTRODUCTION

The COVID-19 Pandemic has impacts that cause changes in the manufacturing and service sector on a global basis. The business environment affected by the COVID-19 pandemic not only compelled institutions and employees to adjust to the new conditions but also prompted a re-evaluation of the functioning and priorities of several business processes and a re-determination of priorities. Considering that one of the most features of the disease is rapid human-to-human transmission, several organizations have been in a state of closure for a certain period. The firms then updated their processes by allowing employees to work from home for tasks that do not require them to be in the office. Institutions have opted to implement considerable changes in working conditions within the context of the Pandemic guidelines, particularly the regulations on the social distance among employees performing jobs that cannot be conducted away from the office. This circumstance had a significant impact on business processes, particularly communication. The Pandemic's negative impact on R&D processes is undeniable. Monitoring technology changes has become increasingly important during crisis periods to understand how the crisis affects innovation. Innovation strategy decision-makers depend heavily on knowledge of technological advancements in making decisions. In times of crisis, quantifying technological change becomes increasingly difficult. Despite years of research, economists, economic historians, historians of technology, and researchers have not come up with a single method of determining technological change. Utilizing patent data and statistics is one approach. Patent statistics have been extensively used in several kinds of research measuring innovation (Nagaoka et al., 2010). This article uses European Patent Office (EPO) patent data to examine technological change. Monitoring and comparing trends among countries, industries, and technical disciplines is another significant area in which patent statistics are extensively employed (Pavitt, 1985). In our study, the researcher examined the overall number of patent applications and looked at 35 different technological disciplines divided into five major categories: Electrical Engineering, Instruments, Chemistry, Mechanical Engineering, and other fields.

The issue of quantifying technological change is an incredibly increasingly difficult task during crisis periods. The general idea is that economic crises are not related to innovation. The knowledge from Schumpete's study of the relationship between innovation and the dynamics of economic growth state that innovation is a significant cause of economic volatility (Filippetti and Archibugi, 2011). Significant changes in how businesses and society perform have been seen, particularly after the emergence of COVID-19. Following the virus's emergence, massive and disruptive technological developments preceded it. Numerous innovation efforts, particularly those focusing on vaccination technology, have provided quick design and production outcomes in response to the global health problem. Using EPO patent application data from 2012 to 2021, the researcher will study the trajectory of technology innovation for 2020 and 2021, which is when the significant impact of COVID-19 is experienced. Technology direction change, technology life cycle, technology research hot spot, and technology evaluation are the primary four heading on technology trend analysis. Among the most common techniques used in patent analysis include time series analysis, simulation analysis, Bayes network method analysis, social network analysis, technology life cycle analysis, international patent classification analysis, patent citation analysis, patent visualization analysis, and text-mining analysis (Huang and Li, 2010). In this research, the time series-dependent Prophet forecasting model has been used. This study aims to measure the impact of COVID-19 on innovation and monitor technical changes throughout the pandemic through patent applications. The research used data from the European Patent Office's yearly total number of patent applications for 35 technological disciplines divided into key categories between 2012 and 2021. In addition to doing a relevant scenario analysis based only on total patent application value, it provided the possibility to conduct the analysis based on the aforementioned number of key categories and technological disciplines. The relevant analysis led to the identification of technological fields whose advancement went above and beyond expectations. This research differs from previously conducted studies due to the fact it analyzes the effects of the pandemic on innovation and technological transformation for 35 distinct technical fields using the Prophet forecasting model based on European Patent Office patent application data.

Productivity is an important factor in gaining a competitive edge at both the micro and macro levels. It is evident that adapting to technology advances is a key component in productivity. It is well known that technological developments have a favourable impact on a variety of parameters of total productivity, especially labour productivity. Patents are one of the most prevalent mechanisms for registering technological change. The relevant situation leads to the use of patent data in analyzing technological change.

The study's progress is shown following. The next section is a review of the literature. Section 3 shows the methodology. Section 4 presents the findings and comments. The final section is conclusion.

