...::KENT AKADEMİSİ | URBAN ACADEMY

Volume: 17 Issue: 2 - 2024 | Cilt: 17 Sayı 2 - 2024

ARTICLE INFO | MAKALE KÜNYESİ

Article Type: Research | Araştırma
Submission Date | Gönderilme Tarihi: 10.01.2024
Admission Date | Kabul Tarihi: 16.03.2024

CITATION INFO | ATIF KÜNYESİ

Unanoglu M., Özarı, Ç. (2024). Assessing the Level of Manufacturing Value Added of G-20 and Its Relation to Innovation Inputs and Outputs, *Kent Akademisi Dergisi*, *17*(2):592-605. https://doi.org/10.35674/kent.1417436

Assessing the Level of Manufacturing Value Added of the G-20 and Its Relation to Innovation Inputs and Outputs

[G-20 Ülkelerinin İmalat Sanayi Katma Değerinin Değerlendirilmesi ve Yenilik Girdi ve Çıktı Göstergeleriyle İlişkisi]

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ÖZ

Bu çalışmanın temel amacı, Küresel İnovasyon Endeksi'nden elde edilen temel boyutları kullanarak G-20 ülkelerinin imalat sanayi katma değer düzeylerini tahmin etmektir. Bir diğer amacı ise, inovasyon göstergelerinin imalat sanayi katma değerindeki farklılıklara ne ölçüde katkı sağladığını belirlemektir. Karmaşık veri kümeleriyle başa çıkma yeteneği ve hassasiyetiyle bilinen makine öğrenme yöntemlerinden rassal orman algoritması, 2013-2022 döneminde G-20 ülkelerinin katma değer düzeylerini tahmin etmek için kullanılmıştır. Ortalama ve standart sapma kullanılarak elde edilen G-20 ülkelerinin imalat sanayi katma değer seviyeleri, inovasyon girdi ve çıkış göstergelerinin yardımıyla %54,14 hata oranıyla tahmin edilmiştir. En iyi tahmin edilen seviye ise ortalamaya yakın olan gruptur. Bu çalışmanın özgünlüğü, ülkelerin katma değer düzeylerini, Küresel İnovasyon Endeksi'nde yer alan inovasyon girdisi ve çıktısı göstergeleri temel alınarak, rassal orman algoritması kullanımı ile tahmin edilmesidir.

Anahtar Kelimeler: Küresel İnovasyon Endeksi, G-20 Ülkeleri, Rassal Orman, Sanayi Katma Değeri, İnovasyon

ABSTRACT

The primary objective of this study is to forecast the manufacturing value added levels of G-20 countries by leveraging the fundamental dimensions extracted from the Global Innovation Index. Another objective is to determine the extent to which innovation indicators contribute to variations in manufacturing value added. The Random Forest algorithm, known for its versatility and precision in dealing with complex datasets, has been employed as a prominent machine learning technique to predict the manufacturing value added levels of G-20 countries during the period 2013-2022. The Manufacturing Value Added (MVA) levels of G-20 countries, obtained using average and standard deviation, were predicted with a 54.14% error rate through the assistance of innovation input and output indicators. The level predicted with the highest accuracy is the one closely aligned with the average. This study's uniqueness lies in its utilization of the Random Forest algorithm to predict value added levels based on innovation inputs and outputs, which constitute the fundamental dimensions of the Global Innovation Index.

Keywords: Global Innovation Index, G-20 Countries, Random Forest, Innovation, Manufacturing Value Added

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INTRODUCTION

A strong MVA plays a significant role in cultivating an innovative culture via its influence on technical progress, facilitation of collaborative efforts, encouragement of skill enhancement, and establishment of a hospitable atmosphere for entrepreneurial endeavours. The aforementioned factor serves as a crucial catalyst that propels the innovation ecosystem inside a given country.

MVA is a metric used to quantitatively assess the economic contribution of the manufacturing sector to a nation's gross domestic product. The metric quantifies the increase in value that occurs to raw materials and components as a result of the manufacturing process. A positive value contributed signifies the sector's active and significant role in driving economic development, generating employment opportunities, and fostering technical progress. A decrease or lack of growth in value added might be indicative of difficulties in maintaining competitiveness, fostering technical innovation, or meeting global demand (Haraguchi et al. 2017). The fluctuations observed in MVA can serve as indicators of industrial patterns, trade dynamics, technological disruptions, and policy influences. These insights can be valuable for governments, policymakers, analysts, and investors, as they make informed choices regarding economic policies, resource allocation, trade strategies, and investment prospects.

The significance and substantial impact of innovation on the overall progress of civilization cannot be overstated. The relevance of it is universally acknowledged by all organizations, countries, communities, and other entities. The significance of this issue is equally relevant to both governmental and commercial sectors, regardless of whether they are situated in developed (Roos, 2016) or developing countries (Ganguly et al., 2022). The Global Innovation Index (GII) is a comprehensive assessment of the innovation ecosystem in different nations. It is developed collaboratively by Cornell University, INSEAD, and the World Intellectual Property Organization (Dutta et al., 2020). Since its first introduction, the GII has gained significant traction as a fundamental framework for evaluating the comparative innovation capabilities of nations (Huarng et al., 2022).

The concepts of MVA and GII are of utmost importance as they provide valuable insights into a nation's economic strength and its capacity for innovation. MVA serves as an indicator of the nation's industrial prowess, capacity for generating employment opportunities, and level of technical progress. In contrast, GII serves as a comprehensive instrument that assesses a nation's innovation performance across several dimensions, including its capacity to cultivate creativity, conduct research, facilitate development, and drive technological advancement. The combination of MVA and GII provides significant contributions to the understanding of economic growth, industrialization, and the prospects for innovation at an international level.

