Assessing the OECD Countries' Industry 4.0 Maturity from Sustainable Development Goals' Perspective: An Integrated PCA and DEA Approach

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Industry 4.0 (I4.0) technologies and relevant research initiatives have been at the focal point of sustainable industrial development initiatives. Adoption of these technologies require a maturity level to create sustainable economic, social, and environmental benefits to society. In this study, we investigated the I4.0 maturity in OECD countries. A two-phase methodology is proposed: principal component analysis (PCA) and data envelopment analysis (DEA). The main contribution of the study to the state-of-art is a statistically reliable analytical framework which yields I4.0 maturity score from relevant United Nations Sustainable Development Goals' perspectives. Results indicate that the proposed two-phase method significantly reduces the potential multi-collinearity impacts on I4.0 maturity performance. Moreover, USA, Sweden, Finland, and Switzerland were found to the on the efficiency frontier in terms of I4.0 maturity whereas Turkey, Chile, Latvia, and Mexico were found to be in the lowest ranks which need substantial policy implementation to increase their digitalization efforts.

Keywords: industry 4.0, maturity, cyber physical systems, sustainable development

INTRODUCTION

Industry 4.0 has been central topic of discussion in emerging economies in terms of its economic, social, and environmental impacts. Considerable productivity gains are projected with the adoption of cyber physical systems and digital manufacturing, while disruptive impacts are also discussed. In this research, we initially conducted a literature review on identifying the macro level key drivers of Industry 4.0 adoption to create a framework for benchmarking emerging economies in terms of their maturity for Industry 4.0 adoption.

The term Industry 4.0 was first introduced during the Hannover Fair in 2011, which was later formally announced in 2013 as a strategic action plan by German government. The overarching aim was to become a leading nation in the transformation of the manufacturing activities into more decentralized, digital, and real-time-manageable format (MacDougall & Bunse, 2014; Moeuf et al., 2018). In retrospective of this strategic act, "the conditions which make the fourth industrial revolution or INDUSTRIE 4.0 possible are unique to Germany; due to the two reasons: 1) Germany's continued role as one of the world's most competitive and innovative manufacturing industry sectors; 2) the country's technological leadership in industrial production research and development (MacDougall & Bunse, 2014). Moreover, cyber physical systems and I4.0 technologies are indispensable to realize sustainable development goals established by United Nations initially in 2015 (Mabkhot et al., 2021) and make the sustainability transitions possible (Köhler et al., 2019; Suleiman et al., 2022).

Thus, this new Industrial Revolution requires a transformation to new systems that bring together physical and digital technologies to an increasingly connected population of active users. Among the other topics explored, such as enabler technologies, the relatives challenges or opportunities and benefits, a great emphasis is been placed on readiness or maturity level required for the transformation strategies of Industry 4.0. In particular, in order to achieve and implement a transformation strategy it is important to understand the current status (Hofmann et al., 2019; Hofmann & Rüsch, 2017; Koh et al., 2019) , since it is a prerequisite to strategy formation, and subsequently affect the path that have to be followed from the starting point to the goal decided. The current status can be evaluated thanks to some assessment, called readiness assessment or maturity (we prefer the term: maturity due to its more common use in the literature and ease of understanding), based on whether a formal transformation process is in progress or not (Koh et al., 2019). Maturity assessment can be either absolute, that evaluates on the basis of a set standard baseline or relative, a comparative analysis of several entities and often performed in areas lacking standard benchmarks (Venkatraman & Ramanujam, 1986).

These models can also employ different lens. For instance, there are the I4.0 maturity models that focus on individual industries, while others that rather assume a macro level assessment to evaluate the readiness of a nation. Various authors who have explored I4.0 readiness for various different countries such as: Hungary (Viharos S.J. et al., 2017), Turkey ((Akdil et al., 2018);(Temur et al., 2019)), Italy (Brozzi et al., 2018), Kazakhstan (Beisekenov et al., 2022) , Poland (Gracel & Lebrowski, 2018), Austria ((Schumacher et al., 2019)), Germany (Demeter et al., 2018; Rubel et al., 2018), the UK (Jones et al., 2019), Chez republic (Basl & Doucek, 2019; Josef & Jakub, 2018), Morocco (El Hamdi et al., 2020), Malaysia (Ratnasingam et al., 2019) and Sweden ((Machado et al., 2019)) have focused on industries within the nation more rather than assessing the maturity of country based on its national innovation environment. Although (Basl, 2018) focused primarily on enterprise information systems in their I4.0 maturity model, their classification in macro and micro factors is noteworthy. The models where assessment is carried out on national level are referred as macro level, and the ones having industry level scope are called micro level (Basl, 2018; Demeteret al., 2018). Basl (2018) introduced the macro approach to study I4.0 maturity and pointed that general precondition for digitalization and innovation in a country is equally important for industrial transformations (Tripathi & Gupta, 2021). Next section explains the recent literature review on I4.0 maturity and the indicator selection process implemented in this paper.

