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An examination of productive capacities in Arab countries compared with some Asian and OECD countries using Principal Components Analysis (PCA)

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Abstract

This paper examines the productive capacities index (PCI) for Arab countries in comparison to selected group Asian and OECD countries in 2022, using principal components analysis (PCA) among the eight PCI categories. The results reveal that 82.66% of the variance shared by eight variables can be explained by the two extracted components. Moreover, most Arab nations lag behind the selected sample, except for the United Arab Emirates and Bahrain, which enjoy higher levels of productive capacities than both Asian and Arab countries and even some OECD countries. Additionally, the analysis highlights that institutions, ICT, human capital, and the private sector are the most influential categories for promoting sustainable economic growth and rising income levels and catching up with developed countries.

Keywords:*Productive Capacities Index.Economic Development.Principal Components Analysis. Comparative Analysis. Arab Countries.*

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.1. *Introduction*

Economic literature attempts to explain how economic growth varies across nations. The subject of why some economies grow faster than others, making some richer and others poorer, is one of the most popular topics that continue to pique researchers' interest.

The United Nations Conference on Trade and Development (UNCTAD) has consistently argued that strengthening the productive capacities of countries helps to boost income, promote sustainable economic growth, and accelerate poverty reduction. Any country must prioritize productivity in general since it is the key to economic development.

More recent attention has focused on the development of productive capacities, and a number of studies analyzing this subject in developing countries are produced by UNCTAD. One of the recent studies (UNCTAD, 2025) adopted by the UNCTAD is the case of Kenya. The evaluation shows significant high scores for institutions and structural change, besides significant difficulties based on scores related to the PCI's infrastructure components like transport and energy, which could obstruct the path of development.

In a study (Salman & Choudhary, 2024), the productive capacities index is critiqued by reporting the necessity of including important metrics and indicators for a more comprehensive evaluation of productive capacities in Pakistan. It shows that the PCI's precision could be decreased if essential elements are neglected.

Other research (Giombini, Grassetti, & Sanchez Carrera, 2023) analyzes a growth model to clarify how productive capacities and productive inefficiencies are the main causes of economic fluctuations. It concludes that more capital per capita and higher productive capacity are essential for economic growth.

In a different study (Gnangnon, 2021a), the relationship between productive capacities and economic growth and volatility in developing countries was examined. This analysis shows that productive capacities not only boost economic growth but also reduce its volatility. Another research study by the same author (Gnangnon, 2021b) examines the relationship between economic complexity and productive capacities and the flows of Aid for Trade (AFT). According to the findings, economic complexity increased when productive capacities were strengthened.

Arab countries, like many developing nations, seek to achieve growth and catch up with developed countries by enhancing their productive capacities and making it the main focus of development policies. This paper seeks to address the following question: How much do Arab countries' productive capacities differ from selected Asian and OECD countries?

In light of the above problem, we put out the hypothesis: The productive capacities of Arab countries are inferior to both Asian and OECD countries.

In order to gather information and to give a more accurate picture of the nature and strength of the interrelationships among the categories in the productive capacities index, this study will explore principal components analysis (PCA) of these categories for Arab states and

the selected sample to uncover patterns of similarity and divergence across regions and the main factors influencing the differences.

The structure of the paper is as follows: The first and second section summarize the literature review on productive capacities. The third section presents data and methods. The fourth section shows and discusses results. Finally, section five concludes.

2. *Productive capacities*

After defining the productive capacities, we present the UNCTAD's productive capacities index and its categories.

According to UNCTAD report, productive capacities are defined as mix of a nation's entrepreneurial capacities and productions linkages, and productive resources that determine its ability to create goods and services that promote its growth and development (UNCTAD, 2006, p. ii).

From the above definition, a nation's power to produce goods and services depends on a combination of entrepreneurial skills, production connections, and productive assets.

UNCTAD developed an index to measure productive capacities in response to the resolution issued by the Economic and Social Council (ECOSOC) on July 24, 2018. This index serves as a roadmap for future policy actions and helps identify the areas where policies are effective and those that need improvement. It also helps identify which areas an economy may be leading or lagging behind in. There are 194 economies covered by the PCI from 2000 to 2022 (UNCTAD, 2025).

