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UNLOCKING GLOBAL INNOVATION: LEVERAGING NONPARAMETRIC ANALYSIS WITH DATA ENVELOPMENT ANALYSIS AND TOBIT INSIGHTS ON EXTERNAL FACTORS

Desbloqueando a inovação global: aproveitando a análise não paramétrica com análise envoltória de dados e insights de tobit sobre fatores externos

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ABSTRACT

In the dynamic landscape of global innovation, researchers increasingly adopt an integrated approach using nonparametric and regression techniques. This study highlights the significance of this method in enabling countries to understand external factors shaping innovation outcomes. Data Envelopment Analysis (DEA) serves as a robust framework for evaluating innovation efficiency, helping countries optimize their innovation processes by scrutinizing resource utilization and identifying areas for improvement. Complementing DEA, Tobit regression analysis offers insights into the nuanced influence of external drivers on innovation. The findings reveal a mixed landscape: while high-income countries dominate innovation efficiency, some lower-middle and low-income countries show notable proficiency. China, classified as an upper-middle-income country, emerges as the most referenced benchmark. Based on benchmarking, inefficient countries can enhance their innovation policies and strategies, helping to bridge the global innovation gap. Despite all input capabilities showing a negative correlation with innovation efficiency, all output variables exhibit a positive correlation. Notably, there was no association between R&D and innovation efficiency in 2020, highlighting the need for judicious use of innovation inputs to avoid wastage. Additionally, the Tobit regression model exhibits a remarkable R-squared value of 0.8523, indicating that the 16 independent factors account for 85.23% of the variation in the innovation efficiency. Amidst technology-driven transformations, leveraging nonparametric analysis methodologies is essential for organizations aiming to thrive in the global innovation arena. This study highlights the crucial role of DEA in assessing innovation efficiency and emphasizes the importance of incorporating nonparametric analysis and regression techniques into strategic decision-making processes to formulate effective innovation policies.
Keywords: Innovation efficiency, Nonparametric analysis, Data Envelopment Analysis, Tobit, External factors.

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DESBLOQUEANDO A INOVAÇÃO GLOBAL: APROVEITANDO A ANÁLISE NÃO PARAMÉTRICA COM ANÁLISE ENVOLTÓRIA DE DADOS E INSIGHTS DA TOBIT SOBRE FATORES EXTERNOS

Unlocking Global Innovation: Leveraging Non-Parametric Analytics with Data Envelopment Analysis and Tobit Insights on External Factors

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RESUMO

No cenário dinâmico da inovação global, os pesquisadores adotam cada vez mais uma abordagem integrada usando técnicas não paramétricas e de regressão. Este estudo destaca a importância desse método para permitir que os países entendam os fatores externos que moldam os resultados da inovação. A Análise Envoltória de Dados (DEA) serve como uma estrutura robusta para avaliar a eficiência da inovação, ajudando os países a otimizar seus processos de inovação, examinando a utilização de recursos e identificando áreas de melhoria. Complementando a DEA, a análise de regressão Tobit oferece insights sobre a influência diferenciada de fatores externos na inovação. Os resultados revelam um cenário misto: enquanto os países de alta renda dominam a eficiência da inovação, alguns países de renda média-baixa e baixa mostram proficiência notável. A China, classificada como um país de renda média-alta, surge como a referência mais referenciada. Com base no benchmarking, os países ineficientes podem aprimorar suas políticas e estratégias de inovação, ajudando a preencher a lacuna global de inovação. Apesar de todas as capacidades de entrada mostrarem uma correlação negativa com a eficiência da inovação, todas as variáveis de saída exibem uma correlação positiva. Notavelmente, não houve associação entre P&D e eficiência de inovação em 2020, destacando a necessidade de uso criterioso de insumos de inovação para evitar desperdícios. Além disso, o modelo de regressão Tobit exibe um valor notável de R-quadrado de 0,8523, indicando que os 16 fatores independentes respondem por 85,23% da variação na eficiência da inovação. Em meio às transformações impulsionadas pela tecnologia, alavancar metodologias de análise não paramétricas é essencial para organizações que desejam prosperar na arena global de inovação. Este estudo destaca o papel crucial da DEA na avaliação da eficiência da inovação e enfatiza a importância de incorporar técnicas de análise e regressão não paramétricas nos processos de tomada de decisão estratégica para formular políticas de inovação eficazes.
Palavras-chave: Eficiência da inovação, Análise não paramétrica, Análise Envoltória de Dados, Tobit, Fatores externos.

INTRODUCTION

Innovation stands as the fundamental force propelling progress, steering economic expansion, societal evolution, and global competitiveness (Binz, & Truffer, 2017; Solow, 1957). Its essence lies in the constant quest to push boundaries, challenge norms, and unearth novel solutions to existing problems or unmet needs. The transformative power of innovation is evident in its capacity to spawn new industries, products, and markets, thus elevating productivity, living standards, and employment opportunities. Moreover, innovative endeavours play a pivotal role in addressing pressing global issues, including climate change, healthcare, and poverty (Azar & Ciabuschi 2017; UNDP, 2001). In an increasingly interconnected and dynamic world, the imperative for global innovation becomes even more pronounced, particularly in navigating the rapid advancements in technology, the forces of globalization, and the disruptions caused by events such as pandemics and economic downturns (Bock, 2016). The ability to innovate serves as a crucial determinant of adaptability and resilience for individuals, organizations, and nations alike.

Global collaboration facilitated by digital platforms and international alliances serves as a catalyst for accelerating problem-solving and solution implementation, transcending geographical boundaries, and fostering inclusivity in innovation ecosystems (Dutta, 2020). Through such collaborative efforts, diverse stakeholders can pool their resources, expertise, and perspectives to tackle complex, cross-border challenges. Likewise, the pursuit of global innovation not only drives economic growth and competitiveness in an increasingly interconnected world but also fosters equitable development and diminishes disparities among nations (Schot, 2016). By embracing inclusivity in innovation ecosystems and promoting accessibility to innovation resources regardless of geographic or socioeconomic constraints, societies can harness the full potential of diverse talents and perspectives. Innovation serves as the linchpin for addressing shared global challenges, fuelling economic progress, and forging a path towards a more sustainable, prosperous, and inclusive future.

Importance of innovation efficiency and its relevance in today’s competitive landscape

In today's fiercely competitive industries, the importance of innovation efficiency cannot be overstated. It serves as a critical determinant of success in an environment where disruption is the norm. Innovation efficiency is about extracting maximum value from the resources—time, capital, and talent—invested in innovation processes. This entails optimizing the journey from ideation to implementation, achieving more with less, and adapting swiftly to changing market dynamics (Zhou et al., 2017). Remaining ahead of the curve in rapidly evolving sectors necessitates a relentless focus on innovation efficiency. Organizations must innovate rapidly, particularly in domains characterized by short product life cycles and evolving consumer preferences, to maintain relevance and capture market share (Zhou et al., 2017). By streamlining innovation processes and minimizing time-to-market, companies can seize opportunities swiftly, outpace competitors, and secure first-mover advantages in emerging markets or disruptive technologies.

The quest for maximizing return on investment (ROI) from innovation initiatives further underscores the importance of innovation efficiency, particularly in an era marked by stringent budgetary constraints and heightened scrutiny over expenditures (Kahn, 2018). Employing lean and agile innovation methodologies enables firms to eliminate wastage, reduce costs, and prioritize projects with the highest potential for value creation and differentiation. Also, fostering innovation efficiency is imperative for fostering a culture of continuous improvement and learning within organizations. Embracing rapid prototyping, iterative design, and feedback loops empowers teams to experiment, fail fast, and iterate towards optimal solutions expeditiously (Kahn, 2018). This iterative approach not only accelerates the pace of innovation but also cultivates resilience, flexibility, and agility among employees, enabling them to pivot swiftly in response to market feedback or unforeseen challenges.