LITERATURE REVIEW

I4.0 is driven by interconnectivity and integration of diverse technological, social and business streams. Its adaptation will depend on the general precondition of national environment for innovation and social factors along with industry-specific readiness (Basl, 2018; Temur et al., 2019). The literature recently became abundant with works that focus on industry 4.0 maturity or readiness. Both maturity and readiness terms have been interchangeably used in the literature. We will use "maturity" in this paper consistently.

One hundred ninety-three United Nations member countries convened to set a new sustainable development agenda at the New York meeting on September 25th, 2015. The new future plan was organized around 17 Sustainable Development Goals (SDGs). Each of the 17 SDGs focuses on specific measurable outcomes to be realized by 2030, called as the "Envision 2030" . The proposed plan was structured around the successes of the Millennium Development Goals, while including new policy focus areas such as digital innovation, inequality, sustainable consumption, peace, and justice, among other priorities (United Nations Department of Economic and Social Affairs, 2015) The proposed 17 SDGs were aimed to cover social, economic, environmental, and ecological aspects of sustainable development assuming that they are interrelated (United Nations Development Programme, 2018)One of the 17 SDGs is entitled as "SDG#9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation. This SDG#9 aims to address sustainable infrastructure development, industrialization and digital innovation to tackle the social, economic, and environmental issues that the world has been facing for decades.

According to a recent study, which focuses on a two-year comparison of OECD countries considering 17 SDGs, it was found that the SDG 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation was found to have the 2nd lowest mean performance after SDG15 – Life on Land (Lamichhane et al., 2021). This finding is also supported by a recent United Nations report indicating that while none of the OECD member countries were on target on SDG#9 along with 5 other SDGs, and a quarter of them did not make any progress at all (OECD, 2022). The nature of this progress is also a subject of discussion among other reports. In this context, Mabkhot et al. (2021) also conducted arguable one of the critical works which focused on mapping UN SDGs towards I4.0 enabling technologies. The objective was to understand the influence and relationship of I4.0 technologies on the achievement of the Sustainable Development Goals (SDGs). Their findings indicated that majority of I4.0 enabling technologies could positively contribute to most SDGs, while some SDGs were found to be more closely connected with the I4.0 technologies than others. Among their findings, while most of the SDGs were found to have a range of effects from weak to strong with I4.0, one UN SDG was found to have significantly strong relationship with all of the I4.0 enabling technologies, which was UN SDG 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation. This is also self-evident from the goal's scope, which exclusively focuses on innovation and resilient infrastructure. Therefore, the focus of this paper's theoretical framework application area was decided to be exclusively on UN SDG 9 due to most recent studies findings which indicate that UN SD9 is strongly related with I4.0 maturity.

A recent review of Tripathi & Gupta (2021) covers 51 academic papers and 174 industry reports and provides a framework that focuses on enabling environment, human capital, infrastructure, ecological sustainability, innovation capability, cyber security domains. The proposed a I4.0 maturity index which consists of 7 dimensions, 17 pillars and 63 indicators. While proposing a work that covers such a large scale of variables and data is advantageous, the potential multicollinearity was not addressed in the methodological framework. This review classified the scope of works into to macro and micro based on the According to their classification method, the macro models include focus areas such as legislation, patents, infrastructure which are common to all industries operating in a country. And, the assessment focus is often at country scale. In contrast, works proposing micro models concentrate on enterprise-specific functions as culture, leadership and strategy. According to this classification, this paper's focus and methods belong to the macro category. Among the 11 works cited, only one of the employed a macro model in academic literature (Demeter et al., 2018), while remaining works were from organization's reports such as World Economic Forum (WEF), World Intellectual Property Organization (WIPO), International Telecommunications Union (ITU). Demeter et al. (2018) focused on select manufacturing sectors and proposed a meso-level assessment of EU countries. Most of the methods employed in these works were based on standardizing the data and calculating an aggregated average; even though indexing approaches that do not take into account the multicollinearity among indicators could potentially produce skewed results in the assessment ((Park et al., 2015a); Lamichane et al., 2021). Table 1 summarizes the list of I4.0 indicators selected by the relevant literature, which are also kept within the scope of our work.

