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THE MEASUREMENT OF INNOVATION PERFORMANCE IN OECD COUNTRIES

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ABSTRACT

Due to globalization, technological advances, and the increase in the dissemination of knowledge exacerbated the national and corporate competitive potential. In this period where economic growth, efficiency, and productivity gained vital importance, innovation was accepted as the key concept. The present study aimed to measure the innovation performance of the Organization for Economic Cooperation and Development (OECD) member countries with Data Envelopment Analysis (DEA). Thus, variables included in the innovation input and output indices in the Global Innovation Index (GII) were employed for OECD countries. The analysis findings demonstrated that the top 3 nations with the highest efficiency score were Switzerland, the United Kingdom (UK), and the United States of America (USA), respectively, and the top 3 countries with the lowest efficiency score were Colombia, Mexico, and Chile, respectively.

Keywords: : *Innovation Performance, Global Innovation Index (GII), Multicriteria Decision-Making (MCDM), Data Envelopment Analysis (DEA).*

JEL Codes: *O30, 050, C44*

1. INTRODUCTION

Since the Industrial Revolution innovations led to unprecedented developments in global welfare. Significant and rapid scientific and technological advances are often associated with these innovations. It was accepted that innovations are the engine of growth in productivity, competitiveness, and employment for individuals, organizations, regions, and nations. Knowledge is the force behind innovations. Thus, the capacities to produce, transmit, absorb, and combine knowledge affect the innovation processes, and consequently, determine corporate and national success (Abrunhosa, 2003: 2).

OSLO Manual described innovation as the development of a novel or significantly improved product (a good or service), process, a novel marketing method or internal organizational approach, workplace organization, or external relations method. In the manual, innovation is classified into four groups: products, processes, marketing, and organization. Innovation is described as all scientific,

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technological, organizational, financial, and commercial activities that lead or are predicted to lead to innovation. Certain innovation activities are inherently innovative, while others are not novel but considered necessary for innovation. Innovation includes R&D, even it is not directly associated with the development of a specific innovation (OECD and Eurostat, 2005: 50-51).

Innovation is one of the most important factors for nations and corporations to improve national and international competitiveness, productivity, economic growth and development, and ultimately to increase welfare and quality of life. OECD determined that the contribution of innovation to economic growth was more than 50%, especially in developed countries in the last 25 years (Işık and Kılınç, 2011: 14).

The measurement of innovation performance that determines national growth and welfare levels is important. International Institute for Management Development (IMD) and the World Economic Forum (WEF) are two global organizations that develop scientific, technological and innovation indexes. Furthermore, institutions such as the OSLO Manual, Commission of the European Communities, the World Bank, The Economist Intelligence Unit, INSEAD, and Fraunhofer Institute develop performance measurement systems. Although several studies (e.g., innovation index development studies by IMD, WEF, OSLO Manual, Commission of the European Communities, and INSEAD) utilize various innovation capacity factors based on their specific international perspectives, the index reflects overall national innovation capacity. These studies are based on different approaches to innovation measurement. The innovation index could be employed to predict technological advances in various countries (Wonglimpiyarat, 2010: 248-249; Hancıoğlu, 2016: 132).

An innovation index could be described as a simple quantitative indicator of the innovation capacity of institutions, research, corporations, and territories in selected fields of research. In other words, it is a tool that measures, monitors, and promotes progress in innovation performance. Furthermore, the innovation index provides significant insights into a nation's potential to sustain productivity growth and competitiveness in the long term. The performance of each nation measured with these criteria could provide guidelines for policymakers to allocate resources that lead to improvements in areas important for the nation. (Wonglimpiyarat, 2010: 248).

The European Innovation Scoreboard (EIS), calculated by the European Commission since 2001 provides a comparative analysis of the research and innovation performances in EU countries, other European nations, and neighbors, and determine relative strengths and weaknesses of the research and innovation systems in these nations. Innovation performance is measured by a composite indicator, the Summary Innovation Index, which reflects the performances of various indicators. The EIS includes the EU Member States, as well as Iceland, Israel, Montenegro, N. Macedonia, Norway, Serbia, Switzerland, Turkey, Ukraine, and the UK. The EIS differentiates four main indicators: framework conditions, investments, innovation activities, and impacts, and ten innovation dimensions. Based on the scores of these indicators, including corporate innovation activities, investment in research and innovation, and human resources and employment factors, EU countries are categorized into four performance groups: innovation leaders, strong innovators, moderate innovators, and modest innovators (Hollanders *et al.*, 2019: 8; European Innovation Scoreboard, 2020: 1).