Additionally, innovation efficiency hinges on fostering collaboration and knowledge-sharing both within organizations and across ecosystems (Brav et al., 2018). In an interconnected world, creativity thrives on the collective insights and perspectives of diverse stakeholders. Leveraging digital platforms, open innovation networks, and collaborative technologies enables firms to tap into external expertise, broaden their perspectives, and co-create value with partners, suppliers, and customers. In today's hypercompetitive landscape, innovation efficiency emerges as a key driver of success. By prioritizing efficiency in innovation processes, companies can gain a strategic edge, foster sustainable growth, and navigate the complexities of evolving market dynamics effectively (Serdyukov, 2017). This entails embracing process simplification, agile methodologies, and fostering a culture of collaboration and continuous learning to thrive in an increasingly dynamic business environment.

1 THEORETICAL REFERENCE FRAMEWORK

1.1 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a powerful analytical tool widely utilized in operations research and management science to evaluate the efficiency of Decision-Making Units (DMUs) based on multiple inputs and outputs (Dobrzanski et al., 2021; Prokop et al., 2021). Its application in assessing innovation efficiency is particularly significant, as it allows for a thorough examination of how effectively organizations utilize resources to generate innovation outputs, such as patents, new products, and technological advancements (Vechkinzova et al., 2019). Unlike traditional methods, DEA does not require explicit functional forms or assumptions about production or cost functions, making it ideal for analysing complex and multidimensional innovation processes (Zhong, 2021). One of DEA's key strengths lies in its ability to compare efficiency scores with peers or benchmarks, enabling academics and practitioners to evaluate the performance of enterprises, organizations, and departments in innovation management (Lafarga, 2015). By considering both the quantity and quality of innovation outcomes relative to resources invested, DEA provides insights into innovation efficiency best practices and benchmarking opportunities (Park et al., 2016; Tone et al., 2020; Zhu, 2014). High-efficiency organizations identified through DEA analysis offer valuable insights into effective tactics, organizational skills, and management practices that contribute to superior innovation performance (Jiang et al., 2015).

Moreover, DEA's flexibility allows researchers to customize the analysis to individual circumstances or goals, addressing various aspects of innovation, such as product, process, or organizational innovation, as well as industry dynamics, regulatory settings, and market situations (Aparicio et al., 2020; Choi & Zo, 2019; Kou et al., 2016; Zeng et al., 2021). This adaptability ensures that DEA findings remain relevant and applicable to real-world innovation challenges, enhancing their utility for informing evidence-based strategies to improve innovation performance and competitiveness (Fang et al., 2020; Zemtsov & Kotsemir, 2019). Additionally, DEA's comprehensive and contextually relevant performance assessment provides actionable insights for innovation efficiency and strategic decision-making (Wang et al., 2016). By identifying inefficiencies or areas for improvement in innovation management, DEA enables organizations and policymakers to allocate resources effectively, establish innovation policies, and implement organizational reforms to enhance innovation ecosystems and competitiveness (De et al., 2020; Wang et al., 2016).

DEA's rigorous analytical framework, coupled with its flexibility and adaptability, makes it a valuable tool for assessing innovation efficiency and driving continuous improvement in innovation ecosystems. By leveraging DEA analysis, organizations and policymakers can gain valuable insights into innovation performance, identify best practices, and implement evidence-based strategies to enhance innovation capabilities and competitiveness.

1.2 Tobit Analysis

Tobit analysis serves as a powerful statistical technique in the realm of econometrics, particularly for exploring the intricate relationship between external factors and innovation efficiency within organizations or industries. Tobit model was introduced by James Tobin in 1958, and it has since found wide application in econometrics and other fields. This methodological approach is particularly relevant in innovation research due to its capability to handle censored data, where efficiency scores may be constrained by practical or theoretical limits, such as industry norms or technological constraints (Odah et al., 2017). In essence, Tobit analysis enables researchers to navigate through such censoring issues and provide unbiased estimates of the influence of external variables on innovation efficiency, even in scenarios where the data is truncated.

A distinctive feature of Tobit analysis is its ability to encompass various external factors that may impact innovation efficiency while simultaneously controlling for other relevant variables. Innovation efficiency, being a multifaceted construct, is influenced by a myriad of internal and external factors, including market dynamics, regulatory environments, technological trends, organizational characteristics, and resource allocation strategies (Guneri & Durmus, 2020). By incorporating these diverse factors into the analysis and accounting for potential confounding variables, Tobit analysis offers a comprehensive understanding of the unique contribution of external factors to innovation performance. This approach enhances the robustness and reliability of the findings, enabling researchers to derive actionable insights for organizational strategies and policy interventions.

Tobit analysis offers flexibility in modelling the relationship between external factors and innovation efficiency, accommodating various functional forms and distributional assumptions. Innovation processes often exhibit nonlinear relationships or complex patterns that may not be adequately captured by linear regression models (Mujasi et al., 2016). Tobit analysis addresses this limitation by allowing researchers to explore alternative functional forms, such as quadratic, logarithmic, or spline functions, thereby capturing the nuanced nuances in the data and providing a more accurate representation of the relationship between external factors and innovation efficiency.

Besides, Tobit analysis facilitates the quantification of the magnitude and direction of the effects of external factors on innovation efficiency through the estimation of regression coefficients and hypothesis testing. This quantitative assessment enables policymakers, industry leaders, and organizational managers to prioritize interventions and allocate resources effectively to enhance innovation capabilities and competitiveness (Barros et al., 2018). By identifying significant drivers of innovation performance, Tobit analysis guides evidence-based decision-making and fosters continual improvement in innovation ecosystems.

Tobit analysis emerges as a versatile and indispensable tool for assessing the impact of external factors on innovation efficiency, offering researchers a robust framework to navigate through censoring issues, control for confounding variables, accommodate complex relationships, and derive actionable insights for organizational strategies and policy interventions (Alam et al., 2020). Leveraging the strengths of Tobit analysis, researchers and decision-makers can gain deeper insights into the determinants of innovation efficiency and develop informed strategies to foster innovation and drive sustainable growth.

2 METHODOLOGY

In our research endeavour, we undertake a comprehensive exploration of global innovation dynamics employing a methodological framework that combines DEA and Tobit regression techniques. This dual analytical approach is informed by rich datasets sourced from the 2020 Global Innovation Index report, a seminal publication by the World Intellectual Property Organization (WIPO). At the heart of our methodology lies the utilization of normalized scores of inputs and outputs for 131 countries, a pivotal aspect facilitated by the DEA methodology. This process of normalization is integral to our analysis as it enables meaningful comparisons across diverse indicators, ensuring a standardized scale where higher or lower values consistently signify superior or inferior performance (Snyder, 2019). By rescaling the set values within a range of 0 to 100, with 0 representing the worst performance and 100 indicating the optimal outcome, we establish a foundation for coherent analysis and decision-making.

DEA is a nonparametric method used to evaluate the relative efficiency of decision-making units (DMUs) based on multiple inputs and outputs. The general formula for DEA efficiency score calculation is as follows:

$$Efficiency_i = \frac{\sum_{j=1}^{m} \lambda_j y_{ij}}{\sum_{k=1}^{n} \mu_k x_{ik}}$$

Where,

- Efficiency_i is the efficiency score of the ith DMU.
- $\lambda_j y_{ij}$ *and* $\mu_k x_{ik}$ are the weights assigned to the outputs and inputs respectively.
- m is *the* number of outputs.
- n is *the* number of inputs.

The efficiency score ranges from 0 to 1, where 1 indicates full efficiency and values less than 1 indicate inefficiency relative to the efficient frontier.