TABLE 1
I4.0 INDICATORS ADDRESSING UN SUSTAINABLE DEVELOPMENT GOAL 9

I4.0 Indicator	Literature
IU: Internet use (%)	(Sachs et al., 2022), (Kamarul Bahrin et al., 2016; *World Economic Forum*, 2020)
MBS: Mobile broadband subscriptions (per 100)	(Sachs et al., 2022), (World Economic Forum 2018), (Blanchet, 2014), (Schumacher et al., 2016)
GCI: Quality of overall infrastructure (1-7)	(Sachs et al., 2022), (World Economic Forum 2018)
LPI: Logistics Performance Index: Infrastructure Quality (1-5)	(Blanchet et al. 2014), (Sachs et al., 2022), (World Economic Forum 2018), (Bahrin et al. 2016),(Rennung et al., 2016; Witkowski, 2017; Zhong et al., 2017)
EXPRAD: Government R&D expenditures (% GDP)	(Sachs et al., 2022), (World Economic Forum 2018), (Bahrin et al. 2016), ((Naudé et al., 2019)
NUMRAD: R&D researchers (per 1000 employed)	(Sachs et al., 2022), (World Economic Forum 2018), (Bahrin et al. 2016), (Blanchet et al. 2014), (Naudé, Surdej, and Cameron 2019)
WIS: Percentage of women tertiary grads in natural sci. and eng.	(Sachs et al., 2022)
INTEQ: Difference in% HH internet access between top and bottom income Qs	(Sachs et al., 2022)
UNI: Top 3 University Rankings (0-100)	(Sachs et al., 2022), (World Economic Forum 2020), (Zhong et al. 2017),
Variable	
GOVEF: Government Efficiency (1-7)	(World Economic Forum 2020), (Naudé, Surdej, and Cameron 2019)
HES: Government Health and Education spending (% GDP)	(World Economic Forum 2020),
EXPDEV: Official development assistance (% GNI)	(World Economic Forum 2020),
COR: Corruption Perception Index (0-100)	(World Economic Forum 2020)
LABQUAL: Labor Quality (skilled workers, low & high-skilled etc.)	(World Economic Forum 2020), (Naudé, Surdej, and Cameron 2019), (Telukdarie et al. 2018), (Blanchet et al. 2014), (Rennung, Luminosu, and Draghici 2016) , (Schumacher, Erol, and Sihn 2016), (Bonekamp and Sure 2015)
J: Number of scientific and technical journal articles (per capita)	(World Economic Forum 2020), (Zhong et al. 2017),