The interconnection and mutual reinforcement between MVA and GII are evident. The expansion of MVA is indicative of a strong manufacturing sector that often stimulates innovation by means of technology assimilation, research, and development. Consequently, these factors have a favorable effect on a nation's GII ranking as they cultivate an environment conducive to the invention, augment the development of human resources, and facilitate inter-industry cooperation. A robust manufacturing industry is positively associated with elevated GII ratings, which signify the presence of an environment conducive to innovation. Conversely, a higher GII ranking has the potential to promote investments in manufacturing, hence enhancing MVA. The interplay between MVA and GII supports a nation's economic development, competitiveness, and ability to sustain ongoing innovation.

The primary objective of this study is to forecast the levels of MVA for member nations of the G-20 group. This forecast is made possible by using fundamental elements obtained from the GII, a comprehensive instrument that assesses several facets of innovation. In addition, this study seeks to explore the relationship between indices of innovation and the differences in MVA observed among the nations of the G-20 group.

1. Literature Review

In this section of the study, MVA, GII and the relationship between MVA and the GII will be discussed, along with relevant studies exploring this relationship.

1.1. Manufacturing Value Added

The concept of MVA is used in the field of economics to measure the economic impact of the manufacturing sector on a nation's total economy. Thus, pertains to the distinction between the aggregate worth of commodities generated by the manufacturing industry and the expenses incurred for the acquisition of intermediary products used throughout the manufacturing procedure. In plain words, it measures the amount of value that is enhanced in the production process of raw materials and components (Baldwin and ITO, 2021).

MVA serves as a vital metric for assessing a nation's industrial output (Boudt et al., 2009). The measurement of MVA has significance as it serves as a key indicator that measures the level of economic productivity and efficiency within the industrial sector. The process considers several elements, including labour, money, technology, and innovation, which together contribute to the conversion of raw materials into final products. A greater magnitude of MVA signifies that a nation's manufacturing industry has the ability to generate a greater amount of value from the resources it employs.

The formula used for the computation of MVA is the difference between the gross output of manufacturing and the intermediate inputs. The gross output of manufacturing encompasses the aggregate value of items generated by the manufacturing industry, including the selling price of the finished products. Intermediate inputs refer to the many resources, components, and services that are procured from external sectors and then used in the process of manufacturing.

The measurement of MVA offers valuable insights into the level of competitiveness shown by a nation's manufacturing sector. An increasing MVA indicates the progressive development of a nation's manufacturing industry, characterized by enhanced innovation, technical sophistication, and operational efficiency, resulting in the ability to augment the worth of its goods. Consequently, this phenomenon may result in positive economic expansion, an increase in employment opportunities, and enhanced quality of life. Conversely, a diminishing MVA may suggest a dearth of competitiveness, use of obsolete production techniques, or dependence on imported components, all of which have the potential to undermine the overall economic efficacy.

MVA is often used by governments, policymakers, and economists as a significant measure for evaluating the vitality of a nation's manufacturing industry and formulating well-informed judgments on industrial policies, trade tactics, and expenditures in research and development. Furthermore, it facilitates the evaluation of manufacturing sector performance across various nations and regions.

In essence, MVA is a fundamental economic term that quantifies the value generated by the manufacturing industry as a result of its production activities. The aforementioned statement elucidates the extent to which the sector's efficiency, innovation, and competitiveness contribute to its overall impact on driving economic growth and development (Cantore et al., 2017). The literature contains various studies that delve into the development of the MVA indicator, its interrelation with various other variables, and the cross-country disparities associated with it (Anyanwu, 2017; Karami et al., 2019; Luken et al., 2022).

1.2. Innovation

In the realm of business, innovation is widely recognized as a catalyst for economic development and a means to establish a competitive edge for both major corporations and small to medium-sized firms. Consequently, it is subject to scrutiny as a determinant of overall organizational efficacy (Onea, 2020). According to Szopik-Depczyńska et al. (2018), innovation activity has considerable importance in driving economic progress and, as they propose, is an integral component of the broader endeavour to achieve enduring and sustainable development. In the realm of innovation, the prevailing understanding pertains to the creation of novel goods, processes, or services (Dziallas and Blind, 2019). According to the authors' assertion, the perception of innovation is contingent upon the vantage point of the commercial endeavour.

The term innovation is often discussed in academic literature due to its significance in assessing a nation's competitive advantage (Quitzow, 2013). Moreover, innovation is commonly linked to a country's economic expansion (Sekuloska, 2015). In the quest of sustainable prosperity, countries endeavour to establish their place in a constantly evolving global economy by effectively leveraging the potential of innovation. The GII was first introduced in 2007 with the objective of assessing and comparing the innovation capabilities and achievements of different nations (Worldbank 2010: 203).

1.3. Global Innovation Index

The GII, an annual analysis and ranking, evaluates the performance and capacity for innovation around the globe. It is published in cooperation with a number of institutions, including Cornell University, INSEAD, and the World Intellectual Property Organization. The GII strives to offer a thorough picture of the innovation landscape across nations and provide insights into the elements that spur innovation and economic development (WIPO, 2023).

The GII index is calculated by 80 parameters that are grouped into seven subcategories. The first five categories in the index are calculated as inputs and the last two subcategories are the outputs for innovation.

1. Institutions: This component evaluates a country's regulatory environment, political stability, and elements that foster innovation.

2. Human Capital and Research: It measures the quality of education, the availability of trained personnel, and the investment in R&D operations.