Simultaneously, our Tobit regression analysis delves into the intricate relationship between external factors and innovation outputs, leveraging a comprehensive dataset comprising 21 sub-indexes for each of the 131 countries. These sub-indexes encapsulate various dimensions of innovation inputs and outputs, offering a granular perspective on the factors shaping a country's innovation capabilities (Ørngreen & Levinsen, 2017). In the DEA methodology, efficiency measurements are derived by comparing countries against an empirical frontier, providing insights into their relative performance in transforming innovation inputs, such as R&D expenditure and education levels, into outputs like technological advancements and creative outputs (Pandey & Pandey, 2021). This approach allows us to identify both over-performers and under-performers, shedding light on opportunities for optimizing resource allocation and utilization to enhance innovation outcomes.

The Tobit regression analysis complements our DEA methodology by investigating how external factors, including economic stability, regulatory environments, and cultural aspects, influence innovation efficiency. By accounting for the left-censoring of efficiency scores at zero, which occurs when a country's output is minimal despite some inputs, this analysis provides insights into the thresholds and constraints hindering a country's innovation potential. Through this dual analytical approach, we not only assess the existing states of innovation efficiency but also elucidate the multifaceted impact of external conditions on innovation outcomes. Tobit analysis is used when the dependent variable is censored, meaning it has a lower or upper bound beyond which it cannot be observed. The general formula for Tobit regression is as follows:

The Tobit model is typically expressed as follows:

$$y_{i*} = \beta_0 + \beta_1 x_i + u_i$$
$$y_i = \{y_i*, 0, \text{if } y_{i*} > 0, \text{if } y_i \leq 0$$

Where:

- y_i is the observed dependent variable.
- y_{i*} is the latent (unobserved) dependent variable.
- x_i is the vector of independent variables.
- β_0 and β_1 are the coefficients to be estimated.
- u_i is the error term.

Ultimately, our findings aim to inform policymakers and stakeholders about strategies for optimizing innovation ecosystems globally. By highlighting the interplay between internal capabilities and external influences, we endeavour to provide actionable insights for fostering innovation-driven growth and competitiveness on a global scale. To conduct the research, DEAP software version 2.1 and Rstudio were employed for benchmarking purposes, ensuring rigorous analysis and accurate findings. In addition, the study employed Tobit model analyses utilizing AER and VGAM within R Studio to explore the determinants of innovation effectiveness in 2020. Figure 1 depicts the model developed for this study.

Table 1 - Model and Research construction. Source: Authors's illustration.

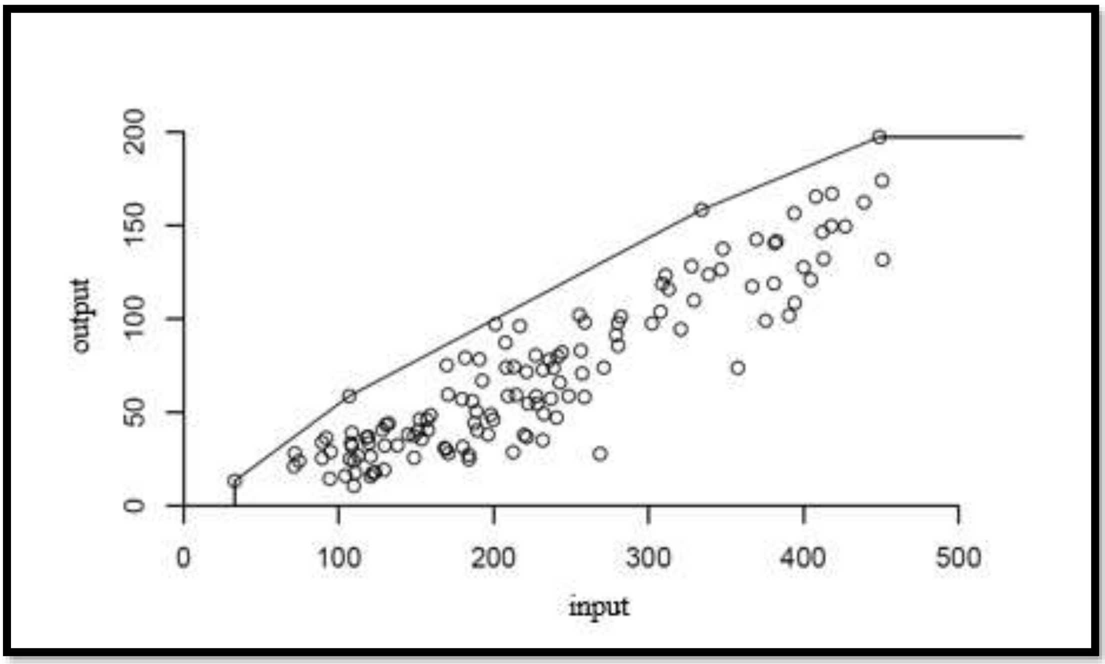
First Stage				Second Stage	
Input	Method	Output	Results	External factors	Method
• Institution (I) • Human resources and research (HRD) • Infrastructure (IF) • Market sophistication (MS) • Business sophistication (BS)	Data Envelopment Analysis (Intermediary approach)	• Knowledge and technology (KT) • Creative (C)	Innovation Efficiency	• Political environment (PE) • Regulatory environment (RE) • Business environment (BE) • Education (E) • Tertiary education (TE) • Research and development (RD) • ICT • General infrastructure (GI) • Ecological sustainability (ES) • Credit (C) • Investment (I) • Trade, competition and market scale (TCMS) • Knowledge workers (KW) • Innovation linkages (IL) • Knowledge absorption (KA) • Knowledge creation (KC) • Knowledge impact (KI) • Knowledge diffusion (KD) • Intangible assets (IA) • Creative goods and services (CGS) • Online creativity (OC)	Tobit Model (Regression)

3 RESULTS

3.1 Global Innovation Efficiency

The examination of relative efficiency scores provides a comprehensive assessment of innovation efficiency across 131 countries. In this study, countries are classified as efficient if they attain a technical efficiency score of 1.000, while those falling below this benchmark are deemed inefficient. Figure 1 showcases the world's input oriented and VRS technical innovation efficiency graph for the year 2020, offering a visual representation of the distribution of innovation efficiency across nations. Complementing this visualization, Table 2 presents the relative innovation efficiency scores derived from standard DEA with input oriented CCR and VRS models for each country analyzed. Remarkably, the innovation efficiency scores obtained in both studies closely mirror those presented in Table 2, underscoring the consistency and reliability of the methodology utilized.

Figure 1 - Innovation efficiency based on input-oriented and VRS



The study's findings reveal a sobering reality: out of the 131 countries scrutinized, only 41 have achieved the pinnacle of technical innovation efficiency, signified by a score of 1.000. This implies that merely 31% of the countries assessed demonstrate efficiency in innovation. Conversely, a staggering 69%, equivalent to 90 countries, fall short of this mark, highlighting prevalent inefficiencies in innovation practices globally throughout the year 2020. Such insights hold significant implications for policymakers, industry leaders, and stakeholders invested in fostering innovation-driven growth and competitiveness on a global scale.