In order to create a single indicator, the overall productive capacities index (PCI) takes the geometric average of eight different categories: natural capital, human capital, energy, transport, ICT, institutions, structural change, and the private sector (UNCTAD, 2021, p. 15).

Productive capacities index is a composite index that combines 42 indicators in eight categories. For more information, see (UNCTAD, 2023).

3. Methods and Materials

This part presents the data description and the methods used in addressing the subject matter.

3.1 Data description

UNCTAD statistics for 2022 provided all the data used in this study. The category indices range from 1 to 100. The eight categories of the productive capacities index are used as the variables in this study (see table n°1 in the appendix).

The data set for this study covers annual measurements on eight variables for 12 Arab countries. Besides six Asian countries and twelve OECD countries for the purpose of both regional and international comparisons. As shown in below table.

Table 1.study'ssample

Arab countries		Asian countries	OECD countries	
Qatar	Tunisia	China	Denmark	Norway
UAE	Morocco	Singapore	Australia	Germany
Bahrain	Jordan	Malaysia	USA	UK
SA	Egypt	Thailand	Netherlands	Switzerland
Oman	Algeria	Indonesia	New Zealand	Belgium
Kuwait	Lebanon	Philippines	Canada	France

3.2 Principal component analysis

To examine the PCI's categories in this paper, the study employes a multivariate data analysis, which is the principal component analysis (PCA).

Principal component analysis (PCA) is the procedure of preserving as much of the diversity in the data set as possible while reducing the dimensionality of a data set with several interconnected variables. Hence, creating a new data set of uncorrelated variables called principal components and organizing them so that the few variables maintain the most of the variation seen in all of the original variables (Mishra, et al., 2017, p. 61).

The objective of PCA is Finding the optimal position for the best information variance and vector dimensional feature reduction. This technique, which was developed by Karl Pearson in 1901, reduces the dimensionality of data by unsupervised learning (Hasan & Abdulazeez, 2021, p. 23).

The table 2 below illustrates the three main steps involved in factor analysis, which are determining the suitability of the data, extracting factors, and rotating and interpreting factors.

Table 2. Main steps of factor analysis

Factor analysissteps	Procedures
Determining the suitability of the data	**A larger sample size for the factor analysis (ten cases per item) is usually considered.**
	The correlation matrix must provide evidence of a coefficient of correlation greater than 0.3 to measure the strength of the relationship between the items.
	Determining whether multicollinearity exist between the variables by using the determinant score, which should be greater than 0.00001 in the correlation matrix.
	The determinant score of the correlation matrix should be different from zero; otherwise, if the correlation matrix is singular, its determinant is zero.
	Using two statistical techniques to assess the factorability of the data: - **Kaiser-Meyer-Olkin (KMO) measures sampling adequacy.** - **Bartlett's test of sphericity.**
Extracting factors that define the	**Kaiser's Criterion: The interesting factors with an eigenvalue greater than one are kept.**

minimum number of fundamental factors	**Scree test: when there is an 'elbow' or leveling of the plot, extracting factors must stop.**
Rotating and interpretingfactors	**Factors identified during the first extraction process are difficult to interpret because of significant cross loadings, where several factors are correlated with many variables. The two main methods for factor rotation are orthogonal (uncorrelated) or oblique (correlated) factor solutions.**

Source: Author preparation based on *Factor Analysis as a Tool for Survey Analysis,* byShrestha, N., 2021, American Journal of Applied Mathematics and statistics, 9(1). pp.6-7.

4. Results and discussion

This section presents the results obtained from the R(4.4.3) software environment for statistical computing and graphics.

4.1 PCI values with ranking

With regard to PCI values and ranking from UNCTAD statistics for 2022 and the study's sample, which indicate the following:

Denmark towers above the rest of the world by scoring (70.3), followed by Australia (69.8) and the United States (69.2). China's score (60.7) emerges to be ahead of the Asian countries sample; it is at the 26th rank in the world, followed by Singapore (52.5) and Malaysia (52.1), which are ranked 57th and 62nd.