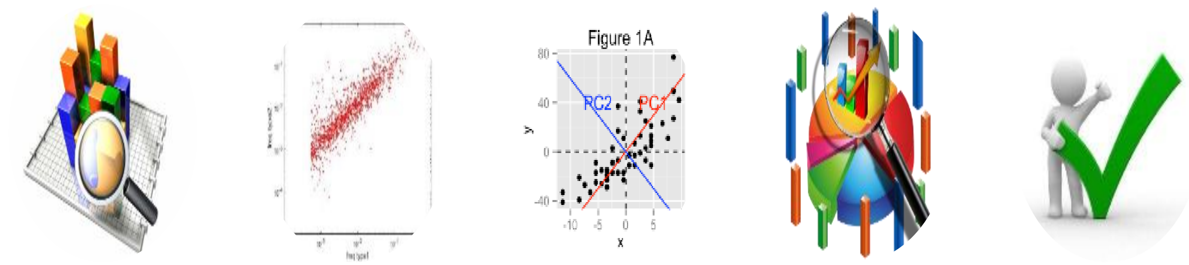
PA: Patent applications (per 100,000 people)	(World Economic Forum 2018), (Blanchet et al. 2014), (Trappey et al. 2017)
CYSEC: Global Cybersecurity Index (Cybersecurity in general)	(World Economic Forum 2020), (Bahrin et al. 2016), (Blanchet et al. 2014), (Benias & Markopoulos, 2017)(Ślusarczyk, 2018), (Vaidya, Ambad, and Bhosle 2018)
CLOUD: Enterprises using cloud computing services, by size, 2016	(Bahrin et al. 2016), (Blanchet et al. 2014), ((Schumacher et al., 2016) (Liu & Xu, 2017) , (Zhong et al. 2017), (Vaidya, Ambad, and Bhosle 2018)
ICTEMP: Employment of ICT specialists across the economy, 2016	(World Economic Forum 2020), (Blanchet et al. 2014), (Zhong et al. 2017), (Schumacher, Erol, and Sihn 2016), Gabriel, 2015
NEWENT: New Enterprise Creation	(World Economic Forum 2020), (Blanchet et al. 2014),
GMCI: Global Manufacturing Competitiveness Index	(World Economic Forum 2018), (Blanchet et al. 2014), (Zhong et al. 2017), (B Ślusarczyk 2018) (Rennung, Luminosu, and Draghici 2016)

As a result of extensive literature review, the aforementioned indicators were selected to be in the scope of the study (see table 1). One of the issues we consistently found in the works where multiple I4.0 indicators are used to derive a I4.0 maturity score was that the multicollinearity was not taken into account. In contrast, Lamichane et al. (2021) found that 17 UN SDGs and their relevant indicators have significantly high degree of correlations (majority of the sub-indicators of have significant and strong correlations), which could critically skew the results of any analytical approach to deriving composite index scores such as I4.0. Similar findings were also discussed and possible remediation methods to the deteriorating impacts of multicollinearity were discussed and demonstrated in various works (Park et al., 2015; Lamichane et al., 2021). While multicollinearity is a significant issue in any parametric or non-parametric analysis, this issue has not been addressed in the I4.0 maturity literature, which could raise questions about the statistical validity of any composite indexing method if the multicollinearity and normality issues were not adequately dealt with. Therefore, this paper proposes a two-phase integrated methodology. In the first step, after data was collected, cleaned, and prepared, principal component analysis (PCA) is deployed. Next, data envelopment analysis is coupled with the results of PCA to derive I4.0 maturity scores of OECD countries. Next section explains the methods in detail.

METHODS

The summary of the methodology is depicted as follows (Figure 1). After conducting literature review on integrated UN Sustainable Development Goals and Industry 4.0 studies, variable are identified and classified into inputs and outputs for the PCA+DEA implementation. Next, data was collected considering the closest available period, cleaned and prepared for PCA procedure. Then, PCA procedure is applied to the data, which was followed up with the DEA procedure. Lastly results are provided along with practical policy implications in the discussions section.

FIGURE 1
OVERVIEW OF THE METHODOLOGY



Phase 1

- Literature review
- Identification of variables
- Classification of variables

Phase 2

- Data Collection
- Data Preparation and Cleaning

Phase 3

- PCA
  - Normalization
  - Correlation Analysis
  - KMO and Bartlett's Tests

Phase 4

- DEA
  - Data Preparation
  - Normalization
  - Experimentation

Phase 5

- Results Interpretation and validation
- Conclusions

Principal Component Analysis (PCA)

PCA is a robust and effective mathematical procedure used for dimension reduction especially when the number of variables is large on a dataset (Shmueli et al., 2017) One of the important and necessary application areas of PCA is that when there is a multivariate data which consists of subsets of measurements that are highly correlated (Lamichhane et al., 2021). PCA bases its theoretical foundation on the orthogonal transformation, which converts a set of correlated quantitative variables into a subset of linearly uncorrelated variables called "principal components (PCs)" (Jolliffe, 2011). The principal components (PCs) are ranked in order, based on the largest possible amount of variation they account for in the original data, where the first PC typically accounts for largest amount of variation. Maximum number of PCs generated is equal to the number of variables used to build PCs. The generated PCs are not correlated to each other, while all PCs together account for the maximum variation in the original data (Lamichhane et al., 2021).