3. Infrastructure: This component assesses the quality of physical and digital infrastructure, such as transportation, communication networks, and internet access.

4. Market Sophistication: It examines factors such as market size, competition, and the ease of doing business in a certain country.

5. Business Sophistication: This dimension considers elements such as corporate governance quality, business collaboration level, and the scope of innovative activity within the business sector.

6. Knowledge and Technology Outputs: It assesses the results of innovation initiatives, such as patents filed, scientific publications, and other technological outputs.

7. Creative Outputs: This dimension assesses sectors such as the cultural and creative industries that contribute to the broader innovation ecosystem.

Oturakci (2021) examines the relationship between innovation input sub-index and innovation output sub-index by canonical correlation analysis. The findings revealed that human and capital research along with business sophistication factors account for 69.2% and 68.7% of the Innovation Input Sub-Index, respectively. Moreover, it was determined that the creative outputs factor significantly explains 98.8% of the innovation output sub-index. In addition, Yu et al. (2021) focuses on uncovering the universal causal complexity within the GII. It was discovered that the causal combination encompasses all preceding factors, with the exception of market sophistication. This widespread causal combination is applicable to all countries, offering a broader perspective than the initial GII approach, which evaluates each nation's innovation capacity according to varied income level.

To compile its rankings, the GII combines quantitative data with survey responses from professionals in the field of innovation. Countries are assessed on each of the aforementioned characteristics, and the results are averaged to create an overall GII score. The higher a country's GII rating, the better it excels in terms of its ability to innovate.

Legislators, corporations, scientists, and investors may use the GII to discover best cases, areas for improvement, and potential for partnership. It assists governments in developing plans for improving their innovation ecosystems, securing investment, and promoting economic growth. Furthermore, the GII rankings permit worldwide comparability and benchmarking of nations' innovation performance.

In essence, the GII is a powerful benchmark that evaluates and ranks nations' capacity for innovation using a wide range of variables. It offers an understanding of the aspects that lead to strong innovation ecosystems and helps both stakeholders and policymakers make accurate choices to support economic growth via innovation.

The literature encompasses a considerable number of research efforts dedicated to exploring the association between the GII and various macroeconomic indicators. Sıcakyüz (2023) explored how the GII affects national income, finding a statistically significant correlation between GII components and the national income, with varying levels of impact. Similarly, Nasir and Zhang (2024) analyzed the GII across 105 countries, identifying crucial influencing factors and demonstrating how effectively these nations employ innovation-enabling elements. They also examined the positive influence of the global innovation output index on the innovation efficiency index. In addition, the study conducted by Yüregir et al. (2022) explored a connection between a country's achievements in the GII and its university achievements. Çemberci et. al (2022) explore a positive and significant relationship between the GII and Gross Domestic Product. Their findings also revealed that Foreign Direct Investment plays a statistically significant mediating role in this relationship. In addition to these relationships, studies that compare countries based on the GII hold a significant place in the literature (Coutinho and Au-Yong-Oliveira, 2023; Erciş and Ünalan, 2016; Stojanović et al., 2022).

1.4. Relation between MVA and GII

Prior studies have examined the correlation between MVA and innovation, yielding significant findings in this area of inquiry. A correlation exists between MVA and the GII, despite their distinct representations of a nation's economic and innovation prowess.

Recent research has used the GII as a tool to investigate the association between innovation and economic performance across diverse sectors and industries. Hlazova (2021) conducted a study on the growth of the digital economy as a measure of the information society, with a particular focus on its possible risks and opportunities. This research elucidates the relationship between technical advancements and economic development, namely by facilitating enhanced efficiency across diverse industries, such as manufacturing. Singh and Paliwal (2017) conducted a study to examine the development potential of India’s Small, and Medium Enterprises by exploring the implementation of innovative techniques. The researchers' results underscored the importance of cultivating an environment that promotes innovation, as it has the potential to greatly enhance the value-added in the industrial sector. Chen et al. (2015) have posited a reciprocal relationship between investment in innovation and economic development among the BRICS-T nations. These studies together provide evidence to support the notion that there exists a positive correlation between levels of MVA and indices of innovation in various situations. The link between the MVA and the GII may be comprehended in the following manner:

1. The use of both MVA and GII as indicators is complimentary in nature, as it allows for a more thorough assessment of a country's economic and innovation environment. The MVA metric primarily examines the economic value provided by the manufacturing sector. In contrast, the GII evaluates a nation's comprehensive innovation capabilities, including many aspects such as research and development, human capital, infrastructure, and market sophistication.

2. Countries that possess a robust manufacturing sector often depend on innovation as a means to sustain competitiveness within the international market. A substantial MVA may suggest that a nation's manufacturing industry has sophisticated technical capabilities, operates with efficiency, and possesses the capacity to generate substantial value from raw resources. The function of innovation in the manufacturing business is of paramount importance as it serves as a key driver of productivity and growth.

3. The GII evaluates a range of elements that contribute to a robust innovation ecosystem, including education, research, infrastructure, and market dynamics. A robust innovation ecosystem has the capacity to facilitate the growth of not only the manufacturing sector, but also several other sectors, hence fostering the development of inventive goods and processes inside the manufacturing domain.

4. The process of innovation often entails the exchange of technology and information across different industries. A robust innovation ecosystem, as indicated by a higher GII score, has the potential to promote the transfer of state-of-the-art technologies and techniques to the manufacturing sector, hence augmenting its value-added capabilities.