## 2. LITERATURE REVIEW

Technology forecasting is the foundation for technological progress and investment. The major barriers limiting technical collaboration and information interchange between businesses are geographical and national. Patent alliances between businesses operating in the same country have become fairly typical (Ma et al., 2022). According to study on the development of internal combustion engine vehicles that used patent data analysis, the number of patent families will reach saturation in 2045. The research raised expectations for the commercialization of innovations that were created in the ten years prior to 2040. These technology could continue to exist after that time (Sinigaglia et al. 2022). Wei et al. (2022) showed explicit evidence on the role of patents in overcoming financing constraints faced by R&D-intensive firms. The availability of a forecasting model has emerged as an important research issue in a crisis ecosystem where various factors have influenced technology. There is a large body of influential literature on the factors influencing technological change (Rip and Kemp, 1998; Romer, 1990). It is critical in macroeconomics, development economics, labor economics, and international trade to determine whether technological change is biased toward specific factors. The price and market size effects are the two major forces influencing equilibrium bias (Acemoğlu, 2002). The three stages of technological change, invention, innovation, and diffusion, are frequently viewed as multidimensional processes involving users, producers, suppliers, and policymakers (del Río González, 2009). The information obtained from patent applications and grants helps monitor technological change. A reliable technology forecasting indicator is highly desirable in monitoring technological change, and patents have been regarded as one of the most critical factors in the field (Chang et al., 2009). The requisite accuracy cannot be attained by employing a single model on time series. In order to increase prediction efficacy, Arslan proposed a forecasting framework that merged Facebook's Prophet with the recurrent neural network model. According to the findings, adopting a hybrid model produces more accurate predictions than using a single model (Arslan, 2022). Monitoring and forecasting the technology progress through patent analysis have long been a topic of significant interest among researchers. Smith and Agrawal (2015) showed how patent groups could be used to construct technology forecasting models. The primary criteria employed in technological forecasting have been identified in research for modeling technology success using patent data as technology life cycle, diffusion speed, patent power, and expansion potential (Altuntas et al., 2015). Despite lacking a standard strategy for integrating quantitative and qualitative methodologies in future-oriented technology analysis, a few research have employed a hybrid of the two methods. Finding prospective futures and reducing uncertainty in Future-oriented technological analysis may be performed using quantitative and qualitative methodologies (Haegeman et al., 2013) Shih et al. (2010) introduced a patent trend change mining approach that could detect and identify patent trend change without the aid of experts. The primary steps of the strategy are patent collecting, patent indicator computation, and change detection. In a different research, time series analysis using patent data was used to establish methods for detecting anomalous deviations in time series models created to predict technical advancement. Studies on the patent data from 2012 revealed that some patents were above the upper control limit. The association between the above-average number of patents and the advent of LCD TVs has been revealed due to the process's development (Durmuşoğlu, 2018). The influence of The Clean Air Act on the volume of patenting in the chemical sector was studied using basic chemical utility patents to identify the impacts of the Act on patenting activities. Following fitting the Autoregressive Integrated Moving Average model, a significant outlier was discovered, concluding that the chemical sector reacted to changes extremely efficiently (Durmuşoğlu, 2017). Based on the results of an analysis comparing Holt-Winters Exponential Smoothing with an Autoregressive Integrated Moving Average model for technology change forecasting using USPTO patent data from 1996 to 2013, Holt-Winters Exponential Smoothing outperformed Autoregressive Integrated Moving Average (Smith and Agrawal, 2015). It has been conducted to evaluate different methods for predicting national patent and trademark applications in the short and medium term for resource planning at the Spanish Patent and Trademark Office and other patent offices, including exogenous variables and predictors. Several advanced prediction models' performances were compared in the analysis, including an ARIMA model with automatic estimation of coefficients, a Simple econometric model with a predictive lag variable, a Polynomial Distributed Lag model, and an Intelligent Transfer Function (Hidalgo and Gabaly, 2013). Patent data was utilized to study Persian lime's technological life cycle trajectory and present status (Martínez-Ardila et al., 2022). In the study, Dikta (2006) used time series analysis to forecast patent applications. Based on an investigation of multiple forecasting strategies employing European trademark and design registration data, emerging techniques based on artificial intelligence have outperformed traditional forecasting techniques (Havermans et al., 2017). Hingley and Park (2016) forecasted patent filings at the EPO using the Log-Linear Regression Model. Auto-distributed lags(ADL) model predictions better than ARIMA does, according to the analysis on defining superior performing Box Jenkins-based times series models, namely ARIMA and ADL for EPO patent application data (Hingley and Dikta, 2019).

COVID-19 caused a significant shift to work from home, affecting all operations, including the R&D process, which impacted the technical transformation trajectory. COVID-19 has also changed the focus of innovation toward solutions that address newly identified demands in a pandemic context. From January to September 2020, the number of new U.S. patent applications related to video conferencing, telecommuting, remote interactivity, and working-from-home technologies more than doubled, far exceeding the previous peak and continuing on an upward trajectory since the Pandemic's inception. The scope of this research showed that technological advancement would improve the quality and efficiency of remote employment, promoting a shift to working from home long after the Pandemic is over(Bloom et al., 2021, p. 363). Among the research following the patent and utility model applications of technological innovation activities throughout the Pandemic, it participates in research utilizing TÜRKPATENT data. Research on the relevant data from the whole patent utility model application of COVID-19 revealed no negative impacts on the figures (Köker and Alan, 2021). Several studies have been carried out to monitor COVID-19-related inventions, including evaluations of patent data in diagnostics, sanitization, personal protection, and vaccine research available from December 2019 to June 2021 (Dubey et al., 2022). Researchers used the Global Innovation Index Reports to analyze the impact of the Pandemic on innovation, and significant changes were found in all three categories, business sophistication, infrastructure, and knowledge and technology output (Onea, 2022). According to the findings, technological change is observed by using the prediction values obtained by patent data usage, particularly in areas where the predictions are made using artificial intelligence techniques, which is a technology area that is not only open to development but also requires extensive academic research.

The study of technological change using patent data from the European Patent Office hasn't been studied extensively. There have not been numerous research efforts undertaken where forecasting models are developed and results are subjected to technological change analysis. The uniqueness of this study is in the analysis of the impact of the pandemic on innovation and technological development for 35 different technical disciplines using the Prophet forecasting model based on European Patent Office patent application data.