The mathematical framework of PCA procedure consists of six steps:

Step 1: The first step is standardization of data. Various normalization procedures could be used in this step. In this study, min-max normalization technique is chosen because of being a robust normalization approach in terms of preserving the relationships in the data (Jayalakshmi & Santhakumaran, 2011). Moreover, min-max normalization procedure (see Eq. 1) is effective standardization method for the scale of data especially when the variables hold varying units of measurement and ranges (Mainali & Silveira, 2015). With min-max procedure, the data can be typically normalized between a range of a and b, where the pair (a, b) could take values of (0,1) or (0,100) as the new range of normalized data. In this study, we used (0,100) normalization scale to increase the sensitivity of Data Envelopment Analysis (DEA) procedure, which took place after the implementation of PCA.

$$x_i' = a + \frac{(x_i - Min\ (x)) * (b-a)}{Max(x) - Min(x)} \qquad i=1,2,3 \ldots n \tag{1}$$

The notation of the eq.1 is as follows. xi is the original data value; max(x) and min(x) are maximum and minimum values of x vector, which contains the original data (sample size=n).

Step 2: In the next step, the correlation (covariance) matrix (R) of the normalized data is calculated (Eq.2).

$$R = \ 1\ r_{12}\ r_{1n}\ r_{21}\ 1\ r_{2n}\ r_{n1}\ r_{n2}\ 1 \qquad i=1,2,3 \ldots n \qquad r \sim [-1,1] \tag{2}$$

Step 3: Furthermore, the eigen values and eigen vector of the correlation matrix are computed. An eigenvalue denotes the extent of variance accumulated in its orthogonal transformation direction. eigenvalues are determined by the following determinant equation,

$$(R - \lambda I) = 0 \tag{3}$$

where R is the correlation matrix (n × n), λ is the eigen vector and I is the unit matrix (Doukas et al., 2012, Lamichane et al., 2021).

Step 4: Solving for λ as n^{th} degree polynomial equation provides n eigenvalues. The eigenvalue with the largest rate is the one that holds most of the variation whereas the eigenvalues with relatively small in other words negligible rate are usually ignored for simplicity and dimension reduction purposes (Park et al., 2015). Then, the following matrix equation (Eq. 4) is solved to identify the eigenvectors.

$$(R - \lambda j I) F j = 0 \tag{4}$$

The equation 4 is expressed as follows. R is the correlation matrix, λ_j is the corresponding eigenvalue, *I* is the identity matrix, and F_j is the matrix of the eigenvector corresponding to the λ_j eigenvalue (Doukas et al., 2012, Lamichane et al., 2021).

Step 5: Obtaining PCA output data.

After running the PCA on SPSS software, factor scores *(F_i)* were obtained and used as the PC weights for composite non-standardized index (NSI) computation. The composite NSI is calculated using the following equation (Eq.5)

$$NSI_{is} = \frac{\sum_{i=1}^{n_s} \lambda_{iks} * F_{is}}{\sum_{i=1}^{n} \lambda_{is}}\ where\ i = 1, \ldots, n_s;\ \ s = 1, \ldots, m; i = 1, \ldots, n_s\ and\ n_s < n \tag{5}$$

where NSI_{is} is the non-standardized sustainability index of the i^{th} country and s^{th} eigen vector. λ_{is} is the corresponding eigenvalue loading and f_{is} is the factor score of sth principal component for i^{th} country.

Step 6: The non-standardized composite index derived from the above equation could be either positive or negative, which creates difficulties in integrating into a Data Envelopment Analysis. Therefore, the NSI scores were standardized by using Eq. 6, which yields nonnegative standardized principal components (Park et al., 2016, Lamichane et al., 2021).

$$PC_{is} = \frac{NSI_{is} - Min\ [NSI_s]}{Max\ [NSI_s] - Min\ [NSI_s]} * 100\ where\ i = 1, \ldots, 35; s = 1, \ldots, m \tag{6}$$

The PCA is conducted by using SPSS software due to the computational advantages of eigen vector calculations. Results of PCA is also verified with KMO and Bartlett's tests which are crucial to assure the suitability of data for structure detection and relative proximity of correlation matrix to identity matrix.

Once the PCA results are verified, standardized principal components were integrated in the data envelopment analysis (DEA) models.