Another important global index is the Global Innovation Index (GII). The GII aims to provide intuitive innovation data and to assist economies in the evaluation of their innovation performances and make informed innovation policy decisions. Since its introduction in 2007, the GII has had impacts in three areas. First, policymakers started to refer to innovation and innovation rankings in economic policy strategies. Furthermore, GII is now considered a bench stone to measure innovation by the UN General Assembly, as mentioned in the resolution on Science, Technology, and Innovation for Sustainable Development Goals (SDGs) in the 74th UNGA session held in 2019. Also, the GII allows economies to analyze innovation performances. Economies invest in cross-ministerial task forces to analyze their GII results and utilize the GII to design adequate innovation and intellectual property (IP) policies. Third, the GII serves as a strong incentive for the economies to prioritize and collect innovation data. The GII is published by Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO), a dedicated United Nations agency. Every year, the GII ranks the innovation performances of about 130 economies in the world (History of the Global Innovation Index, https://www.globalinnovationindex.org/about-gii#history. Accessed on August 14, 2020; Cornell University, INSEAD and, WIPO 2018: 28).

The present study aimed to analyze the innovation performances of a group of homogeneous nations selected based on GII. Thus, the innovation performance efficiency of countries was investigated with Data Envelopment Analysis (DEA) conducted on GII input and output sub-index data for these countries. It was suggested that the study will contribute to the literature through the analysis of innovation performance efficiencies based on GII and DEA.

2. LITERATURE

The literature review section includes significant studies on the analysis of innovation performance based on the present study.

Lovell *et al.* (1995) investigated the macroeconomic performances of 19 OECD countries between 1970 and 1990. The performance was defined based on the ability of national macroeconomic administrators to provide certain services for their citizens: a high real GDP per capita, low inflation, low unemployment, and a favorable trade balance. They employed DEA to develop a best practice macroeconomic performance margin, and to measure the annual performance of each nation based on the margin. The analysis findings revealed that Switzerland was the top-ranked nation, where the government provided over 95% macroeconomic best practices for the citizens. The second tier of countries included Sweden, Germany, Norway, the USA, New Zealand, Denmark, and Japan. Spain and

Portugal were in a different class at the bottom of the ranking, where the government provided less than 50% macroeconomic best practices for the citizens.

Abbasi *et al.* (2010) analyzed and compared the efficiency of innovation systems across selected countries with the DEA. The analysis inputs included the number of scientists in research and development (R&D), education, and R&D expenditures, and outputs included patent count, royalty revenues, license fees, high technology exports, and manufacturing exports. Furthermore, Tobit and Ordinary Least Squares (OLS) regression models were employed to investigate the likelihood of changes in inefficiency through country-specific factor analysis.

Chen *et al.* (2011) compared R&D the efficiencies of various nations based on several R&D efficiency indices developed with the DEA using a 24-nation panel series (OECD members and non-OECD members) for the 1998–2005 period. Total R&D manpower and R&D expenditures were employed as input variables, while patents, scientific journal articles, royalty, and licensing fees were employed as output variables. Empirical results demonstrated that nations had similar R&D efficiencies for patents and royalties, while their performances for journal publications were quite different. Furthermore, the mean R&D efficiency in OECD nations was significantly higher when compared to that of non-OECD nations. Hungary, Israel, the UK, and the US was determined to exhibit optimal R&D efficiency across various indices. In contrast, Romania, Russia, and Mexico performed the worst in each R&D efficiency indices.

Afzal (2014) investigated national innovation system input-output components to model a robust efficiency measurement instrument with the DEA Bootstrap technique. Demographic structure, ICT infrastructure, financial structure, R&D, education, market conditions, governance, openness, natural resources, and endowments were employed as input variables and economically viable knowledge creation was used as the output variable. The efficiency scores obtained with this technique demonstrated that Australia, China, Japan, South Korea, the Philippines, Singapore, Taiwan, Denmark, and Switzerland were the most efficient countries based on the Constant Returns to Scale (CRS) assumption.

Hancıoğlu (2016) investigated the correlation between the innovation input and output sub-index variable sets included in the GII for OECD countries for the period of 2011-2015 with canonical correlation analysis. The analysis revealed a significant correlation between the two variable sets. Based on the analysis findings, the first original variable that explained the variation in the first canonical innovation input sub-index variable the most was business sophistication, which included knowledge workers, innovation links, and knowledge absorption variables, and the second was research and human capital including education, higher education, and R&D.

Ayçin and Çakın (2019) measured the innovation performances of nations with entropy and MABAC methods. The criteria employed for the analysis of innovation performance were based on EIS

2018 indicators. Criteria were weighted with the entropy method and it was determined that intellectual assets, innovators, finance, and support variables were the most significant criteria. The analysis findings demonstrated that countries with the highest innovation included Switzerland, Sweden, and Denmark, while those with the lowest performance included Ukraine, Romania, and Macedonia.