## 3. METHODOLOGY

Throughout the Pandemic, data from the EPO patent application was utilized to track technological changes. The yearly statistics for 2012 and 2021 for EPO patent applications may be accessed through the official website, and the data for the relevant time were utilized in the study. The collection includes complete applications from more than 170 countries. Data on 35 different technical domains were acquired and analyzed under five main headings: electrical engineering, instruments, chemistry, mechanical engineering, and other fields (Statistics and Trends Centre, 2023). Recently prominent linear statistical techniques like the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model might be a significant alternative forecasting technique that could be applied in our research. Atasever et al. (2022) showed in their research the Prophet model have higher accuracy than SARIMA. The prophet model has not yet been used for EPO patent forecasting in the literature. Due to the aforementioned factors, the prophet forecasting model with time series dependence has been chosen. Based on the annual total number of patent applications from 35 different technical disciplines between 2012 and 2019 in order to predict 2020 and 2021 values. Python 3.9.12 was used to build the forecasting model. Prophet is open-source software developed by Facebook's Core Data Science team that can be implemented in R and Python. Prophet is a method for forecasting time series data using an additive model with non-linear trends. The yearly seasonality has been set in the forecasting model. The interval width parameter has been set to 0,95, establishing the uncertainty interval for calculating the confidence interval around the forecast (Prophet, 2023). Prophet employs a time series decomposable model (Harvey and Peters, 1990) with three key model elements: trend, seasonality, and holidays. Following are the Equations 1-3 that integrate them, where g(t) represents non-periodic changes, s(t) represents periodic changes, h(t) represents the effects of holidays on potentially irregular schedules, and $\varepsilon_t$ is an error term that is not taken into account by the model (Taylor and Letham, 2018).

$$\mathrm{y(t) = g(t) + s(t) + h(t) + \varepsilon} \tag{1}$$

$$g(t) = (k + a(t)^T \delta)t + (m + a(t)^T \gamma) \tag{2}$$

$$s(t) = \sum_{n=1}^{N} \left( a_n \cos\frac{(2\prod nt)}{P} + b_n \sin\frac{(2\prod nt)}{P} \right) \tag{3}$$

The main notations used for the equation mentioned above are briefly defined as follows: k the growth rate, δ the rate adjustments, m the offset parameter, P the regular period holidays and events frequently do not follow a periodic pattern, hence their efects are not properly modeled by a smooth cycle (Toharudin et al., 2023).

Mean squared error (MSE) and mean absolute error (MAE) were calculated as error functions for the forecasting model. MSE and MAE are given in the following Equations 4-5 (Kisi et al., 2014).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_{i_{observed}} - Y_{i_{estimated}})^2 \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_{i_{observed}} - Y_{i_{estimated}}\right| \tag{5}$$

where Yi $_{observed}$ and Yi $_{estimated}$ represent the observed and estimated values, respectively. The model's performance in terms of fit is measured by coefficient of determination ($R^2$), and the Equation 6 is provided below (Rahman et al, 2020).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_{i_{observed}} - Y_{i_{estimated}})^2}{\sum_{i=1}^{N(}(Y_{i_{observed}})^2 - \frac{(\sum_{i=1}^{N(} Y_{i_{observed}})^2}{N}} \tag{6}$$

## 4. RESULTS and DISCUSSION

The research's initial phase was counting the overall number of patent applications across all technological domains. The relevant indicator is one of the most important indicators for assessing whether the Pandemic has positively or negatively influenced technical development. During the years 2012 and 2021, a total of 160 different nations filed patent applications to EPO. The number of patent applications filed by the top 30 countries with the most patent applications in the specified years is shown in the Table 1 below (Statistics and Trends Centre, 2023).

The following countries are listed by the total share of EPO patent applications received over the stated period: 25% USA, 16% Germany, 13% Japan, 6% France, 5% China, 5% Switzerland, 4% Republic of Korea, 4% Holland, and 3% U.K. It is observed that the countries mentioned above account for more than 80% of all applications. When the figures from 2021 to 2019 are compared, it can be observed that China, with a 33% rise, and Korea, with an 11% increase, stand out significantly from other top-performer countries, according to EPO patent application data. Comparing the years 2019-2020 across the countries with a significant share of EPO patent applications shows that China and Korea generate the most significant success. It is one of the topics that should be investigated during the period when the heavy effects of the 2020 pandemic were felt, and drastic measures were taken on a global scale that the two far eastern countries, which had to struggle intensively with epidemics such as COVID-19 in previous years, have achieved this success.

In examining outstanding percentage change values for 2019-2020, Saudi Arabia has an increase of 35%, Türkiye has an increase of 28%, and Singapore has an increase of 20%. The three countries featured are among the top at innovating during the early stages of pandemics within the scope of EPO patent applications. Comparing the 2021 data to the 2019 EPO patent application data shows that Singapore and Türkiye stand out from other nations, with 29% and 36% increases, respectively.