5. The global competitiveness of a nation is influenced by both the MVA and the GII. A country's export competitiveness may be positively influenced by a high MVA and a robust manufacturing sector. Additionally, a high GII score signifies the capacity to produce novel ideas, products, and technologies, which can further bolster a country's worldwide standing.

6. Policy Implications: Policymakers may use the findings from both the MVA and the GII to develop effective measures that promote economic development and encourage innovation. As an example, a nation characterized by a comparatively modest MVA, yet a substantial GII rating may prioritize the utilization of its innovation capacities to bolster its manufacturing industry and augment value-added endeavours.

There is a fundamental correlation between MVA and the GII since both factors play a significant role in fostering a nation's economic growth and enhancing its competitive advantage. For instance, in the study conducted by Yönkul and Ünlü (2022), they analyzed and showed the effects of countries' absorptive capacities on their innovation capabilities based on their tendencies to produce medium and high technology. This also enables the measurement of the relationship between MVA and innovation. A nation that adopts a harmonized strategy, whereby manufacturing and innovation complement each other, is expected to see enduring economic expansion and enhanced results.

2. RESEARCH METHODOLOGY

In this section, the data source used for the research and the characteristics of the indicators utilized for the analysis are discussed (Section 2.1). Additionally, Section 2.2 will delve into the research methodologies employed during the study.

2.1. Data

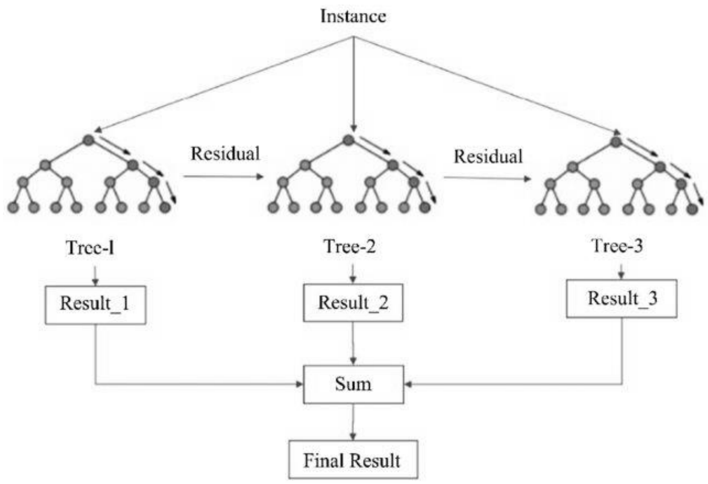
Since the objective of this study is to examine the impact of innovation on the expansion of MVA across the complete spectrum of G20 countries, including Argentina, Australia, Brazil, Canada, China, Germany, France, India, Indonesia, Italy, Japan, Korea, Mexico, Russia, Saudi Arabia, South Africa, Turkey, the United Kingdom, and the United States of America, the key dimensions of GII and the MVA indicator have been selected. The dataset that is analyzed in this study was obtained from https://www.globalinnovationindex.org/analysis-indicator and https://databank.worldbank.org/. Table 1 illustrates the relevant variables over the period 2013-2022 to make the prediction and investigate the relation.

Table 1. Main Dimensions of GII

Symbol	Dimension	Symbol	Dimension
X_1	Institutions	X_5	Business sophistication
X_2	Human capital and research	X_6	Knowledge and technology outputs
X_3	Infrastructure	X_7	Creative outputs
X_4	Market sophistication	Y	Manufacturing Value Added

2.2. Random Forest

Random forest is an enhanced and evolved version of the bagging algorithm introduced by Breiman (2001), which achieves the final output by amalgamating multiple decision trees into a forest-like structure. The trees exhibit a higher degree of uncorrelation, as only a subset of variables is used during the split of the tree rather than greedily choosing the best split point in the construction of the tree (Swamynathan, 2017: 285). It is an efficient and widely employed statistical learning algorithm for both classification and regression problems (Breiman, 2001). The popularity of random forest categorization stems from its versatile advantages, including its applicability for both classification and regression, its ability to mitigate overfitting with an adequate number of trees, and its capability to handle missing and categorical data while providing robust modelling (Pallathadka et al., 2023). The Random Forest algorithm involves two main stages, namely training to acquire a classification model using training samples and decision tree theory, and classification to determine the altered category of each super-pixel utilizing the established training model (Eisavi and Homayouni, 2016; Feng et al., 2018; Liu et al., 2012; Wessels et al., 2016). The specific process of random forest algorithm is shown in Graph 1.