3. THE DATASET AND METHOD

In the study, 37 OECD member states were included in the analysis. The OECD data obtained from the GII 2019 report were employed in the analysis. The GII includes 7 indices and 21 associated sub-indices. These indices are presented in Table 1, and detailed information about the general GII framework and sub-indices is provided below (Cornell University, INSEAD and, WIPO 2019: 9; 206-210).

Table 1. Global Innovation Index

Index	Sub-indices
	Input sub-index
Institutions (INS)	Political environment
	Regulatory environment
	Business environment
Human capital and research (HCR)	Education
	Tertiary education
	Research and development (R&D)
Infrastructure (INF)	Information and communication technologies (ICTs)
	General infrastructure
	Ecological sustainability
Market sophistication (MS)	Credit
	Investment
	Trade, competition, & market scale
Business sophistication (BS)	Knowledge workers
	Innovation linkages
	Knowledge absorption
	Output sub-index
Knowledge and technology outputs (KTO)	Knowledge creation
	Knowledge impact
	Knowledge diffusion
Creative outputs (CO)	Intangible assets
	Creative goods and services
	Online creativity

The GII helps the development of an environment where innovation factors are analyzed continuously. The index provided detailed innovation metrics for 129 economies in 2019. It included the data for 91.8% of the global population and 96.8% of the global GDP. It included three indices: total GII, the Innovation Input Sub-Index, and the Innovation Output Sub-Index (Table 1).

The Innovation Input Sub-Index includes five columns that include national economy figures that lead to innovative activities: (1) INS, (2) HCR, (3) INF, (4) MS, and (5) BS. The Innovation Output Sub-Index provides information on innovative activities in economies. There were two output columns: (6) KTO and (7) CO. The total GII score is the average of the Input and Output Sub-Indices.

Institutions: Strengthening the institutional framework that attracts businesses and fosters growth via good governance and adequate protection and incentive levels are essential for innovation. The 'institutions' column reflects the institutional framework in an economy. It includes the political environment, regulatory environment, and business environment sub-indices.

Human capital and research: The national innovation capacity is determined by education level and standards and research activities in an economy and includes education, tertiary education and, R&D sub-indices. This column measures the human capital in an economy.

Infrastructure: An efficient and ecologically friendly infrastructure of communication, transport, and energy facilitates the production and exchange of ideas, services, and commodities, and nourish the innovation system through high productivity and efficiency, better access to markets, lower transaction costs, and sustainable growth. It includes three sub-indices: ICTs, General infrastructure and, Ecological sustainability.

Market sophistication: The availability of investment-friendly loans and environment, international market access, market scale, and competition are critical factors in business development and innovation. It includes credit, investment and trade, competition, and market scale sub-indices.

Business sophistication: The last facilitator column reflects the level of business sophistication to analyze the corporate attitude towards innovation activities. The 'human capital and research' column reflects the fact that human capital accumulation through education, especially higher education, and focus on R&D activities, is essential for innovation. This could be improved by the assertion that the employment of highly qualified professionals and technicians would foster the productivity, competitiveness, and innovation potential of the businesses. It includes knowledge workers, innovation links, and knowledge absorption sub-indices.

Knowledge and technology output: Innovation outputs include the consequences of innovative activities in an economy. Even though the Output Sub-Index only has two columns, it has the same weight as the Input Sub-Index in the calculation of the total GII score. It includes knowledge creation, knowledge impact, and knowledge diffusion sub-indices.

Creative outputs: The impact of creativity is still inadequately appreciated in the measurement of innovation and policy debates. Since its introduction, the GII has always focused on the measurement of creativity in the Innovation Output Sub-Index. It includes three sub-indices: creative goods and services, intangible assets, and online creativity.

3.1. Data Envelopment Analysis

DEA, introduced by Charnes, Cooper, and Rhodes in 1978 is an instrument to monitor the organizational performances of nonprofit and public organizations. DEA is based on the method proposed in "The Measurement of Productive Efficiency" published by Farrell (1957) (Charnes *et al.*, 1978: 435).

DEA is a "data-oriented" approach that aims to analyze the performance of peer entity sets called Decision-Making Units (DMUs) that transform multiple inputs into multiple outputs. A DMU is a generic and flexible set. In recent years, several DEA applications were employed in the analysis of the performances of various entities that conduct several activities in different contexts in various countries. These applications employed various DMU forms to analyze the performances of entities such as hospitals, the US Air Force divisions, colleges, cities, courts, corporations, and others, including the performances of nations, regions, etc. Since it requires few assumptions, DEA introduced novel possibilities for cases that previously resisted other approaches due to the complex (often unknown) correlations between the multiple inputs and multiple outputs in DMUs (Cooper *et al.*, 2011: 1-2).