Gulf countries appear to perform better than other Arab and Asian countries. Qatar's PCI value (63.6) and the UAE's (63.5), which are ranked 15th and 16th, respectively, out of 194 economies, are the highest scores not only compared to the remaining Arab and Asian countries but also higher than some of the OECD countries, which are Belgium (62.9) and France (62.8), ranked 19th and 20th.

Algeria (43.8) and Lebanon (41) scored worse than the other Arab countries; they only ranked 118th and 135th, respectively; which are at the tail of countries ranking regarding this sample.

4.2Descriptive statistics

The table below illustrates the descriptive statistics of study's variables:

Table 3. Descriptive statistics of data

variable	Minimum	Maximum	Mean	SD
HC	**39.7**	**90.3**	**62.51**	**18**
NC	**3.1**	**62.2**	**35.42**	**13.07**
ENRG	**53.8**	**100**	**71.95**	**10.61**
TRAN	**22.6**	**68.1**	**44.61**	**13.92**
ICT	**28.8**	**87.3**	**65.63**	**15.93**
INST	**31.4**	**96**	**68.42**	**20.58**

PVS	**42.1**	**98.4**	**68.98**	**15.29**
STC	**48.2**	**99**	**70.38**	**15.04**

Source*:* Author calculations based on *UNCTAD statistics,* using R (4.4.3).

Concerning the study's data in 2022, and from the table above, it is apparent that:

- The Philippines scores the minimal value of human capital (39.7), while the maximal value is scored by Denmark (90.3). The mean score for the human capital category is about 62.51.
- Singapore's score in the Natural Capital stood at (3.1), which is the minimal value of this category of the PCI, when Saudi Arabia has the highest (62.2). The Natural Capital category has a mean score of almost 35.42.
- Singapore has the greatest score (100) in the Energy category of the PCI, while the lowest score in this category (53.8) is achieved by Morocco. A mean score of around 71.95 is observed in the Energy category.
- The performance of the transport category of the Philippines is the worst (22.6) compared to the rest of the countries, where the better score (68.1) is obtained by Qatar. A mean score for the transport categoryis about 44.61.
- For the ICT category of the PCI, Germany beat all of the countries by attaining the greatest score (87.3), while Lebanon earned the worst (28.8). The ICT category has a mean score of about 65.63.
- Concerning the institutions category, Denmark achieves the best score (96), while Lebanon has the worst (31.4). The mean score of thiscategoryisaround 68.42.
- In the private sector category, Singapore performs well by achieving 98.4, and Algeria has the lowest value (42.1). Besides, the mean score for thiscategoryis about 68.98.
- With regard to the structural change category, the highest score is achieved by China (99), while Lebanon has the lowest score (48.2). The mean score for structural change categoryisaround 70.38.
- Compared to the other categories, the energy category has the lowest standard deviation value, indicating greater tight clustering around the mean. The institutions category achieves the highest value, indicating that its values are more dispersed than the rest of the data.

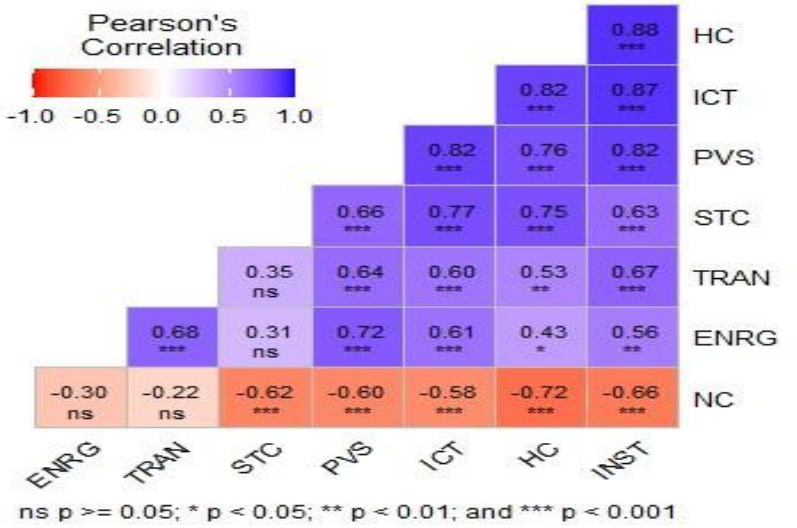
4.3 Determining the suitability of the data

To reveal if the data set is appropriate for undertaking a factor analysis, we check the following:

4.3.1Sample size and the strength of the relationship

There are thirty cases for each variable in this study, which is sufficient for factor analysis. Furthermore, the strength of the relationship between the variables is shown by coefficients of correlation greater than 0.3, as shown in Figure 1 below, which supports the use of component analysis.