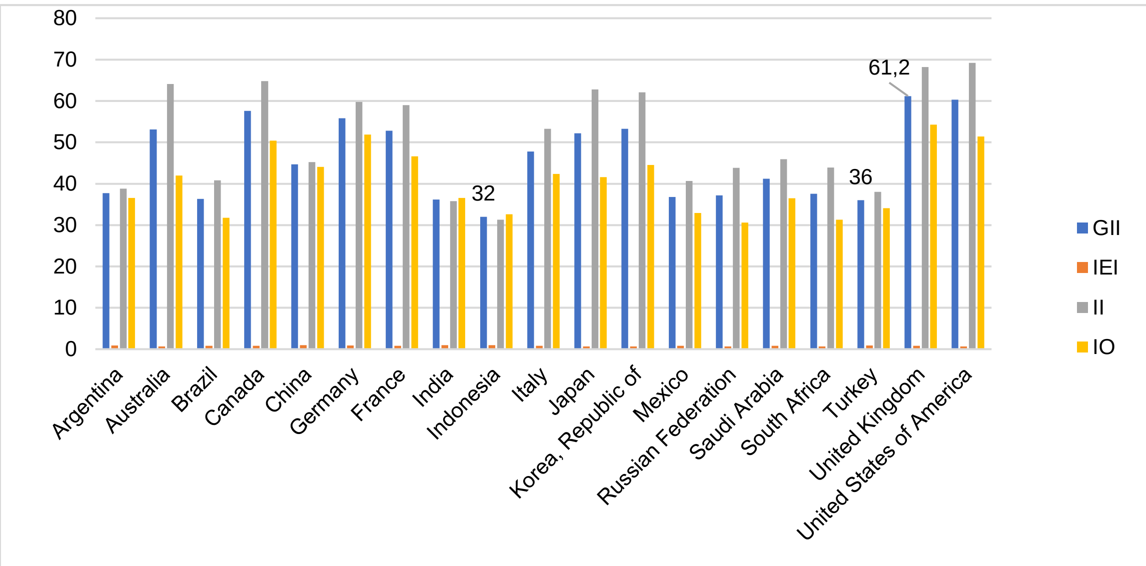


Graph 1. Random Forest Schematic (Chen, 2023)

In the literature review, one can find instances of the RF algorithm being employed in diverse areas such as medicine, finance, e-commerce and exhibited good performance (Calderoni et al., 2015; Farnaaz and Jabbar, 2016; Shaikhina et al., 2019; Wang et al., 2021). For instance, RF is utilized for determining optimal technical indicators in finance (Thakur and Kumar, 2018) and for price prediction (Lohrmann and Luukka, 2019; Ghosh et al., 2022) and to develop some decision based on financial datasets and/or trading support systems (Baba and Sevil, 2020; Cındık and Armutlulu, 2021; Kaczmarczyk and Hernes, 2020).

3. RESULTS AND DISCUSSION

This section presents the outcomes of the conducted studies in the chronological sequence of their implementation. Right after obtaining the results, the primary focus of this section lies in discussing these findings. The initial step of the study involved acquiring MVA indicator values, in conjunction with the 7 key dimensions outlined in Table 1, for the G20 countries during the period 2013-2022. The Innovation Efficiency Index, Innovation Input, Innovation Output, and GII values obtained from these dimensions for the year 2023 in the G-20 countries have been tabulated in Graph 2, facilitating cross-country evaluations.



Graph 2. GII and Related Indices for G-20 Countries: 2013

As evident from Graph 2, for the year 2013, Indonesia exhibits the lowest GII value, whereas the United Kingdom holds the highest GII value. Turkey's GII value stands at 36, a figure 4 points higher than the country with the lowest value.

By evaluating the average and standard deviation values of the MVA, countries were classified into five categories: "Very Bad," "Bad," "Normal," "Good," and "Very Good," based on the covered time frame of the countries in the sample. Table 2 presents the MVA indicator value and the corresponding MVA group, alongside indicator values of randomly chosen countries for time periods selected randomly from the study sample.

Table 2. Randomly Selected G-20 countries' GII sub-dimension and MVA values for random time periods

Country	Year	X_1	X_2	X_3	X_4	X_5	X_6	X_7	MVA	MVA Group
Argentina	2013	50.7	36.7	35	37.3	34.2	25.6	47.5	1.50	Normal
Australia	2013	89.4	57.8	52.7	72.7	48.2	30.9	53.1	-3.30	Bad
France	2014	78.6	55.9	54.7	61	47.4	44.2	45.5	1.62	Normal
India	2014	50.8	22.7	32.1	51.2	28	32.2	28.6	7.90	Good
Argentina	2015	48	37.7	38.2	35.9	36.3	22.2	36.5	0.77	Normal
United Kingdom	2015	87.3	57.5	63	74.3	53.6	54.9	60.5	0.74	Normal
Argentina	2016	47.2	37.3	43.3	35.7	30.8	18	25.3	-5.60	Bad
Australia	2016	88.8	59.7	65.1	65.8	45	34.3	48.2	-2.20	Bad
Canada	2017	91	53.3	62.1	73.7	47.8	38.7	44.8	1.94	Normal
China	2017	54.8	49.2	57.9	54.7	54.5	56.4	45.3	0.00	Normal
Russian Federation	2018	57.8	48.4	45.2	48.1	39.9	28.9	26.9	3.96	Good
Saudi Arabia	2018	51.9	47.7	49.4	51.7	33	20.2	23.4	-2.88	Bad
Argentina	2019	56.7	38.7	45.8	37.9	32.6	19.2	24	-6.16	Bad
Australia	2019	88.8	57.7	60.9	68.3	46.1	31.6	41.1	-0.97	Bad
United Kingdom	2020	86.1	58	60.3	74.4	51	54.4	52.7	0.11	Normal
United States of	2020	88.9	56.3	54.7	81.4	62.8	56.8	47.7	-4.60	Bad
Brazil	2021	60.6	37.5	41.2	44.9	36	25.3	23.5	4.48	Good
Canada	2021	90.1	52.4	53.7	84.7	50.1	38.3	41.9	4.65	Good
Korea	2022	70.5	66.4	60.3	48	58	54.7	55.1	1.37	Normal
Mexico	2022	48.2	33.6	44.2	36.3	25.2	24.3	24.7	5.23	Good

In the second step, these categories were forecasted utilizing the random forest algorithm, aided by the utilization of the 7 key indicators found within the GII index. The Random Forest technique is employed using both innovation input and output indicators, and it was implemented using the "randomForest" package of R version 4.3.1. However, due to its nature as a machine learning model, the data has been divided into training and test datasets. Specifically, 70% of the dataset has been designated for training purposes, leaving the remaining portion for the test set. This implies that out of a total of 190 observations, 133 have been selected for the training dataset, while the remaining 57 observations form the test set.