Using this method, management analysts could determine the relative production efficiency of each unit among comparable organizational units based on the optimal theoretical performance of each organization. Thus, the analyzed organizational units are assigned as DMUs. These DMUs could be distinct corporations or institutions, or they could be separate sites or branches of a single corporation or institution. The key advantage of DEA over other performance analysis methods is its capacity to analyze several outputs and inputs simultaneously independent of the measurement units of these variables (Blose *et al.*, 2005: 10).

DEA is a multi-factor productivity analysis model to measure the relative efficiencies of a homogenous set of DMUs. In the case of multiple inputs and outputs, the efficiency score is calculated as follows (Talluri, 2000: 8):

Efficiency = (weighted sum of outputs) / (weighted sum of inputs)

The proposed DEA models could be further classified based on the assumed returns to scale, which may be either constant (CRS) or variable (VRS). This classification is based on orientation; a model could lack orientation, could be input-oriented or output-oriented (Ali, 1994: 65). The input-oriented models determine the degree that the inputs of inefficient DMUs should be reduced to reach a certain output level. The output-oriented models aim to determine the degree that the output should be increased to improve the efficiency of DMUs for a given input combination. While input-oriented models aim to minimize the number of utilized inputs, output-oriented models aim to maximize the number of outputs (Kecek, 2010: 64).

DEA is a combination of concepts and methodologies that are incorporated into a set of models. Particularly, the Charnes-Cooper-Rhodes (CCR) ratio model, the Banker-Charnes-Cooper (BCC) model, the additive model, and the multiplicative model are mentioned in the literature (Charnes *et al.*, 1994: 23-24). The main model is the CCR input-oriented CCR model proposed by Charnes *et al.* (1978). The model assumes that the basic hypothesis in the measurement of all DMUs is the CRS. The model is based on the assumption that *n* DMUs produce s outputs with m inputs. The proposed measure of the efficiency of any DMU is calculated as the maximum of a ratio of weighted outputs to weighted inputs based on the condition that the similar ratios for every DMU would be less than or equal to unity. In a more precise form (Charnes *et al.*, 1978: 430),

$$\begin{aligned} &\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \\ &\textit{subject to} \\ &\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad j = 1,\dots,n \\ &u_r,\ v_i \geq 0; \quad r = 1,\dots,s; \quad i = 1,\dots,m \end{aligned} \tag{1}$$

where y_{rj}, x_{ij} are the known outputs and inputs of *j*th DMU (all positive) and $u_r,\ v_i \geq 0$ are the variable weight that will be determined when the problem is solved, e.g., by the data on *all* DMU's used as a reference set. The efficiency of one unit in this reference set of $j = 1,\dots,n$ DMU's is rated relative to the others.

The fractional programming model given in Equation 1 could be converted to a linear programming model given in Equation 2 (Cooper *et al.*, 2011: 9; Kecek, 2010: 67):

$$\begin{aligned} &\max z = \sum_{r=1}^{s} \mu_r y_{r0} \\ &\textit{subject to} \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \\ &\sum_{i=1}^{m} v_i x_{i0} = 1 \\ &\mu_r,\ v_i \geq 0 \end{aligned} \tag{2}$$

The above problem is run n times to identify the relative efficiency scores for all DMUs. Each DMU selects the input and output weights that would maximize its efficiency score. In general, a DMU is considered efficient when the score is 1, and a score of less than 1 implies inefficiency (Talluri, 2000: 8). The input- and output-oriented versions of the CCR model are presented in Table 2 as a multiplier model.

Table 2. CCR DEA model

Input-oriented	Output-oriented
Multiplier model	Multiplier model
$\max z = \sum_{r=1}^{s} \mu_r y_{r0}$	$\min q = \sum_{i=1}^{m} v_i x_{i0}$
subject to	*subject to*
$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$	$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0$
$\sum_{i=1}^{m} v_i x_{i0} = 1$	$\sum_{r=1}^{s} \mu_r y_{r0} = 1$
$\mu_r,\ v_i \geq 0$	$\mu_r,\ v_i \geq 0$

Source: (Cooper *et al.*, 2011: 13)

After the CCR model is run under the CRS assumption, Banker et al. (1984) proposed the BCC model, which is based on the Variable Returns to Scale (VRS) assumption and adds the convexity constraint to the CCR model. The input- and output-oriented versions of the BCC model are presented in Table 3 as a multiplier model.