**Table 1. Patent applications by country**

| | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|---|---|---|---|
| USA | 35,268 | 34,011 | 36,668 | 42,597 | 40,032 | 42,463 | 43,789 | 46,177 | 44,250 | 46,533 |
| Germany | 27,249 | 26,510 | 25,633 | 24,807 | 24,932 | 25,539 | 26,663 | 26,762 | 25,882 | 25,969 |
| Japan | 22,490 | 22,405 | 22,118 | 21,421 | 20,943 | 21,774 | 22,591 | 22,086 | 21,954 | 21,681 |
| France | 9,897 | 9,835 | 10,614 | 10,760 | 10,484 | 10,619 | 10,468 | 10,233 | 10,614 | 10,537 |
| China | 3,751 | 4,075 | 4,680 | 5,728 | 7,092 | 8,641 | 9,480 | 12,227 | 13,436 | 16,665 |
| Switzerland | 6,746 | 6,742 | 6,910 | 7,116 | 7,302 | 7,354 | 7,961 | 8,266 | 8,125 | 8,442 |
| Republic of Korea | 5,721 | 6,333 | 6,166 | 6,407 | 6,687 | 6,457 | 7,263 | 8,339 | 9,084 | 9,394 |
| Netherlands | 5,067 | 5,852 | 6,874 | 7,147 | 6,860 | 7,043 | 7,142 | 6,942 | 6,386 | 6,581 |
| United Kingdom | 4,716 | 4,587 | 4,764 | 5,051 | 5,175 | 5,321 | 5,761 | 6,129 | 5,698 | 5,627 |
| Italy | 3,744 | 3,706 | 3,649 | 3,986 | 4,154 | 4,360 | 4,404 | 4,469 | 4,619 | 4,919 |
| Sweden | 3,518 | 3,674 | 3,873 | 3,839 | 3,547 | 3,783 | 4,055 | 4,395 | 4,422 | 4,954 |
| Belgium | 1,886 | 1,882 | 1,927 | 2,041 | 2,211 | 2,152 | 2,348 | 2,422 | 2,406 | 2,485 |
| Austria | 1,874 | 1,993 | 1,964 | 1,989 | 2,024 | 2,209 | 2,281 | 2,346 | 2,306 | 2,317 |
| Denmark | 1,605 | 1,942 | 1,983 | 1,920 | 1,855 | 2,089 | 2,385 | 2,415 | 2,420 | 2,642 |
| Finland | 1,851 | 1,894 | 2,182 | 1,993 | 1,796 | 1,797 | 1,728 | 1,705 | 1,899 | 2,111 |
| Canada | 2,427 | 1,865 | 1,708 | 1,632 | 1,572 | 1,513 | 1,591 | 1,841 | 1,759 | 2,083 |
| Spain | 1,544 | 1,504 | 1,471 | 1,518 | 1,574 | 1,671 | 1,781 | 1,885 | 1,794 | 1,954 |
| Chinese Taipei | 1,273 | 1,236 | 1,119 | 1,264 | 1,422 | 1,622 | 1,756 | 1,598 | 1,367 | 1,472 |
| Israel | 1,096 | 1,047 | 1,048 | 1,103 | 1,215 | 1,388 | 1,433 | 1,545 | 1,683 | 1,717 |
| Australia | 855 | 813 | 788 | 818 | 757 | 841 | 969 | 997 | 966 | 1,019 |
| Ireland | 609 | 566 | 622 | 614 | 727 | 660 | 826 | 882 | 980 | 956 |
| India | 554 | 562 | 541 | 577 | 761 | 678 | 699 | 642 | 701 | 820 |
| Norway | 555 | 509 | 529 | 510 | 523 | 531 | 610 | 646 | 652 | 640 |
| Türkiye | 397 | 377 | 403 | 447 | 523 | 911 | 574 | 471 | 605 | 732 |
| Poland | 383 | 372 | 482 | 566 | 393 | 446 | 519 | 463 | 478 | 539 |
| Singapore | 318 | 316 | 368 | 389 | 470 | 435 | 492 | 505 | 607 | 715 |
| Luxembourg | 449 | 429 | 454 | 425 | 556 | 533 | 431 | 415 | 402 | 430 |
| Liechtenstein | 199 | 250 | 278 | 371 | 374 | 380 | 432 | 437 | 439 | 494 |
| Saudi Arabia | 126 | 212 | 290 | 183 | 251 | 140 | 261 | 364 | 494 | 379 |

The time series-dependent prophet forecasting model was developed and used to forecast values for 2020 and 2021. The forecasted model was evaluated using $R^2$, MSE and MAE, and the corresponding values have been given for each technical field in the Table 2 beneath.