Table 3 depicts the relationship between the class obtained from MVA and the class that predicted from the random forest algorithm with innovation input and output indicators. In other words, Table 3 illustrates the confusion matrix of the model.

Table 3. Confusion Matrix

Observed Class Obtained from MVA	Predicted Random Class					
	Bad	Good	Normal	Very Bad	Very Good	Class Error
Bad	3	2	14	0	0	0.8421
Good	1	7	17	2	0	0.7407
Normal	8	11	51	0	1	0.2817

Very Bad	1	2	4	0	0	1.0000
Very Good	1	2	5	1	0	1.0000

In the initial row, the number 3 signifies that the classification "Bad" was accurately predicted, whereas the numeral 2 suggests that the model incorrectly assigned the "Bad" class twice as "Good". Among the five classes, it has been remarkably observed that the best-predicted class is Normal. As evident from Table 3, the error rate is approximately 28%. For the class categorized as Normal, it has been predicted as Bad 8 times, as Good 11 times, as Normal 51 times, and only once as Very Good.

The total error rate of the model is observed to be 54.14%. The main objective of the study is to demonstrate the influence of innovation variables on the MVA value, affirming the presence of a certain level of effect. Despite the dataset being comprised of panel data, it was randomly obtained since the focus is not solely on predicting future classes, but rather on illustrating the general impact. When the algorithm model run multiple times, consistent results were obtained.

CONCLUSION

The integration of innovative practices not only enhances the value generated within the MVA but also contributes to broader economic aspects such as job creation, market expansion, and sustainable resource utilization. This relation between innovation and MVA emphasizes their combined role in fostering gradual industrial advancement and contributing to economic well-being. Consequently, the exploration centered on the potential of forecasting countries' MVA levels through the utilization of innovation inputs and outputs.

In essence, the main aim of this study, in essence, is to endeavour the prediction of the MVA value exclusively through the sub-indices contained within the GII. In doing so, the intention is to deduce that the MVA value is impacted to a certain degree by these sub-indices. It is pertinent to note that harbouring high expectations for a substantial prediction rate would be unwise, given the clear indication that there exist additional economic and financial variables that exert influence upon the MVA value. In the obtained findings, the prediction error has been determined to be 54.14%.

The prediction methodology employed in the study involves the application of the random forest algorithm, one of the most widely used machine learning techniques for both classification and regression analyses. In essence, the approach of the random forest algorithm was proposed and adopted to forecast the MVA levels of G-20 countries.

The MVA levels of countries have been computed using the average and standard deviation values of the G-20 countries during the sample period. The method's success in predicting the “Normal” class, coupled with its inability to predict “Very Good” and “Very Bad” classes, constitutes the most significant findings of the study.

This research has the potential to provide valuable insights into the policy initiatives that may be implemented by G-20 countries in order to boost their MVA via innovation. The identification of certain areas where focused policy actions, such as greater investment in research and development or improvements in intellectual property protection, has the potential to provide significant economic gains.

Through a comparative investigation of the correlation between innovation and MVA in various G-20 countries, potential trends specific to certain areas or economic circumstances might be uncovered. This study has the potential to enhance comprehension about the worldwide variations in innovation-driven industrial growth.

The methodology has the potential to find distinct dimensions or indicators within the GII that have a more pronounced impact on MVA. For example, it may be disclosed that variables such as investment in research and development, safeguarding of intellectual property, and the transfer of technology are pivotal in influencing the expansion of manufacturing. By engaging in additional study in these areas, individuals may get a more profound comprehension of the particular aspects within the GII that exert the most robust and consistent influence on the value-added in manufacturing across the G-20 countries. This body of research has the potential to provide valuable insights for the development of policy recommendations and strategies aimed at promoting economic growth driven by innovation. One of the most significant limitations of this study is that it was conducted only within the G-20 countries, while another limitation is that the study encompasses only a specific period.

Compliance with Ethical Standard

Conflict of Interest: The authors declare that they do not have a conflict of interest with themselves and/or other third parties and institutions, or if so, how this conflict of interest arose and will be resolved, and author contribution declaration forms are added to the article process files with wet signatures.

Ethics Committee Approval: In this article, ethics committee approval is not required, and a consent form affirming that a wet-signed ethics committee decision is not necessary has been added to the article process files on the system.

Funding Disclosure: No financial support was required in this study.

REFERENCES

Anyanwu, J. C. (2017). Manufacturing Value Added Development in North Africa: Analysis of Key Drivers, Asian Development Policy Review, 5(4), 281-298. https://doi.org/10.18488/journal.107.2017.54.281.298

Baldwin, R., & Ito, T. (2021). The Smile Curve: Evolving Sources of Value Added in Manufacturing, Canadian Journal of Economics/Revue Canadienne D'économique, 54(4), 1842-1880. https://doi.org/10.1111/caje.12555.

Baba, B., & Sevil, G. (2020). Predicting IPO Initial Returns Using Random Forest, Borsa Istanbul Review, 20(1), 13-23. https://doi.org/10.1016/j.bir.2019.08.001.

Boudt, K., Todorov, V., & Upadhyaya, S. (2009). Nowcasting Manufacturing Value Added for Cross-Country Comparison, Statistical Journal of the IAOS, 26(1,2), 15-20.

Breiman, L. (2001). Random Forests, Machine Learning, 45, 5-32.

Calderoni, L., Ferrara, M., Franco, A., & Maio, D. (2015). Indoor Localization in a Hospital Environment Using Random Forest Classifiers, Expert Systems with Applications, 42(1), 125-134. https://doi.org/10.1016/j.eswa.2014.07.042.