Table 2 - Innovation Technical Efficiency Scores

	Country	Income group	Innovation efficiency	
			DEAP versi 2.1	Rstudio
1	Albania	UM	0.4861	0.4861
2	Algeria	UM	0.8632	0.8632
3	Argentina	UM	0.7030	0.7030
4	Armenia	UM	1.0000	1.0000
5	Australia	H	0.6191	0.6191
6	Austria	H	0.8139	0.8139
7	Azerbaijan	UM	0.5217	0.5217

8	Bahrain	H	0.4386	0.4386
9	Bangladesh	LM	1.0000	1.0000
10	Belarus	UM	0.8471	0.8471
11	Belgium	H	0.7592	0.7579
12	Benin	L	0.7680	0.7660
13	Bolivia	LM	0.5769	0.5769
14	Bosnia & Herzegovina	UM	0.6585	0.6585
15	Botswana	UM	0.4932	0.4932
16	Brazil	UM	0.5961	0.5961
17	Brunei Darussalam	H	0.3564	0.3564
18	Bulgaria	UM	1.0000	1.0000
19	Burkina Faso	L	0.5498	0.5498
20	Cabo Verde	LM	0.9271	0.9271
21	Cambodia	LM	0.9847	0.9847
22	Cameroon	LM	0.6782	0.6558
23	Canada	H	0.6957	0.6939
24	Chile	H	0.4848	0.4848
25	China	UM	1.0000	1.0000
26	Colombia	UM	0.4918	0.4918
27	Costa Rica	UM	0.7751	0.7751
28	Cote D'Ivoire	LM	0.8024	0.8024
29	Croatia	H	0.8103	0.8103
30	Cyprus	H	0.8958	0.8958
31	Czech Republic	H	0.9447	0.9447
32	Denmark	H	0.8311	0.8311
33	Dominican Republic	UM	0.5773	0.5773
34	Ecuador	UM	0.6312	0.6312
35	Egypt	LM	0.8809	0.8809
36	El Salvador	LM	0.5475	0.5475
37	Estonia	H	0.9761	0.9761
38	Ethiopia	L	1.0000	1.0000
39	Finland	H	1.0000	1.0000
40	France	H	0.8927	0.8927
41	Georgia	UM	0.5546	0.5513
42	Germany	H	1.0000	1.0000
43	Ghana	LM	0.7427	0.7427
44	Greece	H	0.6875	0.6875
45	Guatemala	UM	0.7180	0.7180
46	Guinea	L	1.0000	1.0000
47	Honduras	LM	0.6163	0.6131
48	Hong Kong	H	1.0000	1.0000
49	Hungary	H	0.9359	0.9359
50	Iceland	H	0.9560	0.9560
51	India	LM	1.0000	1.0000
52	Indonesia	LM	0.8231	0.8231
53	Iran	UM	1.0000	1.0000
54	Ireland	H	1.0000	1.0000
55	Israel	H	1.0000	1.000
56	Italy	H	1.0000	1.0000
57	Jamaica	UM	1.0000	1.0000
58	Japan	H	0.7722	0.7722
59	Jordan	UM	0.5487	0.5439
60	Kazakhstan	UM	0.3989	0.3989
61	Kenya	LM	0.8091	0.7863
62	Kuwait	H	0.5901	0.5901
63	Kyrgyzstan	LM	0.5121	0.5121
64	Lao	LM	0.8514	0.8477

65	Latvia	H	0.8343	0.8343
66	Lebanon	UM	0.6449	0.6449
67	Lithuania	H	0.7298	0.7298
68	Luxembourg	H	1.0000	1.0000
69	Madagascar	L	1.0000	1.0000
70	Malawi	L	1.0000	1.0000
71	Malaysia	UM	0.6926	0.6926
72	Mali	L	1.0000	1.0000
73	Malta	H	1.0000	1.0000
74	Mauritius	UM	1.0000	1.0000
75	Mexico	UM	0.7056	0.7056
76	Mongolia	LM	0.9607	0.9607
77	Montenegro	UM	0.9071	0.9071
78	Morocco	LM	0.8373	0.8373
79	Mozambique	L	0.7154	0.7154
80	Myanmar	LM	1.0000	1.0000
81	Namibia	UM	0.7552	0.7552
82	Nepal	L	0.5791	0.5791
83	Netherlands	H	1.0000	1.0000
84	New Zealand	H	0.6405	0.6405
85	Niger	L	1.0000	1.0000
86	Nigeria	LM	0.6532	0.6532
87	North Macedonia	UM	0.6195	0.6195
88	Norway	H	0.7104	0.7104
89	Oman	H	0.4977	0.4977
90	Pakistan	LM	1.0000	1.0000
91	Panama	H	1.0000	1.0000
92	Paraguay	UM	0.5936	0.5936
93	Peru	UM	0.3541	0.3541
94	Philippines	LM	1.0000	1.0000
95	Poland	H	0.7815	0.7815
96	Portugal	H	0.9052	0.9052
97	Qatar	H	0.6729	0.6729
98	Republic of Korea	H	0.8157	0.8143
99	Republic of Moldova	LM	1.0000	1.0000
100	Romania	UM	1.0000	1.0000
101	Russian Federation	UM	0.6056	0.6056
102	Rwanda	L	0.4471	0.4471
103	Saudi Arabia	H	0.4465	0.4465
104	Senegal	LM	1.0000	1.0000
105	Serbia	UM	0.9255	0.9255
106	Singapore	H	0.6804	0.6627
107	Slovakia	H	0.9954	0.9954
108	Slovenia	H	0.7575	0.7575
109	South Africa	UM	0.5722	0.5638
110	Spain	H	0.8883	0.8883
111	Sri Lanka	UM	1.0000	1.0000
112	Sweden	H	1.0000	1.0000
113	Switzerland	H	1.0000	1.0000
114	Tajikistan	L	1.0000	0.9422
115	Thailand	UM	0.7557	0.7495
116	Togo	L	0.7747	0.7747
117	Trinidad and Tobago	H	0.5685	0.5685
118	Tunisia	LM	1.0000	1.0000
119	Turkey	UM	0.6943	0.6943
120	Uganda	L	1.0000	1.0000
121	Ukraine	LM	1.0000	1.0000
122	United Arab Emirates	H	0.5742	0.5742

123	United Kingdom	H	1.0000	1.0000
124	United Republic of Tanzania	L	1.0000	1.0000
125	United States of America	H	0.9656	0.8960
126	Uruguay	H	0.7546	0.7546
127	Uzbekistan	LM	0.5067	0.5067
128	Viet Nam	LM	0.9858	0.9747
129	Yemen	L	1.0000	1.0000
130	Zambia	LM	0.5589	0.5589
131	Zimbabwe	LM	1.0000	1.0000
	Global mean		0.7974	0.7956

The list of countries with innovation efficiency scores of 1.000 includes China, Ethiopia, Finland, Germany, Guinea, Hong Kong, India, Iran, Ireland, Israel, Italy, Jamaica, Luxembourg, Madagascar, Malawi, Mali, Malta, Mauritius, Myanmar, the Netherlands, Niger, Pakistan, Panama, the Philippines, the Republic of Moldova, Romania, Senegal, Sweden, Switzerland, Tajikistan, Tunisia, Uganda, Ukraine, the United Kingdom, the United Republic of Tanzania, and Zimbabwe. These countries demonstrate maximum efficiency in innovation, while the remaining 90 countries exhibit scores below 1.000, indicating inefficiency. Peru ranks as the country with the lowest technical innovation efficiency score at 0.3541, emphasizing the need for improvement in innovation strategies. The global average technical innovation efficiency for 2020 stands at 0.7974, with a median of 0.8157, indicating a right-skewed distribution where most values are concentrated on the higher end.

Each country receives a score ranging from 0 to 1, with 1 indicating maximum efficiency in innovation. Results from both methods show consistency, with high-income countries often achieving scores of 1.000, reflecting robust innovation capabilities facilitated by infrastructure and policies. Conversely, some low-income and low-middle-income countries also achieve maximum efficiency scores, suggesting successful policies or sectors driving innovation despite economic constraints. Notably, countries like the United Kingdom, Sweden, and Switzerland exhibit maximum efficiency scores despite their high-income status, highlighting strong investment in research and development and robust technology infrastructures. Conversely, countries such as Rwanda and Uganda, despite lower income statuses, achieve maximum efficiency scores, indicating effective resource deployment or specific government policies driving innovation.

The global average efficiency score stands at 0.7956, serving as a benchmark for comparing countries' innovation performance against the global standard and identifying areas for improvement. These findings offer insights for policymakers and researchers to understand disparities in innovation efficiency and inform strategies for fostering innovation on a global scale. Figure 2 on the world map illustrates global innovation efficiency levels. Among the countries studied, only 11, or 8.4%, scored below 0.5 in technical innovation efficiency. The majority, comprising 79 countries or 60.3%, achieved scores between 0.5 and less than 1.000, while 41 countries attained a perfect score of 1.000. These findings, detailed in Table 3, underscore the suboptimal state of innovation management globally, with the lowest technical innovation efficiency score observed at 0.8. Notably, 31.3% of countries achieved innovation efficiency levels equal to or higher than 1.000, while 8.4% scored below 0.5, highlighting disparities in innovation performance. These findings provide valuable insights for understanding global innovation trends and identifying areas for enhancement in innovation management practices.