Table 3. BCC DEA model

Input-oriented	Output-oriented
Multiplier model	Multiplier model
$\max \sum_{r=1}^{s} \mu_r y_{r0} - \mu_0$	$\min q_0 = \sum_{i=1}^{m} v_i x_{i0} - v_0$
subject to	*subject to*
$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0$	$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} - v_0 \geq 0$
$\sum_{i=1}^{m} v_i x_{i0} = 1$	$\sum_{r=1}^{s} \mu_r y_{r0} = 1$
$u_r,\ v_i \geq \varepsilon;\quad u_0$ free in sign.	$\mu_r,\ v_i \geq \varepsilon;\quad v_0$ free in sign.

Source: (Banker *et al.*, 2011: 44)

The additive model for DEA analysis is another model proposed by Charnes, Cooper, Golany, Seiford, and Stutz (1985). This model avoids the problem of input and output orientation selection. In other words, the model simultaneously maximizes the outputs and minimizes the inputs (Banker, 2011: 57). Also, unlike the piecewise linear envelopment offered by most DEA models, multiplicative DEA models were developed to allow for a piecewise log-linear or a piecewise Cobb-Douglas envelopment. The Units Invariant Multiplicative model by Charnes, Cooper, Seiford, and Stutz (1983) includes the application of the Additive model to the logarithms of the original data (Charnes, 1994: 29).

4. EMPIRICAL FINDINGS

In the study, the innovation performance efficiencies of 37 OECD member states were measured and analyzed based on GII 2019 data. Thus, the 2019 GII input and output sub-index data for these nations were employed as variables and analyzed with the DEA. The GII included 5 input sub-indices, namely institutions (INS), human capital and research (HCR), infrastructure (INF), market sophistication (MS) and business sophistication (BS), and 2 output sub-indices including knowledge and technology outputs (KTO) and creative outputs (CO). These 7 sub-indices and associated items are detailed in Table 1. Certain pre-analysis statistics for these sub-indices are presented in Table 4.

Table 4. Sub-index summary statistics

Criteria	Mean	Std. Dev.	Min.	Max.	Range
INS	81,38	9,18	57,40	93,90	36,50
HCR	48,96	10,28	27,00	66,50	39,50
INF	58,87	5,63	48,30	69,90	21,60
MS	57,81	9,83	43,60	87,00	43,40
BS	48,33	11,57	29,40	68,80	39,40
KTO	40,80	13,10	19,50	70,30	50,80
CO	42,15	8,010	22,30	56,60	34,30

Since the aim of the study was to provide maximum output with the available inputs, output-oriented DEA with the CRS assumption was applied. INS, HCR, INF, MS, and BS are accepted as input variables and KTO and CO as output variables. Since it was accepted that the efficiency of any analyzed country is directly correlated with an increase in inputs, the analysis was conducted with 1/input variable that included all input variables. In this approach that was also observed in previous studies, the reduction of these input values would mean a reduction in the ratio of the 1/input variable. This would reflect an increase in the input variable values. The efficiency scores calculated with the DEA and reference nations for inefficient countries are presented in Table 5.

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Table 5. CCR-CRS Efficiency Scores and Reference Countries

Countries	Score	Rank	Reference Country	
Australia	0.7248	20	Switzerland	UK
Austria	0.7114	21	Switzerland	
Belgium	0.6260	27	Switzerland	
Canada	0.8393	11	Switzerland	UK
Chile	0.3937	35	Switzerland	
Colombia	0.2964	37	Switzerland	
Czech Republic	0.6717	23	Switzerland	
Denmark	0.8837	9	Switzerland	
Estonia	0.8376	12	Switzerland	
Finland	0.8927	8	Switzerland	
France	0.7424	18	Switzerland	
Germany	0.8947	7	Switzerland	
Greece	0.4253	34	Switzerland	
Hungary	0.4912	31	Switzerland	
Iceland	0.8675	10	Switzerland	
Ireland	0.7868	16	Switzerland	
Israel	0.8059	14	Switzerland	
Italy	0.5663	29	Switzerland	
Japan	0.7291	19	Switzerland	
Latvia	0.6552	24	Switzerland	
Lithuania	0.6073	28	Switzerland	
Luxembourg	0.8993	6	Switzerland	
Mexico	0.3748	36	Switzerland	UK
Netherlands	0.9589	4	Switzerland	
New Zealand	0.7707	17	Switzerland	
Norway	0.8044	15	Switzerland	
Poland	0.4729	32	Switzerland	
Portugal	0.6391	26	Switzerland	
Republic of Korea	0.8371	13	Switzerland	
Slovakia	0.5378	30	Switzerland	
Slovenia	0.6870	22	Switzerland	
Spain	0.6490	25	Switzerland	
Sweden	0.9346	5	Switzerland	
Switzerland	1	1	Switzerland	
Turkey	0.4625	33	Switzerland	
UK	1	1	UK	
USA	1	1	USA	

The review of the findings presented in Table 5 revealed that Switzerland, the UK, and the USA were efficient nations. It was observed that other countries were not effective, and Colombia had the lowest efficiency score among all nations. Switzerland was the most referenced country in the table for inefficient nations to improve efficiency, followed by the UK. Potential improvement values for inefficient countries are presented in Table 6.