**Table 2. Forecasting model performance values**

| *Main Headings* | *Technical Domains* | *$R^2$* | *MSE* | *MAE* |
|---|---|---|---|---|
| Electrical engineering | Total | 0.9944 | 714,994.2 | 792.3 |
| | Elec. machinery | 0.6316 | 86,914.3 | 260.4 |
| | Audio-visual | 0.2668 | 12,636.7 | 83.8 |
| | Telecomm. | 0.1454 | 36,100.9 | 149.0 |
| | Digit. comm. | 0.8915 | 198,934.7 | 346.3 |
| | Basic comm. | 0.3056 | 1,882.8 | 38.6 |
| | Computer | 0.9811 | 32,320.8 | 126.2 |
| | IT methods | 0.9422 | 6,798.8 | 68.9 |
| | Semiconductors | 0.3407 | 22,352.2 | 125.0 |
| Instruments | Optics | 0.8424 | 16,065.8 | 107.2 |
| | Measurement | 0.9836 | 10,845.1 | 81.2 |
| | Analysis bio. mat. | 0.4425 | 2,564.7 | 47.0 |
| | Control | 0.9539 | 8,491.5 | 73.2 |
| | Med. tech. | 0.9650 | 53,114.3 | 194.7 |
| Chemistry | Organic chem. | 0.3730 | 19,955.7 | 127.3 |
| | Biotech | 0.7775 | 61,901.3 | 213.8 |
| | Pharma | 0.6348 | 232,253.2 | 403.7 |
| | Polymers | 0.9730 | 626.4 | 22.1 |
| | Food chem. | 0.5666 | 3,398.3 | 53.3 |
| | Basic mat. chem. | 0.6192 | 20,508.2 | 108.0 |
| | Metallurgy | 0.9837 | 1,227.7 | 27.5 |
| | Coatings | 0.8607 | 3,744.8 | 51.0 |
| | Nano-tech. | 0.7378 | 399.6 | 12.9 |
| | Chemical eng. | 0.9225 | 3,799.9 | 47.4 |
| | Environment | 0.9374 | 483.4 | 19.3 |
| Mechanical engineering | Handling | 0.8408 | 20,130.8 | 122.4 |
| | Machine tools | 0.9196 | 1,031.4 | 29.3 |
| | Engines, pumps | 0.4882 | 82,233.1 | 233.3 |
| | Text & pap. mach. | 0.8688 | 5,084.9 | 64.5 |
| | Other machines | 0.9844 | 8,725.3 | 73.7 |
| | Thermal proc. | 0.9217 | 403.9 | 17.1 |
| | Mech. elements | 0.9321 | 2,568.5 | 49.6 |
| | Transport | 0.9846 | 9,276.7 | 94.2 |
| Other field | Furniture | 0.8998 | 2,455.9 | 40.8 |
| | Consumer goods | 0.9239 | 19,242.4 | 109.2 |
| | Civil eng. | 0.9642 | 795.3 | 19.5 |

The relevant performance figures demonstrate that the established model produces considerably successful performances. Results from the study were obtained for each technological field for 2020 and 2021 based on the forecasted values and the actual values retrieved from EPO patent applications data. The forecasted and actual values presented in the Figure 1 and Table 3.