Figure 2 - Global innovation efficiency 2020

Table 3 - Summary of Global Technical Innovation Efficiency Achievement for the year 2020

Efficiency Range	Countries	%
0.3<= E <0.4	3	2.3
0.4<= E <0.5	8	6.1
0.5<= E <0.6	17	13.0
0.6<= E <0.7	16	12.2
0.7<= E <0.8	17	13.0
0.8<= E <0.9	16	12.2
0.9<= E <1.0	13	9.9
E =1	41	31.3

*E= Technical Efficiency Values

Table 4 provides a comprehensive overview of the 2020 innovation reference frequency analysis, shedding light on the visibility and influence of countries within the global innovation landscape. Notably, all countries listed attained a perfect technical efficiency score of 1.0000, indicating optimal efficiency in innovation. The "Frequency of references" reveals the extent to which each country is cited in studies, reports, or databases related to innovation, with China and Switzerland emerging as the most frequently referenced nations, garnering 54 and 52 references, respectively. Such high citation frequencies suggest robust participation in global innovation networks, likely bolstered by substantial investments in research and development. Table 4, it provides a detailed analysis of the 2020 innovation reference set, listing countries that can serve as benchmarks for enhancing innovation skills. Each entry includes a technical proficiency score alongside a reference set of countries, offering nuanced insights into comparative analysis or collaborative efforts. These benchmark countries, identified through rigorous DEA analysis, serve as exemplars for nations striving to elevate their innovation efficiency to achieve a perfect score of 1.000. The comprehensive list of benchmark countries allows for a thorough examination of technical proficiency, global cooperation dynamics, and regional expertise, providing policymakers and researchers with invaluable insights into fostering innovation excellence on a global scale.

Table 4 - Innovation Reference Set Analysis

Country	Innovation efficiency value	Reference set
Albania	0.4861	Myanmar, Switzerland, Iran, China, Sweden
Algeria	0.8632	Hong Kong, Switzerland, Myanmar
Argentina	0.7030	Iran, Sweden, Hong Kong, Malta
Australia	0.6191	Switzerland, Iran, Ukraine, China, Malta
Austria	0.8139	Malta, Germany, Bulgaria, Netherlands, Hong Kong
Azerbaijan	0.5217	Iran, Myanmar, Guinea, China
Bahrain	0.4386	Switzerland, India, Hong Kong, Sweden, China, Myanmar
Belarus	0.8471	Myanmar, Hong Kong, Tunisia, Ukraine
Belgium	0.7592	Netherlands, Ukraine, India, Finland, Hong Kong
Benin	0.7680	Sweden, Myanmar, Zimbabwe
Bolivia	0.5769	Switzerland, China, Sweden, Myanmar
Bosnia & Herzegovina	0.6585	Armenia, Tunisia, Myanmar, Switzerland, Ukraine
Botswana	0.4932	Madagascar, China, Ukraine, Sweden, Switzerland, Myanmar
Brazil	0.5961	Myanmar, Sweden, Ukraine, China, Iran
Brunei Darussalam	0.3564	Malta, Ethiopia, Jamaica, Sweden, China
Burkina Faso	0.5498	Myanmar, Hong Kong, Sweden, Guinea
Cabo Verde	0.9271	Malta, Switzerland, Iran
Cambodia	0.9847	China, Myanmar, Hong Kong, Malawi, Guinea
Cameroon	0.6782	Pakistan, Mali, Sweden, Ukraine, Myanmar
Canada	0.6957	Ukraine, India, Armenia, Switzerland, China
Chile	0.4848	Armenia, Ukraine, Hong Kong, Myanmar, Iran, India, China
Colombia	0.4918	India, Hong Kong, Myanmar, China, Philippines, Sweden
Costa Rica	0.7751	Hong Kong, India, Malta, Switzerland, China, Bulgaria, Ukraine
Cote D'Ivoire	0.8024	Myanmar, Guinea, Malawi, Hong Kong
Croatia	0.8103	Switzerland, Armenia, Bulgaria, Hong Kong, Ukraine
Cyprus	0.8958	Bulgaria, Hong Kong, China, Ukraine, Armenia
Czech Republic	0.9447	Germany, Ukraine, Ireland, Bulgaria, Netherlands, China
Denmark	0.8311	Switzerland, Germany, Switzerland, Malta
Dominican Republic	0.5773	Myanmar, Sweden, Hong Kong, Switzerland, China
Ecuador	0.6312	Myanmar, Switzerland, Sweden, India, China
Egypt	0.8809	India, China, Switzerland, Sweden, Myanmar
El Salvador	0.5475	Myanmar, Sweden, China, Iran, Ukraine, Madagascar
Estonia	0.9761	Iran, United Kingdom, Hong Kong, Switzerland, China
France	0.8927	China, Switzerland, India, Bulgaria, Malta, Germany
Georgia	0.5546	China, Ukraine, Senegal, Madagascar, Myanmar
Ghana	0.7427	Sweden, Hong Kong, Switzerland, , Myanmar
Greece	0.6875	Myanmar, Ukraine, Tunisia, Switzerland, Hong Kong
Guatemala	0.7180	Sweden, Malawi, Guines, China, Hong Kong

Honduras	0.6163	Philippines, Armenia, Myanmar, India, China, Sweden
Hungary	0.9359	Germany, Hong Kong, Ireland, Ukraine
Iceland	0.9560	Switzerland, Germany, India, Malta, Ukraine
Indonesia	0.8231	Sweden, India, Myanmar, Switzerland, China
Japan	0.7722	China, Switzerland, Ireland, Armenia, Philippines
Jordan	0.5487	Ukraine, Ethiopia, Zimbabwe, Tajikistan, Madagascar, Myanmar
Kazakhstan	0.3989	India, Hong Kong, Switzerland, China,Sweden, Myanmar
Kenya	0.8091	India, Ukraine, Armenia, China, Malawi, Pakistan
Kuwait	0.5901	India, Myanmar, China, Switzerland, Sweden
Kyrgyzstan	0.5121	Sweden, Myanmar, Ukraine, Switzerland
Lao	0.8514	Ukraine, India, Sweden, Malta, China
Latvia	0.8343	China, Switzerland, Bulgaria, India, Malta
Lebanon	0.6449	China, India, Ukraine, Iran, Sweden, Myanmar
Lithuania	0.7298	Bulgaria, China, Switzerland, Armenia, India, Ukraine
Malaysia	0.6926	China, Switzerland, Ukraine, Armenia, India, Iran
Mexico	0.7056	Hong Kong, Armenia, Switzerland, China, India, Myanmar
Mongolia	0.9607	China, Switzerland, Hong Kong
Montenegro	0.9071	Iran, Switzerland, China, Malta
Morocco	0.8373	Armenia, Tunisia, Switzerland, Senegal
Mozambique	0.7154	Myanmar, Sweden, Ethiopia
Namibia	0.7552	Myanmar, Guinea, China, Madagascar
Nepal	0.5791	India, Bangladesh, Sri Lanka, Sweden, Iran
New Zealand	0.6405	Iran, Switzerland, Armenia, United Kingdom, China
Nigeria	0.6532	Guinea, Malawi, Myanmar, Sweden, Hong Kong, Yemen
North Macedonia	0.6195	China, Armenia, Switzerland, Myanmar, India
Norway	0.7104	Germany, Switzerland, Malta, India, Bulgaria
Oman	0.4977	Sweden, Hong Kong, Switzerland, Myanmar
Paraguay	0.5936	Sweden, Hong Kong, Myanmar, Switzerland, China
Peru	0.3541	Sweden, Switzerland, Malta, Tanzania, Iran
Poland	0.7815	Ukraine, Switzerland, Armenia, Hong Kong, Bulgaria
Portugal	0.9052	Ukraine, Bulgaria, China, Germany, Switzerland
Qatar	0.6729	China, Switzerland, Malta, Hong Kong
Republic of Korea	0.8157	China, Switzerland, Ukraine, Malta, Netherlands
Russian Federation	0.6056	Ukraine, Myanmar, India, Switzerland, China, Sweden
Rwanda	0.4471	Malawi, Ethiopia, Sweden, Myanmar, Iran, Guinea
Saudi Arabia	0.4465	India, Switzerland, Sweden, Malta
Serbia	0.9255	Armenia, Ukraine, Tunisia, Romania, Myanmar
Singapore	0.6804	Armenia, China, Ukraine, Malawi, India
Slovakia	0.9954	Ukraine, Italy, China, Armenia, Bulgaria
Slovenia	0.7575	Bulgaria, Hong Kong, Ukraine, Malta, Germany
South Africa	0.5722	Armenia, Sweden, Myanmar, China, Ukraine, India