Cantore, N., Clara, M., Lavopa, A., & Soare, C. (2017). Manufacturing as an Engine Of Growth: Which is The Best Fuel?, Structural Change and Economic Dynamics, 42, 56-66. https://doi.org/10.1016/j.strueco.2017.04.004.

Chen, D.; Zheng, S., & Gou, L. (2015). The Impact of Science and Technology Policies on Rapid Economic Development in China, The Global Innovation Index 2015, chapter 6, https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2015-chapter6.pdf.

Chen, S. (2023). Predicting Lung Cancer Stage by Expressions of Protein-Encoding Genes. Advances in Bioscience and Biotechnology, 14(8), 368-377.

Cındık, Z., & Armutlulu, I. H. (2021). A Revision of Altman Z-Score Model and a Comparative Analysis of Turkish Companies' Financial Distress Prediction, National Accounting Review, 3(2), 237-255. https://doi.org/10.3934/NAR.2021012

Coutinho, E. M. O., & Au-Yong-Oliveira, M. (2023). Factors Influencing Innovation Performance in Portugal: A Cross-Country Comparative Analysis Based on the Global Innovation Index and on the European Innovation Scoreboard. Sustainability, 15(13), 10446. https://doi.org/10.3390/su151310446

Çemberci, M., Civelek, M. E., & Cömert, P. N. (2022). The Role of Foreign Direct Investment in The Relationship Between Global Innovation Index and Gross Domestic Product. GURUKUL BUSINESS REVIEW-GBR, 18., 101-111. https://doi.org/10.48205/gbr.v18.8

Dutta, S., Lanvin, B., & Wunsch-Vincent, S. (Eds.). (2020). Global Innovation Index 2020. Johnson Cornell University.

Dziallas, M., & Blind, K. (2019). Innovation Indicators Throughout the Innovation Process: An Extensive Literature Analysis. Technovation, 80-81, 3-29. https://doi.org/10.1016/j.technovation.2018.05.005.

Eisavi, V., & Homayouni, S. (2016). Performance Evaluation of Random Forest and Support Vector Regressions in Natural Hazard Change Detection, Journal of Applied Remote Sensing, 10(4), 046030-046030. https://doi.org/10.1117/1.JRS.10.046030

Erciş, A., & Ünalan, M. (2016). Innovation: A Comparative Case Study of Turkey and South Korea. Procedia-Social and Behavioral Sciences, 235, 701-708. https://doi.org/10.1016/j.sbspro.2016.11.071

Farnaaz, N., & Jabbar, M. A. (2016). Random Forest Modeling for Network Intrusion Detection System, Procedia Computer Science, 89, 213-217. https://doi.org/10.1016/j.procs.2016.06.047.

Feng, W., Sui, H., Tu, J., Huang, W., & Sun, K. (2018). A Novel Change Detection Approach Based on Visual Saliency and Random Forest from Multi-Temporal High-Resolution Remote-Sensing Images, International Journal of Remote Sensing, 39(22), 7998-8021. https://doi.org/10.3390/rs8110888.

Ganguly, S., Das, S., & Pandya, S. (2022). Influence of Strategy Typology on Innovation: Evidence from The Manufacturing Sector, International Journal of Electronic Government Research (IJEGR), 18(2), 1-16. http://doi.org/10.4018/IJEGR.298156.

Ghosh, P., Neufeld, A., & Sahoo, J. K. (2022). Forecasting Directional Movements of Stock Prices for Intraday Trading Using LSTM and Random Forests, Finance Research Letters, 46, 1-8. https://doi.org/10.1016/j.frl.2021.102280.

Haraguchi, N., Cheng, C. F. C., & Smeets, E. (2017). The Importance of Manufacturing in Economic Development: Has This Changed?, World Development, 93, 293-315. https://doi.org/10.1016/j.worlddev.2016.12.013.

Hlazova, A. (2021). Researching The Problems of Digital Economy Development as an Indicator of The Information Society: Potential Threats and Prospects, Technology Audit and Production Reserves, 6(4(62)). https://doi.org/10.15587/2706-5448.2021.248124.

Huarng, K. H., & Yu, T. H. K. (2022). Analysis of Global Innovation Index by Structural Qualitative Association, Technological Forecasting and Social Change, 182, 121850. https://doi.org/10.1016/j.techfore.2022.121850.

Kaczmarczyk, K., & Hernes, M. (2020). Financial Decisions Support Using the Supervised Learning Method Based on Random Forests, Procedia Computer Science, 176, 2802-2811. https://doi.org/10.1016/j.procs.2020.09.276.

Karami, M., Elahinia, N., & Karami, S. (2019). The Effect of Manufacturing Value Added on Economic Growth: Empirical Evidence from Europe, Journal of Business Economics and Finance, 8(2), 133-147. http://doi.org/10.17261/Pressacademia.2019.1044.

Liu, Y., Wang, Y., & Zhang, J. (2012). New Machine Learning Algorithm: Random Forest, In Information Computing and Applications: Third International Conference, ICICA 2012, Chengde, China, September 14-16, 2012. Proceedings 3, 246-252. Springer Berlin Heidelberg.

Lohrmann, C., & Luukka, P. (2019). Classification of Intraday S&P500 Returns with a Random Forest, International Journal of Forecasting, 35(1), 390-407. https://doi.org/10.1016/j.ijforecast.2018.08.004.