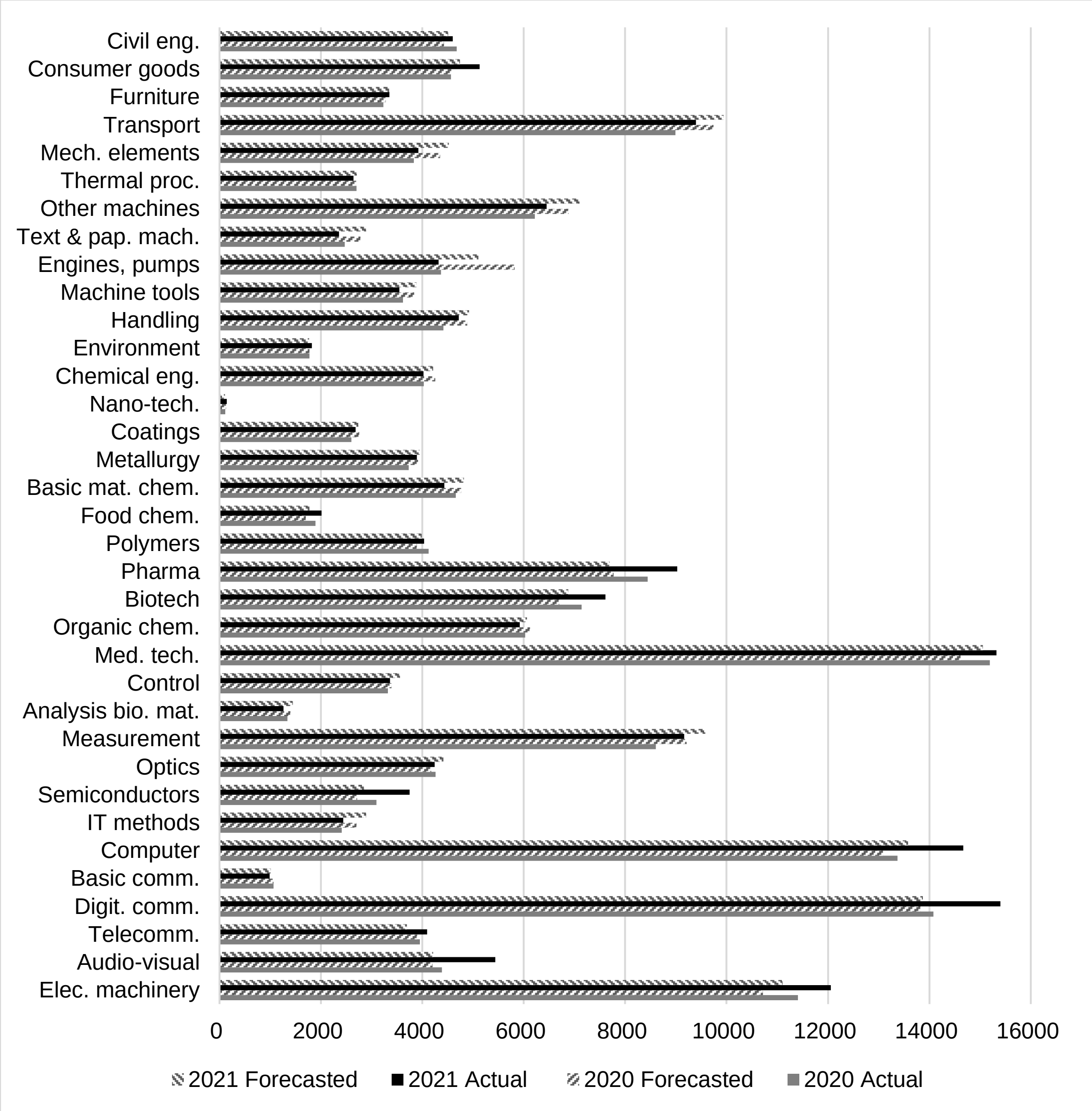


**Figure 1. Patent applications: Actual and forecasted values**

**Table 3.Patent applications: Actual and forecasted values**

| | | *Forecasted Values* | | *Actual Values* | |
|---|---|---|---|---|---|
| *Main Headings* | *Technical Domains* | *2020* | *2021* | *2020* | *2021* |
| Electrical Engineering | Total | 183,076 | 188,469 | 180,417 | 188,600 |
| | Elec. machinery | 10,719 | 11,102 | 11,409 | 12,054 |
| | Audio-visual | 4,200 | 4,215 | 4,388 | 5,440 |
| | Telecomm. | 3,896 | 3,696 | 3,952 | 4,092 |
| | Digit. comm. | 13,825 | 13,869 | 14,077 | 15,400 |
| | Basic comm. | 1,068 | 1,010 | 1,066 | 988 |
| | Computer | 13,084 | 13,578 | 13,370 | 14,671 |
| | IT methods | 2,703 | 2,892 | 2,408 | 2,438 |
| | Semiconductors | 2,712 | 2,850 | 3,097 | 3,748 |
| Instruments | Optics | 4,179 | 4,415 | 4,262 | 4,242 |
| | Measurement | 9,212 | 9,578 | 8,606 | 9,167 |
| | Analysis bio. mat. | 1,401 | 1,448 | 1,340 | 1,260 |
| | Control | 3,391 | 3,559 | 3,320 | 3,360 |
| | Med. tech. | 14,617 | 15,056 | 15,193 | 15,321 |
| Chemistry | Organic chem. | 6,122 | 6,062 | 6,029 | 5,923 |
| | Biotech | 6,699 | 6,880 | 7,141 | 7,611 |
| | Pharma | 7,771 | 7,693 | 8,446 | 9,026 |
| | Polymers | 3,890 | 3,989 | 4,124 | 4,033 |
| | Food chem. | 1,704 | 1,777 | 1,894 | 2,010 |
| | Basic mat. chem. | 4,767 | 4,820 | 4,658 | 4,432 |
| | Metallurgy | 3,918 | 3,946 | 3,730 | 3,890 |
| | Coatings | 2,754 | 2,738 | 2,601 | 2,686 |
| | Nano-tech. | 129 | 111 | 115 | 146 |
| | Chemical eng. | 4,257 | 4,213 | 4,030 | 4,026 |
| | Environment | 1,773 | 1,768 | 1,774 | 1,823 |
| Mechanical engineering | Handling | 4,887 | 4,920 | 4,418 | 4,719 |
| | Machine tools | 3,840 | 3,887 | 3,620 | 3,549 |
| | Engines, pumps | 5,818 | 5,108 | 4,366 | 4,318 |
| | Text & pap. mach. | 2,777 | 2,894 | 2,472 | 2,359 |
| | Other machines | 6,888 | 7,100 | 6,216 | 6,450 |
| | Thermal proc. | 2,696 | 2,708 | 2,702 | 2,641 |
| | Mech. elements | 4,349 | 4,524 | 3,833 | 3,925 |
| | Transport | 9,739 | 9,945 | 8,993 | 9,399 |
| Other field | Furniture | 3,276 | 3,345 | 3,230 | 3,348 |
| | Consumer goods | 4,570 | 4,741 | 4,563 | 5,130 |
| | Civil eng. | 4,430 | 4,510 | 4,679 | 4,598 |

In addition to comparing the expected and achieved values for 2021-21, a percentage change comparison with the results for 2019 were conducted. The relevant findings are presented in the Table 4 below. It shows no significant percentage change in the total number of applications for 2020 and 2021.