Spain	0.8883	United Kingdom, Switzerland, Italy, Armenia
Thailand	0.7557	India, Armenia, Sweden, China, Pakistan, Ukraine
Togo	0.7747	Guinea, Sweden, Madagascar, Myanmar
Trinidad and Tobago	0.5685	Iran, Guinea, Myanmar, Ethiopia
Turkey	0.6943	China, Myanmar, India, Switzerland, Sweden
United Arab Emirates	0.5742	China, Hong Kong, Switzerland, Malta, Sweden
United States of America	0.9656	Ukraine, Israel, China, Switzerland
Uruguay	0.7546	Iran, Armenia, Bulgaria, China, Ethiopia
Uzbekistan	0.5067	India, Sweden, Myanmar, Switzerland
Viet Nam	0.9858	Malawi, China, Philippines, Armenia
Zambia	0.5589	Bangladesh, Sweden, Myanmar

4 EXTERNAL FACTORS ANALYSIS

Model Tobit scrutinized 21 independent variables, revealing that 16 of them (76.2%) significantly influence global innovation efficiency. Notably, positive associations were found with KC, KI, KD, IA, CGS, and OC, while negative associations were observed between innovation efficiency and variables such as RE, E, ICT, ES, C, I, TCMS, KW, IL, and KA. Further analysis indicated that the addition of one unit to certain variables led to marginal decreases or increases in innovation efficiency. Subsequently, a refined model was constructed, excluding insignificant variables while reaffirming the importance of all 16 tested independent factors for global innovation efficiency in 2020. Negative relationships persisted with RE, E, ICT, ES, C, I, TCMS, KW, IL, and KA, while positive relationships were evident with KC, KI, KD, IA, CGS, and OC. The statistical significance of these variables for global innovation efficiency was underscored by Wald statistic values and p-values at a 1% level of significance. This comprehensive analysis offers valuable insights into the multifaceted dynamics shaping innovation effectiveness on a global scale.

The table presents a detailed statistical analysis of coefficients in a regression model, outlining the impact and significance of various independent variables on the dependent variable. Each row represents a different variable, such as "RE" or "OC," with corresponding coefficients of variation, standard deviations, t-statistics, and probabilities. The coefficient of variation indicates the expected change in the dependent variable for a one-unit increase in the corresponding independent variable, assuming other variables remain constant. For instance, the coefficient for "KC" (0.0052) suggests that as "KC" increases by one unit, the dependent variable increases by 0.0052 units. Standard deviations reflect the variability or precision of the coefficient estimates, with smaller values indicating more precise estimates. T-statistics are used to determine the statistical significance of coefficients, calculated as the coefficient divided by its standard deviation. High absolute values of t-statistics indicate coefficients that are significantly different from zero. Probability values (p-values) help assess the significance of results, with notation denoting levels of significance ("" for $p \leq 0.01$, "" for $p \leq 0.05$, and "" for $p \leq 0.1$). For example, "constant" has a highly significant p-value (< 2.16e-16), indicating strong evidence against the null hypothesis that the coefficient is zero.

Table 4 - Tobit analysis

	Coefficient of variation	Standard Deviation	t-statistic	Probability
Constant	1.354	0.0659	20.552	<2e-16***
RE	-0.0015	0.0007	-2.304	0.0212**
E	-0.0025	0.0007	-3.520	0.0004***
ICT	-0.0042	0.0007	-5.643	1.67e-8***
ES	-0.0022	0.0010	-2.250	0.0244**
C	-0.0019	0.0007	-2.906	0.0037***
I	-0.0025	0.0005	-4.732	2.23e-6***
TCMS	-0.0063	0.0010	-6.313	2.73e-10***
KW	-0.0024	0.0009	-2.720	0.0065***
IL	-0.0038	0.0010	-3.927	8.58e-5***
KA	-0.0029	0.0013	-2.303	0.0213**
KC	0.0052	0.0009	5.511	3.57e-8***
KI	0.0066	0.0012	5.638	1.72e-8***
KD	0.0042	0.0011	3.995	6.48e-5***
IA	0.0084	0.0011	7.770	7.86e-15***
CGS	0.0042	0.0009	4.930	8.21e-7***
OC	0.0042	0.0009	4.907	9.24e-7***

Remarks:*** $p \leq 0.01$, **$p \leq 0.05$

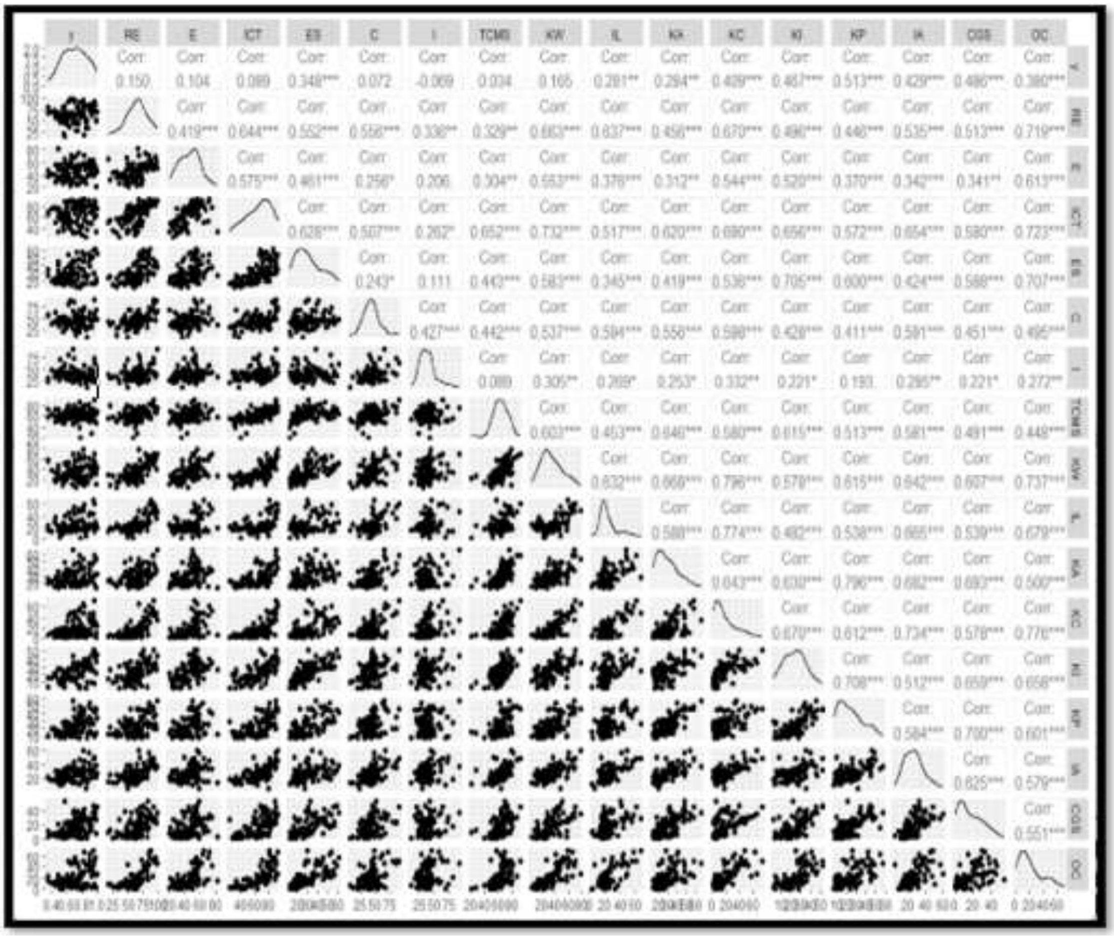
The Tobit model equation derived from the analysis is as follows:

$$\mathbf{y = 1.354 - 0.0015RE - 0.0025E - 0.0042ICT - 0.0022ES - 0.0019C - 0.0025I - 0.0063TCMS - 0.0024KW - 0.0038IL - 0.0029KA + 0.0052KC + 0.0066KI + 0.0042KD + 0.0084IA + 0.0042CGS + 0.0042OC}$$

This equation encapsulates the relationship between the independent variables and the dependent variable, with the signs of coefficients indicating the direction of influence each variable has on the outcome.

Figure 4 illustrates the relationship between the independent variables and the dependent variable, as well as the interconnections among the independent variables. Notably, the Tobit regression model exhibits a remarkable R-squared value of 0.8523, indicating that the 16 independent factors account for 85.23% of the variation in the dependent variable. With an R-squared value exceeding 70%, the model effectively elucidates the relationship between the independent and dependent factors. Specifically, variations in independent variables such as RE, E, ICT, ES, C, I, TCMS, KW, IL, KA, KC, KI, KP, IA, CGS, and OC explain 85.23% of the fluctuations in the efficiency of technical progress globally in 2020. This high explanatory power underscores the robustness of the Tobit regression model in capturing the complex dynamics influencing innovation efficiency on a global scale.

Figure 4 - Relationship between all independent variables



5 DISCUSSION

The findings align with Cooper et al.'s (2006, 2007) emphasis on the significance of the DEA approach in assessing country efficiency. DEA, emerging as a robust methodology since 1978, reveals intricate relationships between inputs and outputs in innovation activities, offering opportunities for efficiency enhancement (Cooper et al., 2007). Esteemed indices such as the Global Innovation Index and the Bloomberg Index advocate prioritizing innovation efforts, prompting numerous studies to gauge global innovation efficiency (Cooper et al., 2006; Cooper et al., 2007).

DEA's non-parametric nature allows it to handle various data types without strict assumptions, making it advantageous for evaluating the multifaceted nature of global innovation processes where traditional econometric approaches may struggle (Cooper et al., 2006). By generating efficiency scores and identifying best practices, DEA provides valuable insights for policymakers and stakeholders to enhance national innovation performance (Narayanan et al., 2022). Thus, DEA serves as a potent tool for benchmarking country efficiency, offering actionable insights for policymakers and practitioners.

The study illustrates the overall performance outcome depicts global innovation efficiency as unsatisfactory considering the global technical innovation efficiency mean score of 0.8. The global mean falls below the value of 1.000. The median technical innovation efficiency in 2020 is 0.8157, which is higher than the global mean (0.7974), indicating a right-skewed distribution of the data where more values are concentrated on the right side of the distribution graph while the left side of the distribution graph is longer (von Hippel, 2005). Approximately 31.3% of countries attain efficiency levels of 1.000, with around 8.4% of the surveyed nations reporting innovation efficiency values below 0.5.

A total of 41 countries demonstrated innovation efficiency in 2020, serving as benchmarks (Charnes et al., 1978; Cook & Seiford, 2009; Cooper et al., 2007; Fried et al., 2008; Thanassoulis, 2001) for the 90 countries that lacked efficiency. Between four to seven countries can serve as benchmarks for the inefficient nations. These benchmarks can aid inefficient countries in enhancing their efficiency (Coelli et al., 2005; Farrell, 1957; Murillo-Zamorano, 2004) levels to 1.000. Furthermore, the study findings reveal that 9 low-income countries and 7 lower-middle-income countries, compared to only 2 high-income countries and 6 upper-middle-income countries, achieved an efficiency scale of 1.000. This illustrates that low-income (Werker et al., 2017) and lower-middle-income (Philpott & Kshetri, 2019) countries are capable of operating at an optimal scale in achieving innovation efficiency.

Countries proficient in innovation have achieved maximum 100% performance in cost (CRSTE), management (VRSTE), and efficiency scale aspects. The study findings reveal that only 22 out of 131 countries, accounting for 16.8%, were proficient in innovation across cost, management, and innovation operation size aspects in 2020. These findings are quite instructive, considering that only two high-income countries, Malta and Panama, achieved innovation proficiency in cost, management, and operation size aspects. However, the encouraging aspect is that nine low-income countries and six lower-middle-income countries are proficient in innovation across cost, management, and innovation operation size aspects for the year 2020.

The study findings indicate that 19 out of 131 countries, accounting for 14.5%, are weak in innovation in terms of cost and innovation operation size aspects for the year 2020. Among these 19 countries, 11 are from the high-income group category, with three countries from the upper-middle-income group category. The weakness in innovation among these 19 countries is attributed to wastage in innovation costs and innovation operation size, each at 9.18%. This illustrates that despite achieving a VRSTE efficiency score of 1.000, most high-income countries have weak capabilities in managing innovation costs and operation sizes (Bloom et al., 2020; Jones & Summers, 2018).

In term of external factors analysis, the external factors studied indicate that most aspects serving as inputs in innovation activities exhibit a negative relationship with the level of global innovation efficiency. Meanwhile, the output factors of these innovation activities demonstrate a positive relationship with the level of global innovation efficiency. Regulatory environment factors negatively impacted global innovation efficiency for the 2020 in several ways. For example, stringent regulations may impose excessive compliance costs on businesses, diverting resources away from innovation activities (Hall & Van Reenen, 2000). Additionally, complex regulatory requirements can create barriers to entry for new firms, reducing competition and stifling innovation (Coe et al., 2020). Moreover, regulatory uncertainty can discourage investment in innovative projects by creating ambiguity about future regulatory changes and their potential impact on business operations (Bloom et al., 2016). Therefore, regulatory factors have the potential to impede innovation efficiency when not appropriately designed or implemented.

External factors related to education can negatively influence innovation efficiency in several ways. For instance, inadequate education systems that fail to cultivate critical thinking, problem-solving skills, and creativity among individuals may lead to a lack of skilled workforce capable of driving innovation (Büchel & Pannenberg, 2020). Additionally, disparities in access to quality education, particularly among marginalized populations, can limit the pool of talent available for innovation, thus hampering overall innovation efficiency. Rigid education systems that prioritize rote learning over experiential learning and interdisciplinary approaches may stifle creativity and innovation. Therefore, addressing deficiencies in education systems and promoting equitable access to quality education are crucial for enhancing innovation efficiency.

External factors such as credit availability and investment opportunities also can have adverse effects on innovation efficiency. Limited access to credit and investment options, particularly for small and medium-sized enterprises (SMEs) and startups, may restrict financial resources for innovation initiatives (Minniti & Naudé, 2010). This can lead to underinvestment in R&D projects and hinder innovation efficiency. Additionally, high borrowing costs and strict lending requirements imposed by financial institutions may deter firms from pursuing innovative but risky ventures, further impeding innovation. Economic instability and downturns can exacerbate credit constraints and reduce investment in innovation, negatively affecting innovation efficiency (Vivarelli, 2017). Therefore, ensuring accessible credit and fostering a conducive investment environment are crucial for promoting innovation efficiency. These findings align with the existing literature on the negative relationship between external factors and innovation efficiency (Aghion et al., 2005; Narula & Kraak, 2021; Radicic & Pugh, 2017; Roper & Love, 2016).