Fig.1. Inter-correlations between variables



Source: Author calculations based on *UNCTAD statistics*, using R (4.4.3).

4.3.2The determinant score

The determinant score of the correlation matrix is 0.00024 higher than 0.00001, which signifies an absence of multicollinearity. It is also different from zero; hence, the correlation matrix is not singular.

4.3.3Factorability of the data

Table 4 demonstrates that the KMO statistics value is equivalent to 0.8 >0.6, indicating that sampling is sufficient and the application of factor analysis is appropriate for the data. the result of the Bartlett's test of Sphericity is equal to 15.721 with a degree of significance less than 5%; this leads to the rejection of the hypothesis that the correlation matrix is an identity matrix.

Table 4. Kaiser-Meyer-Olkin and Bartlett's Test of Sphericity

KMO test	**0.8**	
Bartlett test	**Bartlett's K-squared**	**15.721**
	df	**7**
	p-value	**0.02**

Source: Author calculations based on *UNCTAD statistics*, using R (4.4.3).

4.4Extracting factors

As can be seen from the table 5 below, there are two components within the data set for the eigenvalues greater than 1. The results show that 82.66% of the variance shared by eight variables can be explained by the two extracted components. The first component has explained 68.43% of the total variance with eigenvalue 5.47. The second component has explained 14.23% of the total variance with eigenvalue 1.13. Together, they have explained 82.66% of the total variance.

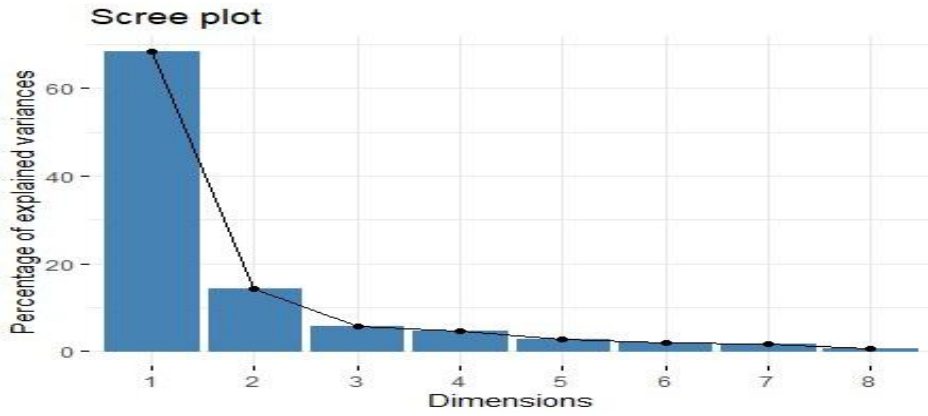
Table 5. Eigenvalues and total variance explained

Factors	Eigenvalues	% of variance	Cumulative % of variance
F1	5.4746	68.4331	68.4331
F2	1.1385	14.2314	82.6645
F3	0.4521	5.6518	88.3163
F4	0.3794	4.7428	93.0592
F5	0.2229	2.7863	95.8455
F6	0.1578	1.9729	97.8183
F7	0.1227	1.5338	99.3521
F8	0.0518	0.6479	100

Source: Author calculations based on *UNCTAD statistics,* using R (4.4.3).

From the figure 2, factor extraction must stop when the plot has a 'elbow.' When we look at the scree plot in our hand, it turns out that there are two factors that account for most of the total variability in data.

Fig.2. Scree plot



Source: Author calculations based on *UNCTAD statistics,* using R (4.4.3).

4.5Factor rotation and interpretation

After rotation, Table 6 below illustrates which variables have high loadings (positive or negative) on the first two principal components. It appears that four variables form and correlate positively with the first principal component, which are ICT, institutions, human capital, and the private sector. This component explains 68.43% of the total variance. Concerning the second principal component that explains 14.23% of the total variance, it is formed by each of energy, transport, structural change, and natural capital; it correlates positively with all variables except for natural capital, which it correlates negatively with.