**Table 4. Patent applications: Actual and forecasted values percentage change**

| Main Headings | Technical Domains | From Forecasted to Actual Values (%Δ) (C1) | | From 2019 Actual to 2020-21 Forecasted Values (%Δ) (C2) | | From 2019 Actual to 2020-21 Actual Values (%Δ) (C3) | | Difference in Percentage Change C4 (C3-C2) | |
|---|---|---|---|---|---|---|---|---|---|
| | | 2020 | 2021 | 2019-20 | 2019-21 | 2019-20 | 2019-21 | 2019-20 | 2019-21 |
| | Total | -1.45% | 0.07% | 0.85% | 3.82% | -0.61% | 3.89% | -1.46% | 0.07% |
| Electrical Engineering | Elec. machinery | 6.44% | 8.58% | -5.11% | -1.73% | 0.99% | 6.70% | 6.11% | 8.43% |
| | Audio-visual | 4.48% | 29.05% | -1.83% | -1.46% | 2.57% | 27.16% | 4.40% | 28.63% |
| | Telecomm. | 1.44% | 10.72% | -3.73% | -8.68% | -2.35% | 1.11% | 1.38% | 9.79% |
| | Digit. comm. | 1.83% | 11.04% | -1.10% | -0.78% | 0.71% | 10.17% | 1.81% | 10.95% |
| | Basic comm. | -0.23% | -2.20% | -0.97% | -6.37% | -1.20% | -8.43% | -0.23% | -2.06% |
| | Computer | 2.19% | 8.05% | 1.75% | 5.59% | 3.97% | 14.09% | 2.23% | 8.50% |
| | IT methods | -10.91% | -15.70% | 8.16% | 15.73% | -3.64% | -2.44% | -11.80% | -18.17% |
| | Semiconductors | 14.19% | 31.52% | -9.11% | -4.50% | 3.79% | 25.60% | 12.90% | 30.10% |
| Instruments | Optics | 1.98% | -3.92% | -1.17% | 4.40% | 0.78% | 0.31% | 1.95% | -4.10% |
| | Measurement | -6.57% | -4.29% | 1.81% | 5.86% | -4.89% | 1.32% | -6.69% | -4.55% |
| | Analysis bio. mat. | -4.35% | -13.00% | 3.16% | 6.65% | -1.33% | -7.22% | -4.49% | -13.86% |
| | Control | -2.10% | -5.59% | 3.89% | 9.04% | 1.72% | 2.94% | -2.18% | -6.10% |
| | Med. tech. | 3.94% | 1.76% | 4.89% | 8.05% | 9.03% | 9.95% | 4.13% | 1.90% |
| Chemistry | Organic chem. | -1.52% | -2.29% | 2.15% | 1.15% | 0.60% | -1.17% | -1.55% | -2.31% |
| | Biotech | 6.60% | 10.62% | -1.69% | 0.97% | 4.80% | 11.70% | 6.49% | 10.72% |
| | Pharma | 8.69% | 17.33% | -0.34% | -1.34% | 8.32% | 15.76% | 8.66% | 17.10% |
| | Polymers | 6.02% | 1.09% | -1.35% | 1.18% | 4.59% | 2.28% | 5.94% | 1.10% |
| | Food chem. | 11.14% | 13.14% | -5.69% | -1.68% | 4.81% | 11.23% | 10.51% | 12.92% |
| | Basic mat. chem. | -2.28% | -8.05% | 1.36% | 2.49% | -0.96% | -5.76% | -2.32% | -8.25% |
| | Metallurgy | -4.80% | -1.42% | 2.06% | 2.79% | -2.84% | 1.33% | -4.90% | -1.46% |
| | Coatings | -5.56% | -1.91% | 4.67% | 4.08% | -1.14% | 2.09% | -5.81% | -1.98% |
| | Nano-tech. | -10.69% | 31.83% | -12.41% | -24.66% | -21.77% | -0.68% | -9.36% | 23.98% |
| | Chemical eng. | -5.32% | -4.43% | 1.11% | 0.06% | -4.28% | -4.37% | -5.38% | -4.43% |
| | Environment | 0.06% | 3.13% | -4.43% | -4.71% | -4.37% | -1.73% | 0.06% | 2.99% |
| Mechanical engineering | Handling | -9.60% | -4.08% | 2.67% | 3.36% | -7.18% | -0.86% | -9.86% | -4.22% |
| | Machine tools | -5.73% | -8.69% | 3.48% | 4.74% | -2.45% | -4.37% | -5.93% | -9.10% |
| | Engines, pumps | -24.95% | -15.46% | 10.84% | -2.69% | -16.82% | -17.74% | -27.66% | -15.04% |
| | Text & pap. mach. | -10.99% | -18.49% | 5.35% | 9.79% | -6.22% | -10.51% | -11.57% | -20.30% |
| | Other machines | -9.76% | -9.16% | 7.31% | 10.61% | -3.16% | 0.48% | -10.47% | -10.13% |
| | Thermal proc. | 0.22% | -2.46% | 0.82% | 1.26% | 1.05% | -1.23% | 0.23% | -2.49% |
| | Mech. elements | -11.86% | -13.24% | 3.05% | 7.20% | -9.17% | -6.99% | -12.22% | -14.19% |
| | Transport | -7.66% | -5.49% | 2.09% | 4.25% | -5.73% | -1.48% | -7.82% | -5.72% |
| Other field | Furniture | -1.42% | 0.10% | 3.49% | 5.65% | 2.02% | 5.75% | -1.47% | 0.10% |
| | Consumer goods | -0.15% | 8.19% | -0.15% | 3.59% | -0.31% | 12.08% | -0.15% | 8.49% |
| | Civil eng. | 5.63% | 1.96% | -4.82% | -3.10% | 0.54% | -1.20% | 5.36% | 1.90% |