Table 6. Potential improvement rates for inefficient countries

Countries							
Australia	INS	HCR	INF	MS	BS	KTO	CO
Data	0.01	0.02	0.02	0.01	0.02	31.60	41.10
Projection	0.01	0.02	0.01	0.01	0.01	70.30	56.70
Difference(%)	0.00	-6.44	-10.35	0.00	-31.24	122.47	37.96
Austria							
Data	0.01	0.02	0.02	0.02	0.02	36.70	41.40
Projection	0.01	0.02	0.02	0.02	0.02	72.29	58.20
Difference(%)	-0.75	0.00	-7.43	-20.63	-18.05	96.96	40.58
Belgium							
Data	0.01	0.02	0.02	0.02	0.02	40.80	38.50
Projection	0.01	0.02	0.02	0.02	0.02	76.39	61.50
Difference(%)	0.00	-3.45	-8.87	-12.15	-12.91	87.22	59.74
Canada							
Data	0.01	0.02	0.02	0.01	0.02	41.30	41.40
Projection	0.01	0.02	0.01	0.01	0.02	53.59	49.33
Difference(%)	0.00	-19.02	-14.32	0.00	-13.47	29.76	19.15
Chile							
Data	0.01	0.03	0.02	0.02	0.03	22.90	27.20
Projection	0.01	0.02	0.02	0.02	0.02	85.80	69.08
Difference(%)	0.00	-35.92	-8.73	-7.75	-40.15	274.69	153.98
Colombia							
Data	0.02	0.04	0.02	0.02	0.03	19.50	22.30
Projection	0.01	0.02	0.02	0.02	0.02	93.46	75.25
Difference(%)	-4.51	-42.01	0.00	-2.04	-35.79	379.28	237.43
Czech Republic							
Data	0.01	0.02	0.02	0.02	0.02	43.80	43.10
Projection	0.01	0.02	0.02	0.02	0.02	79.69	64.16
Difference(%)	0.00	-20.52	-6.26	-13.16	-22.24	81.94	48.87
Denmark							
Data	0.01	0.02	0.02	0.01	0.02	46.40	48.60
Projection	0.01	0.02	0.01	0.01	0.01	68.31	55.00
Difference(%)	0.00	-0.95	-6.26	-4.97	-14.93	47.21	13.16
Estonia							
Data	0.01	0.02	0.02	0.02	0.02	36.00	51.70
Projection	0.01	0.02	0.02	0.02	0.02	76.67	61.73
Difference(%)	0.00	-25.83	-1.66	-16.13	-31.17	112.97	19.39
Finland							
Data	0.01	0.02	0.02	0.02	0.02	55.10	48.10

Table 6. Continues

Projection	0.01	0.02	0.01	0.01	0.01	66.92	53.88
Difference(%)	0.00	-2.50	-13.32	-20.26	-9.89	21.45	12.01
France							
Data	0.01	0.02	0.02	0.02	0.02	45.00	45.00
Projection	0.01	0.02	0.02	0.02	0.02	75.29	60.61
Difference(%)	0.00	-3.46	-2.17	-1.52	-15.44	67.30	34.70
Germany							
Data	0.01	0.02	0.02	0.02	0.02	52.70	49.60
Projection	0.01	0.02	0.01	0.01	0.01	68.85	55.44
Difference(%)	-5.03	0.00	-10.96	-16.09	-18.60	30.65	11.77
Greece							
Data	0.01	0.02	0.02	0.02	0.03	25.10	30.10
Projection	0.01	0.02	0.02	0.02	0.02	87.91	70.78
Difference(%)	-5.69	0.00	-5.20	-8.04	-39.98	250.24	135.15
Hungary							
Data	0.01	0.02	0.02	0.02	0.02	42.80	34.60
Projection	0.01	0.02	0.02	0.02	0.02	87.48	70.43
Difference(%)	0.00	-17.58	-3.84	-16.86	-24.78	104.40	103.57
Iceland							
Data	0.01	0.02	0.02	0.02	0.02	37.60	50.40
Projection	0.01	0.02	0.02	0.02	0.02	72.16	58.10
Difference(%)	0.00	-24.71	-10.90	-15.96	-27.01	91.92	15.28
Ireland							
Data	0.01	0.02	0.02	0.02	0.02	56.90	43.30
Projection	0.01	0.02	0.02	0.02	0.02	72.31	58.22
Difference(%)	-1.29	-19.57	0.00	-17.89	-14.96	27.09	34.46
Israel							
Data	0.01	0.02	0.02	0.02	0.02	56.90	46.30
Projection	0.01	0.02	0.01	0.01	0.02	71.36	57.45
Difference(%)	-11.26	-10.63	-16.51	-8.88	0.00	25.41	24.09
Italy							
Data	0.01	0.02	0.02	0.02	0.02	38.90	36.80
Projection	0.01	0.02	0.02	0.02	0.02	80.71	64.99
Difference(%)	-2.97	-15.79	0.00	-13.72	-28.22	107.49	76.59
Japan							
Data	0.01	0.02	0.02	0.02	0.02	50.80	37.90
Projection	0.01	0.02	0.01	0.01	0.01	69.67	56.10
Difference(%)	0.00	-21.38	-6.99	-4.66	-17.04	37.15	48.01
Latvia							
Data	0.01	0.03	0.02	0.02	0.03	27.50	42.80
Projection	0.01	0.02	0.02	0.02	0.02	81.14	65.32
Difference(%)	0.00	-31.20	-14.54	-8.21	-36.05	195.04	52.63