On the other hand, the presence of knowledgeable workers and their ability to absorb and apply new knowledge significantly influence innovation efficiency. When there's a shortage of skilled workers, innovation potential is constrained, as the workforce lacks the expertise necessary to drive innovative ideas forward (Adams et al., 2016). Moreover, insufficient training programs can exacerbate this issue by leaving employees ill-equipped to contribute effectively to innovation processes. Furthermore, within organizations, ineffective mechanisms for absorbing knowledge can lead to missed opportunities for innovation. This occurs when there are gaps in the sharing and integration of knowledge across different departments or when external knowledge sources are not effectively identified and leveraged (Kogut & Zander, 1992; Cohen & Levinthal, 1990).

Our analysis shows that knowledge creation, impact, and diffusion play crucial roles in driving global innovation efficiency. Firstly, knowledge creation involves the generation of new ideas, technologies, and solutions. This process fuels innovation by providing the foundation for novel products, services, and processes (Nonaka & Takeuchi, 1995). By continuously generating new knowledge, organizations and economies can stay ahead of the curve and adapt to changing market demands, thereby enhancing innovation efficiency. Secondly, the impact of knowledge refers to the tangible outcomes resulting from its application, such as increased productivity, improved quality, and enhanced competitiveness. When knowledge is effectively applied in practice, it can lead to transformative changes within organizations and industries (Kline & Rosenberg, 1986). These positive impacts contribute to innovation efficiency by driving growth and driving continuous improvement. Then, knowledge diffusion involves the spread of knowledge across individuals, organizations, and regions. By facilitating the exchange of ideas, best practices, and lessons learned, knowledge diffusion accelerates innovation by enabling stakeholders to leverage existing knowledge and build upon the successes of others (Rogers, 2003). This democratization of knowledge fosters collaboration reduces duplication of efforts and promotes innovation efficiency on a global scale. Knowledge creation, impact, and diffusion are essential drivers of global innovation efficiency, as they enable the continuous generation, application, and dissemination of knowledge, leading to sustained economic growth and societal advancement.

Creative goods and services, along with online creativity, contribute significantly to global innovation efficiency. Creative goods and services refer to innovative products and offerings that meet emerging market needs or redefine existing markets. These novel offerings often result from creative thinking and problem-solving, leading to increased consumer satisfaction and market competitiveness (Hennessey & Amabile, 2010). Online creativity, on the other hand, encompasses the generation and sharing of innovative ideas, content, and solutions through digital platforms and networks. The internet provides a vast ecosystem for collaboration, idea exchange, and co-creation, enabling individuals and organizations to leverage collective intelligence and accelerate innovation processes. Overall, creative goods and services, coupled with online creativity, play a pivotal role in enhancing innovation efficiency by fuelling idea generation, market responsiveness, and collaborative innovation ecosystems in the global economy.

This suggests that the resources used in innovation activities are abundant, but success is limited. Therefore, every country must ensure that the innovation resources used are not wasted in achieving a high level of innovation efficiency performance. Innovation efficiency is based on the level of success that can be generated from innovation resources. Therefore, benchmarking can assist less capable and efficient countries in formulating and developing innovation policies equivalent to those of more capable countries. Indeed, it cannot be denied that countries from the middle- and low-income groups are also able to achieve good innovation efficiency (Hausmann & Rodrik, 2003). This is because these countries can utilize limited innovation resources to produce higher levels of success. Therefore, this study demonstrates that external factors, whether directly or indirectly, serve as sources or inputs to innovation activities and should be used judiciously to avoid wastage.

However, the most surprising result of the analysis is that R&D showed no relationship with the level of global innovation efficiency for the year 2020. Our findings are consistent with previous research indicating no significant relationship between R&D expenditure and innovation efficiency (Crescenzi & Rodríguez-Pose, 2012; Edler & Slater, 2019; Svejnar & Munich, 2010).). The lack of significance of R&D in influencing innovation efficiency may be attributed to several factors. One study by Teece (1986) suggests that while R&D is important for innovation, its effectiveness depends on complementary assets and capabilities within the organization.

Furthermore, according to Cohen and Levinthal (1990), firms may face challenges in leveraging their R&D investments effectively due to limitations in absorptive capacity, hindering the translation of R&D outcomes into innovative products or processes. Additionally, Aghion et al. (2005) highlight the role of competition and market structure in mediating the relationship between R&D and innovation efficiency, indicating that other contextual factors may overshadow the direct impact of R&D on innovation outcomes.

CONCLUSION

Utilizing non-parametric analysis, particularly DEA and Tobit regression, offers a robust approach to understanding and enhancing global innovation efficiency. DEA enables organizations to assess their performance relative to peers and identify areas for improvement in fostering a culture of continuous innovation and competitiveness (Cooper at al., 2006). Tobit regression analysis complements DEA by evaluating the impact of external factors such as regulatory environment, market competition, and technological change on innovation outcomes, enabling organizations to adapt their strategies accordingly (Zhang, 2020). The integration of DEA and Tobit regression provides a comprehensive view of the innovation process, considering both internal capabilities and external drivers (Chen & Malhotra, 2009; Kleinknecht & Verspagen, 2012; Soete & Freeman, 2010). This understanding empowers countries to refine their innovation strategies, driving sustainability and long-term success in a dynamic global innovation landscape (Aghion et al., 2013; Morgan & Nauwelaers, 2009). As technology evolves and markets become more interconnected, leveraging non-parametric analysis becomes crucial for sustaining innovation excellence globally (Smith & Johnson, 2021).

While the analysis relied on traditional DEA methodology, it's important to note that there are advanced versions such as bootstrapping, super efficiency, and slack-based DEA models available (Cook & Seiford, 2009). These advanced DEA models can potentially offer more accurate and scientifically validated measures of innovation efficiency. Therefore, future studies could benefit from applying these advanced DEA models to better identify and quantify innovation efficiency values. Bootstrapping enhances efficiency scores through a multiple-sampling approach (Simar & Wilson, 1998). These scores address the limitations of standard DEA techniques by providing more reliable solutions (Edquist et al., 2018). Bootstrapping estimation minimizes bias, reduces outliers and maintains the integrity of sample distributions and standard deviations (Simar & Wilson, 2007). Meanwhile, the super efficiency DEA technique, pioneered by Anderson and Peterson (1993), aims to create an improved ranking system and offer more discriminating power and accurate efficiency measures.

On the other hand, external factors influencing global innovation efficiency, considered crucial, exhibit both negative, positive, and non-direct relationships with global innovation efficiency. Important factors like R&D show no relationship with global innovation efficiency. Several crucial external factors such as ICT, education, investment, and regulatory measures show an inverse relationship with global innovation efficiency. Possible reasons include ineffective R&D resource allocation, management practices, or study limitations. To address this, future research should explore these factors to enhance its impact on innovation efficiency. Innovation is recognized as a vital driver of economic growth and societal advancement, addressing global challenges such as climate change, healthcare disparities, and poverty (Gallouj & Gallouj, 2018; Mazzucato & Perez, 2015). By fostering creativity, experimentation, and collaboration, innovation enhances resilience and adaptability in an ever-changing world. Moreover, efficient innovation processes are essential for maintaining competitiveness in rapidly evolving industries, enabling organizations to seize opportunities and maximize returns on investment (Casali et al., 2021; Kohtamäki et al., 2020).

The changing dynamics of globalization, which are becoming increasingly drastic, will cause the factors influencing the innovation efficiency of a country or globally to fluctuate based on environmental changes. Therefore, policymakers and innovation strategies of a country must be sensitive to environmental conditions to make the necessary improvements and renewals promptly and accurately to lead in innovation.

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