Table 6. loadings on initial principal components

Variables	PC. 1	PC. 2
ICT	0.40	-0.02
INST	0.40	-0.01
HC	0.39	-0.23
PVS	0.39	0.11
ENRG	0.29	0.55
TRAN	0.30	0.53

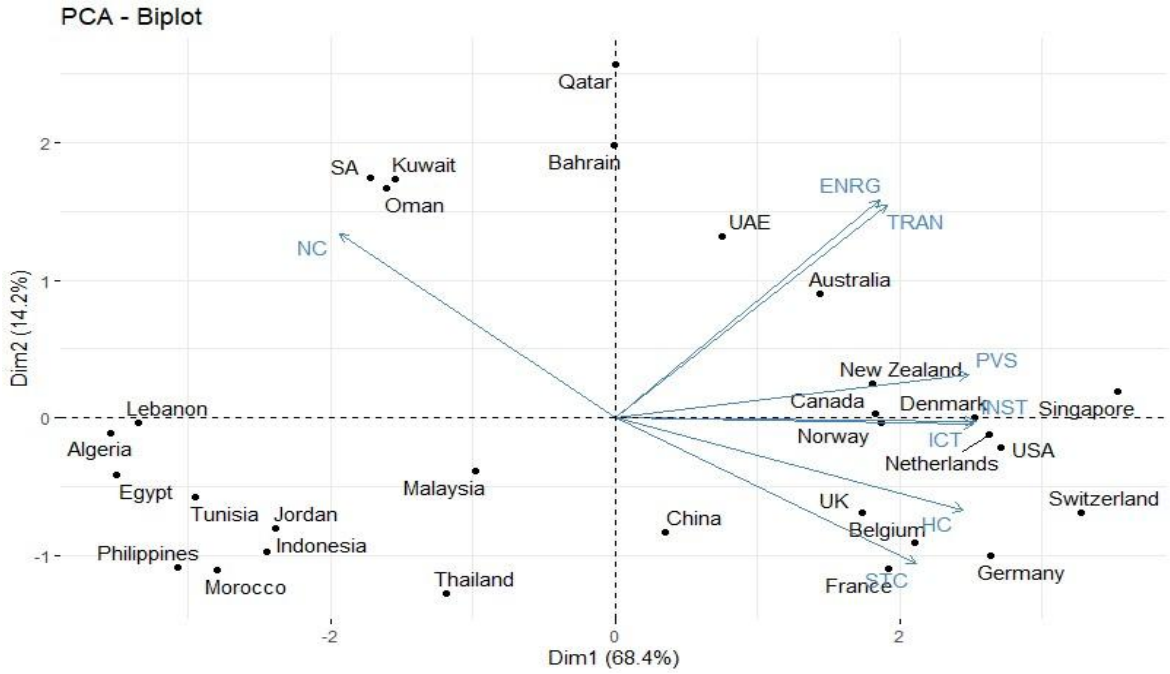
NC	**-0.31**	**0.46**
STC	**0.33**	**-0.37**

Source: Author calculations based on *UNCTAD statistics,* using R (4.4.3).

Figure 3 below presents the PCA biplot, it shows the first two dimensions of the data which account for 82.66% of the information contained in the data, it appears the following:

- ICT, institutions, human capital, and the private sector have large positive loadings on component 1. Therefore, this component reflects the strong interrelationships between these categories. Promoting human capital boosts institutions and fosters technology, which leads to empowering the private sector.
- Energy, transport, and structural change have large positive loadings on component 2, but natural capital has a negative loading.
- The arrows represent the productive capacities index categories; since the angles between arrows indicate the correlations between measures, the below biplot shows an almost perfect correlation between energy and transport, and also between human capital and institutions. The acute angle points to a high positive correlation between structural change and each of human capital, ICT, institutions, and the private sector.
- The right angle reveals almost no correlation to energy and transport with each of structural change and natural capital. In this case, energy use may be harmful to natural capital, turning the link statistically insignificant (see figure 02 above). Furthermore, infrastructure such as energy and transport might not lead to structural transformations.
- The obtuse angle indicates the negative correlation between natural capital and the rest of the categories.
- Arab countries such as Algeria, Lebanon, Egypt, Tunisia, Jordan, and Morocco are close together and to some Asian countries such as the Philippines and Indonesia, which means they have similar characteristics regarding PCI categories. They locate on the opposite side of almost all variables except the natural capital. So that these countries have a weakness and ineffectiveness, especially in sectors such as institutions, ICT, the private sector, and human capital.
- Saudi Arabia, Kuwait, and Oman are close together and to the natural capital vector, which means they have the highest scores for this variable. Furthermore, they are projected in the middle compared to the rest of the vectors because they have average scores.
- Qatar, Bahrain, and particularly the United Arab Emirates are close to energy and transport vectors, which means they have high scores for these categories, and they have the greatest ratings for the remaining categories compared to Arab and Asian countries.
- Singapore is situated close to the OECD countries, which means they have similar characteristics regarding PCI categories, especially institutions and ICT.

Fig.3. PCA Biplot



Source: Prepared by the author based on *UNCTAD statistics,* using R (4.4.3).

5. Conclusion

In order to determine productive capacities in Arab countries, we compared them with some Asian and OECD countries in 2022. This paper used principal components analysis. The results show that with the exception of the United Arab Emirates and Bahrain, which have higher levels of productive capacities than both Asian and even some OECD countries, Arab nations perform less than the OECD and certain Asian countries, for that, we accept the study's hypothesis. Institutions, ICT, human capital, and the private sector are the categories of the productive capacities index that matter more than the rest and that promote sustainable economic growth and rising income levels, which are enjoyed by developed countries.

The productive capacities index helps nations to identify weaknesses and strengths. With regard to the results, it is necessary for Arab countries to take into account the following points:

- Building human capital by improving education and health, and make the skills much with the needs of the labor market. Also, by improving the working conditions to prevent brain drain.

- It's required to enhance industrialization and technological progress, and preserve natural capital through the use of sustainable resources. Also, promoting research and development (R&D), improving the private sector through regulatory and fiscal policy reforms, and drawing investment in the manufacturing industries.

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6. *Appendices*

Table 1. The study's variables (categories of PCI)

Variable	Categoryname	Definition

HC	**Human capital**	**Reflects the health, education, and skills levels of individuals by the number of researchers and the amount spent on research activities. One indicator of the gender dimension is the fertility rate, which lowers the human capital score with each increase.**
NC	**Natural capital**	**Determines the amount of extractive and agricultural resources that are available, which also includes the rents obtained from the extraction of natural resource's extraction, less the cost of extracting the resource. Natural capital decreases as material intensity increases, reflecting reliance on commodities.**
ENRG	**Energy**	**Measures the efficiency, sustainability and availability of power source. Therefore, it is made up of energy use and access, reductions in distribution and renewability of energy sources and components, and includes the GDP produced by each unit of oil.**
TRAN	**Transport**	**gauges a system's ability to move people or goods from one location to another. It is defined as the capillarity of road, rail networks and air connectivity.**
ICT	**Information, Communication &Technology (ICT)**	**Estimates the population's communication systems and integration and accessibility. It covers the users of fixed line and mobile phones, likewise internet accessibility and server security.**
INST	**Institutions**	**Seek to measure the effectiveness and stability of politics by the quality of its regulations, their efficacy, ability to combat corruption, criminality and terrorism, protection of citizen's freedom of expression and association.**
PVS	**Private Sector**	**Defined by the ease of cross-border trade, which covers the time and monetary costs of importing and exporting, and the support to businesses regarding domestic credit, speed of contract enforcement, and the time needed to launch a business.**
STC	**Structural Change**	**Refers to the transfer of labor and other productive resources from economic activities with low productivity to those with high productivity. The intensity of fixed capital, the sophistication and diversity of exports, and the weight of industry and services on total GDP all currently reflect this shift.**

Source: Author preparation based on *Productive Capacities Index* by UNCTAD. (2025, 03 18), retrieved from United Nation Trade & Development: https://unctad.org/topic/least-developed-countries/productive-capacities-index?