Luken, R. A., Saieed, A., & Magvasi, M. (2022). Industry-related Sustainable Development Goal-9 Progress and Performance Indices and Policies for Sub-Saharan African Countries, Environmental Development, 42, 1-14.
https://doi.org/10.1016/j.envdev.2021.100694

Nasir, M. H., & Zhang, S. (2024). Evaluating Innovative Factors of The Global Innovation Index: A Panel Data Approach. Innovation and Green Development, 3(1), 100096. https://doi.org/10.1016/j.igd.2023.100096.

Onea, I. A. (2020). Innovation Indicators and the Innovation Process- Evidence from The European Innovation Scoreboard, Management & Marketing, 15(4), 605-620. https://doi.org/10.2478/mmcks-2020-0035

Oturakci, M. (2021). Comprehensive Analysis of The Global Innovation Index: Statistical and Strategic Approach. Technology Analysis & Strategic Management, 35(6), 676-688. https://doi.org/10.1080/09537325.2021.1980209.

Pallathadka, H., Ramirez-Asis, E. H., Loli-Poma, T. P., Kaliyaperumal, K., Ventayen, R. J. M., & Naved, M. (2023). Applications of Artificial Intelligence in Business Management, E-Commerce And Finance, Materialstoday: Proceedings, 80, 2610-2613.
https://doi.org/10.1016/j.matpr.2021.06.419.

Quitzow, R. (2013). Towards an Integrated Approach to Promoting Environmental Innovation And National Competitiveness, Innovation and Development, 3(2), 277-296. https://doi.org/10.1080/2157930X.2013.825070.

Roos, G. (2016). Design-based Innovation for Manufacturing Firm Success in High-Cost Operating Environments, She Ji: The Journal of Design, Economics, and Innovation, 2(1), 5-28. https://doi.org/10.1016/j.sheji.2016.03.001

Sekuloska, J. D. (2015). Innovation Oriented FDI As a Way of Improving the National Competitiveness, Procedia-Social and Behavioral Sciences, 213, 37-42. https://doi.org/10.1016/j.sbspro.2015.11.400.

Shaikhina, T., Lowe, D., Daga, S., Briggs, D., Higgins, R., & Khovanova, N. (2019). Decision Tree and Random Forest Models for Outcome Prediction In Antibody Incompatible Kidney Transplantation. Biomedical Signal Processing and Control, 52, 456-462. https://doi.org/10.1016/j.bspc.2017.01.012.

Sıcakyüz, Ç. (2023). How Does the Global Innovation Index Score Affect Income? A Policy for Innovativeness. Journal of Research in Business, 8(1), 1-19. https://doi.org/10.54452/jrb.1022938.

Singh, S. & Paliwal, M. (2017). Unleashing The Growth Potential of Indian MSME Sector, Comparative Economic Research. Central and Eastern Europe, 20(2), 35–52. https://doi.org/10.1515/cer-2017-0011

Stojanović, I., Puška, A., & Selaković, M. (2022). A Multi-Criteria Approach to The Comparative Analysis of The Global Innovation Index on The Example of The Western Balkan Countries. Economics, 10(2), 9-26.

Swamynathan, M. (2017). Mastering Machine Learning with Python In Six Steps: A Practical Implementation Guide To Predictive Data Analytics Using Python, Apress, Almanya.

Szopik-Depczyńska, K., Kędzierska-Szczepaniak, A., Szczepaniak, K., Cheba, K., Gajda, W., & Ioppolo, G. (2018). Innovation in Sustainable Development: An Investigation of The EU Context Using 2030 Agenda Indicators, Land Use Policy, 79, 251-262. https://doi.org/10.1016/j.landusepol.2018.08.004

Thakur, M. & Kumar, D. (2018). A Hybrid Financial Trading Support System Using Multi-Category Classifiers and Random Forest, Applied Soft Computing, 67, 337-349. https://doi.org/10.1016/j.asoc.2018.03.006

Yu, T. H. K., Huarng, K. H., & Huang, D. H. (2021). Causal Complexity Analysis of The Global Innovation Index. Journal of Business Research, 137, 39-45. https://doi.org/10.1016/j.jbusres.2021.08.013

Yönkul, N. G., & Ünlü, H. (2022). How Does The Effect of Absorptive Capacity on Innovation Capacity Change According To Countries' Technology Manufacturing Value-Added Levels?, In Strategic Innovation: Research Perspectives on Entrepreneurship and Resilience, 127-164, Springer International Publishing.

Yüregir, O. H., Sıcakyüz, Ç., & Güler, S. (2022). Comparison of Relationship Between Global Innovation Index Achievements and University Achievements in Terms of Countries. International Research Journal of Social Sciences, 11(2), 1-12.

Wang, J., Sun, X., Cheng, Q., & Cui, Q. (2021). An Innovative Random Forest-Based Nonlinear Ensemble Paradigm of Improved Feature Extraction and Deep Learning for Carbon Price Forecasting, Science of the Total Environment, 762, 143099. https://doi.org/10.1016/j.scitotenv.2020.143099

Wessels, K. J., Van den Bergh, F., Roy, D. P., Salmon, B. P., Steenkamp, K. C., MacAlister, B., Swanepoel D., & Jewitt, D. (2016). Rapid land Cover Map Updates Using Change Detection and Robust Random Forest Classifiers, Remote Sensing, 8(11), 1-24. https://doi.org 10.3390/rs8110888

WIPO. (2023). Global Innovation Index (GII). Global Innovation Index (GII). Retrieved August 15, 2023, from https://www.wipo.int/global_innovation_index/en/index.html

World Bank. (2010). Innovation Policy: A guide for Developing Countries. The World Bank.