Table 6. Continues

Lithuania							
Data	0.01	0.03	0.02	0.02	0.03	24.40	40.30
Projection	0.01	0.02	0.02	0.02	0.02	82.42	66.36
Difference(%)	0.00	-31.25	-11.13	-12.76	-34.00	237.78	64.66
Luxembourg							
Data	0.01	0.02	0.02	0.02	0.02	42.20	56.20
Projection	0.01	0.02	0.02	0.02	0.02	77.62	62.49
Difference(%)	0.00	-25.62	-4.97	-24.30	-0.71	83.93	11.20
Mexico							
Data	0.02	0.03	0.02	0.02	0.03	25.50	29.20
Projection	0.02	0.02	0.02	0.02	0.02	94.63	77.91
Difference(%)	-1.14	-24.02	0.00	0.00	-36.42	271.11	166.82
Netherlands							
Data	0.01	0.02	0.02	0.02	0.02	61.80	53.20
Projection	0.01	0.02	0.01	0.01	0.01	68.91	55.48
Difference(%)	0.00	-17.02	-11.18	-16.60	-7.50	11.50	4.28
New Zealand							
Data	0.01	0.02	0.02	0.01	0.02	29.80	42.20
Projection	0.01	0.02	0.01	0.01	0.01	68.01	54.76
Difference(%)	0.00	-17.79	-13.61	-3.12	-40.66	128.22	29.75
Norway							
Data	0.01	0.02	0.01	0.02	0.02	33.70	43.20
Projection	0.01	0.02	0.01	0.01	0.01	66.71	53.71
Difference(%)	0.00	-17.38	-2.75	-18.71	-29.43	97.94	24.32
Poland							
Data	0.01	0.02	0.02	0.02	0.03	30.90	32.40
Projection	0.01	0.02	0.02	0.02	0.02	85.11	68.52
Difference(%)	0.00	-19.42	-4.50	-15.22	-31.13	175.42	111.48
Portugal							
Data	0.01	0.02	0.02	0.02	0.03	29.80	39.40
Projection	0.01	0.02	0.02	0.02	0.02	76.57	61.65
Difference(%)	0.00	-16.06	-9.28	-20.70	-39.81	156.96	56.48
Republic of Korea							
Data	0.01	0.02	0.02	0.02	0.02	50.20	44.10
Projection	0.01	0.02	0.01	0.01	0.01	65.44	52.68
Difference(%)	-16.74	0.00	-15.93	-12.50	-20.57	30.35	19.47
Slovakia							
Data	0.01	0.03	0.02	0.02	0.03	34.00	37.10
Projection	0.01	0.02	0.02	0.02	0.02	85.69	68.99
Difference(%)	0.00	-36.20	-3.13	-15.53	-35.72	152.02	85.95
Slovenia							
Data	0.01	0.02	0.02	0.02	0.02	30.70	42.10