The critical assumption of the research is that the values acquired from the predictions generated from the analysis are equal to the probable values that may occur in a situation where the Pandemic is not encountered. The first part of the research compared forecasted and actual patent application values for 2020 and 2021, displayed under the heading C1 in the above table. Essentially, the appropriate indicator is crucial in demonstrating the primary influence of the Pandemic on technological change and innovation. The change in the total number of applications for 2020 and 2021 could illustrate the relative finding. It shows no significant percentage change in the total number of applications for 2020 and 2021. This finding is consistent with Köker and Alan's published research, which used patent and utility model application obtained from TÜRKPATENT. The performance of the Semiconductors and Food Chemistry industries in

2020 was shown to be positively decomposed from other Technological Domains. We can see that the Nanotechnology, Semiconductors, Audio-Visual, Pharma, Telecommunications, Digital Communication, Biotechnology, Pharma, and Food Chemistry fields are significantly different, in a positive direction, when compared to other technical fields in the highlights of the percentage change from forecasted to actual values for 2021. The most crucial difference between 2020 and 2021 is in the nanotechnology sector regarding percentage change: from forecasted to actual values.

In the following research stage, the percentage change was measured for the actual and predicted values for 2019, 2020, and 2021. The difference between the relevant periods is an essential indicator of the impact of the relevant crisis period on technological change. The difference in percentage change in the above table under the C4 heading helps us understand the change rate. Semiconductors and Food Chemistry are the industries that stand out well when the values for the years 2019-2020 are analyzed. For the outstanding industries, the percentage change from forecasted to actual values for 2020 shows the same outcome as the outstanding industries for the previous year. Analyzing the difference in percentage change for 2019-2021 showed that six significant fields stand out. Semiconductors, Audio-visual, Pharma, Food Chemistry, Digital Communication, and Biotechnology. According to research using patents to quantify technological change throughout the crisis, semiconductors, audio-visual, and nanotechnology are the top three sectors that exhibited outstanding advancement throughout the crisis. (WHO, 2023)

## 5. CONCLUSION

Historically, significant global crises have been triggered by several factors, including economic, security, and health. The characteristic features and effects of COVID-19 are significantly different from other frequently seen crises. Business, R&D, education, tourism, and the health system are among the priority components where the harmful impact of COVID-19 has been most dramatically observed. The scale of this crisis's long-term consequences is unlikely to be established. Although COVID-19 restrictions have been considerably eased in significant parts of the world, the Pandemic caused by the virus is still continuing. It is known that WHO continues its work on identifying pathogens that may cause future outbreaks and pandemics (WHO, 2023). A structure similar to COVID-19 may re-emerge in the near future, which is one of the scenarios that should be researched extensively. Besides the health crisis, economic, financial, and social crises have been affecting the global economy since the COVID-19 outbreak. There have been several studies on monitoring technological advancement in times of crisis and the influence of crises on innovation, particularly during economic crises.

The effects of COVID-19 and other similar formations on technological change and innovation have not been thoroughly researched. The research's primary objective is to analyze technical change throughout the relevant crisis era and expose its impact on innovation through patent applications. As consequence of monitoring technological advancements on patent data, it is one of the crucial indications since it might be the precursor of a significant technical leap in the relevant field of study. It is well recognized that advancements in technology and invention have a significant effect on humanity on a worldwide scale. The relevance of technical development and innovation studies in minimizing damage to other impacted factors, particularly in the recovery from pandemic crises, has been highlighted, particularly during the COVID-19 Pandemic. The most significant contribution to the academic study in the related field is the use of patent data to track technical advancement and relevant data to assess the impact of the Pandemic on innovation. Study findings indicate no significant difference between actual numbers and not only the 2019 values but also the forecasted values of patent applications filed during the Pandemic on the total number of patent applications. Apart from the detrimental influence of various measures implemented throughout the pandemic phase on innovation studies, one of the most notable discoveries is that the enormous global economic crisis did not considerably slow down overall technological growth. When the forecasted numbers are compared to the actual levels for 2020 and 2021, it is clear that more patent applications were submitted than expected in 15 technical disciplines in 2020 and 16 technical domains in 2021. The relevant circumstance exposes the technological development boundaries in the pandemic process and the limited detrimental influence on the innovation process based on technical areas. One of the study's most significant limitations is that the patent applications were based on data from a single institution. Future investigations will yield more comprehensive data from the analytical results gained by examining patent applications collected from many sources. Another limitation is that not all innovation research results in patent application submission. A broader analysis will be feasible by merging relevant research with studies in other disciplines, including but not limited to the R&D expenditure budget and R&D personnel count. This research primarily gives information on the global impact of epidemics on crisis periods, gauging the trajectory of technological progress and the influence on innovative activities. The related research in these areas of interest is thought to be enlightening in terms of increasing technical improvements and innovative activities during the crisis and overcoming the crisis with the minimum collateral damage.

**Conflict of Interest**

No potential conflict of interest was declared by the author.

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**Compliance with Ethical Standards**

It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

**Ethical Statement**

It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

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