Table 6. Continues

Projection	0.01	0.02	0.02	0.02	0.02	76.11	61.28
Difference(%)	0.00	-18.50	-14.44	-30.99	-29.27	147.91	45.55
Spain							
Data	0.01	0.02	0.02	0.02	0.03	37.20	39.70
Projection	0.01	0.02	0.02	0.02	0.02	75.98	61.17
Difference(%)	-5.26	-17.93	0.00	-5.98	-38.03	104.25	54.09
Sweden							
Data	0.01	0.02	0.01	0.02	0.01	61.80	51.90
Projection	0.01	0.02	0.01	0.01	0.01	68.97	55.53
Difference(%)	-0.79	-1.57	-0.60	-10.93	0.00	11.61	7.00
Switzerland							
Data	0.01	0.02	0.01	0.01	0.01	70.30	56.60
Projection	0.01	0.02	0.01	0.01	0.01	70.30	56.60
Difference(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Turkey							
Data	0.02	0.03	0.02	0.02	0.03	23.00	34.20
Projection	0.01	0.02	0.02	0.02	0.02	91.85	73.95
Difference(%)	-15.83	-23.38	0.00	-2.97	-42.90	299.34	116.22
UK							
Data	0.01	0.02	0.02	0.01	0.02	56.60	52.20
Projection	0.01	0.02	0.02	0.01	0.02	56.60	52.20
Difference(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
USA							
Data	0.01	0.02	0.02	0.01	0.02	59.70	45.50
Projection	0.01	0.02	0.02	0.01	0.02	59.70	45.50
Difference(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00

General analysis of Table 6 would demonstrate that the highest rate of improvement was suggested in HCR, BS, and MS input variables for inefficient nations to become effective. The highest potential input variable improvement was suggested for Turkey in the BS variable (42.90%). Also, the second-highest potential input variable improvement was suggested for Colombia in the HCR variable (42.01%). The third highest potential input variable improvement was proposed for New Zealand in the BS variable (40.66%). These proposals suggested that Turkey should increase BS expenditures by 42.90% and New Zealand by 40.66%. Similarly, Colombia should increase HCR expenditures by 42.01% to be effective. The analysis of the potential improvement suggestions based on the output variables revealed that the highest improvement suggestion was in the KTO variable. For this variable, the highest improvement was recommended for Colombia (379.28%), followed by Turkey (299.34%).

CONCLUSION

Productivity and competitiveness are among the most important factors that influence national development level. Competitiveness is possible only through scientific and technological advances and innovation. Thus, it is beneficial to measure a key concept, innovation performance. The present study aimed to analyze the efficiency of innovation performances based on 37 OECD member state data. DEA findings demonstrated that the top 3 countries with the highest efficiency scores were Switzerland, the UK, and the USA, respectively, while the 3 countries with the lowest efficiency scores were Colombia, Mexico, and Chile. These findings were consistent with those reported by Chen *et al.* (2011), Afzal (2014), and Ayçin and Çakın (2019). To improve efficiency, Colombia, Mexico, and Chile should improve 2 input variables, namely Human capital and research (HCR) and Business sophistication (BS). Also, high improvement in Knowledge and technology outputs (KTO) and Creative outputs (CO) variables are suggested for these nations. It was determined that inefficient countries should take Switzerland as a reference to improve their efficiency. This could be expected since Switzerland ranked 1st in GII every year since 2011. Furthermore, this finding was consistent with the findings reported by Lovell *et al.* (1995).

It was an expected finding that the countries with the highest innovation scores were those with high income and in very good socio-economic standing. It was determined that innovation spending was adequate in these nations and they employed the allocated resources efficiently and effectively. Thus, as determined in the analysis, these countries could serve as role models for other nations. Countries with the lowest scores were weak based on the above-mentioned characteristics. For these countries to improve their efficiency, it was suggested that they should improve in Human capital and research (HCR) and Business sophistication (BS) variables the most. That would improve corporate productivity, competitiveness, and innovation potential, the employment of qualified personnel due to the improvements in human capital through investments in the education system and R&D activities. Thus, it was predicted that Knowledge and technology outputs (KTO) will improve similar to efficient nations.

The analysis findings for Turkey revealed that the country ranked 33rd among 37 nations in efficiency score and was an inefficient nation. In particular, Turkey was recommended to improve Knowledge and technology outputs (KTO) at high rates. Furthermore, an improvement of 42.90% in the Business sophistication (BS) variable, 23.38% in the Human capital and research (HCR) variable, and 15.83% in the Institutions (INS) variable were suggested. Turkey ranked 49th among 129 countries in the 2019 GII ranking, it was 7th among 34 countries in the upper-middle-income economy category, and 5th among 19 countries in the NAWA (Northern Africa and Western Asia) ranking. The analysis of the position of Turkey in 2011-2019 rankings demonstrated that scores reflected an upward trend towards higher rankings; however, further efforts are required. Thus, effective educational and R&D policies should be adopted further resources should be allocated to improve human capital, and efficient use of resources should be ensured. As a consequence, innovation performance would also improve due to the education and employment of a qualified workforce, strong innovation links, and continuous support of public/private/academic partnerships. Undoubtedly, the state should encourage entrepreneurship and private industry development by ensuring good governance, quality public services, and political stability. Furthermore, the state should adopt policies to protect the rule of law in cancellation of work contracts and working hours, contract enforcement, and property rights.

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