Data Envelopment Analysis (DEA)

In this study, input-oriented DEA with variable returns to scale (VRS) method is employed to conduct the pairwise I4.0 maturity assessment of the OECD countries. The mathematical framework of DEA method is expressed as follows (Park et al., 2018; Ezici et al., 2020).

Notation:

- *j*: the index of decision-making units (35 OECD countries in this study)
- DMU_j: decision making unit *j (each OECD country)*
- *θ:* the efficiency rating of the decision-making unit under the evaluation
- k_{rj} is the amount of output *r* produced by decision making unit *j*,
- p_{ij} is the amount of input (*i*), used by decision making unit *j*,
- *i:* index of input variables
- *r*: index of output variables,
- u_r: the coefficient or weight assigned by DEA to output *r*, and
- v_i : coefficient or weight assigned by DEA to input *i*.

$$\theta = \frac{\sum_{r=1}^{k} u_r k_{ro}}{\sum_{i=1}^{m} v_i p_{ij}} \tag{7}$$

subject to

$$\sum_{i=1}^{m} v_i p_{io} = 1 \tag{8}$$

$$\theta_j = \frac{u_1 k_{1j} + u_2 k_{2j} + \cdots + u_r k_{rj}}{v_1 p_{1j} + v_2 p_{2j} + \cdots + v_m p_{mj}} \tag{9}$$

where $u_1, \dots, u_s \geq 0$ *and* $v_1, \dots v_m \geq 0$.

Data

The data was collected for OECD countries, since these countries have the most cutting edge technology and potential for establishment and advancement of Industry 4.0 besides their substantial contribution to the global economy. The OECD brings together member countries and partners that collaborate on key global issues at national, regional and local levels (OECD, 2019). Following is the list of OECD countries studied (Table 2).

TABLE 2
OECD COUNTRIES

1	Australia	11	Germany	21	Luxembourg	31	Sweden
2	Austria	12	Greece	22	Mexico	32	Switzerland
3	Belgium	13	Hungary	23	Netherlands	33	Turkey
4	Canada	14	Iceland	24	New Zealand	34	United Kingdom
5	Chile	15	Ireland	25	Norway	35	United States
6	Czech Republic	16	Israel	26	Poland	36	Lithuania
7	Denmark	17	Italy	27	Portugal		
8	Estonia	18	Japan	28	Slovak Republic		
9	Finland	19	Korea, Rep.	29	Slovenia		
10	France	20	Latvia	30	Spain		

UN Sustainable Development Goals, which were established by the United Nations General Assembly (UNGA) as part of the Post-2015 Development Agenda in 2015 New York meeting. The 17 SDGs were no poverty; zero hunger; good health and well-being; quality education; gender equality; clean water and sanitation; affordable and clean energy; decent work and economic growth; industry, innovation and infrastructure; reduced inequalities; sustainable cities and communities; responsible consumption and production; climate action; life below water; life on land; peace, justice, and strong institutions; and partnerships for the goals. Among the 17 SD Gs, UN SDG 9 is the one that focused on building resilient infrastructures, promoting inclusive and sustainable industrialization and foster innovation.

TABLE 3
DESCRIPTIVE STATISTICS OF RAW DATA

	IU	*MBS*	*GCI*	*LPI*	*EXPRAD*	*NUMRAD*	*WIS*	*INTEQ_INV*	*UNI*	*GOVEF*	*HES*	*EXPDEV*	*COR*	*LABQUAL*	*J*	*PA*	*CYSEC*	*CLOUD*	*ICT_EMP*	*NEWENT*	*GMCI*
Scale	0-100	per 100	1-7	1-5	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-100	0-1	0-10	0-150	0-1	0-100	0-100	0-200	10-100	
Missing Data (%)	0.00	0.00	0.00	0.00	0.00	0.14	0.17	0.00	0.00	0.03	0.09	0.00	0.17	0.00	0.00	0.00	0.09	0.20	0.51	0.40	
Mean	82.84	90.64	5.18	3.69	1.99	8.74	28.02	61.56	52.17	52.81	10.13	0.37	68.63	0.14	1.32	30.60	0.65	21.48	3.31	98.73	57.34
Standard Error	1.86	4.34	0.12	0.08	0.17	0.64	0.84	2.75	4.92	4.88	0.33	0.05	2.66	0.01	0.09	5.92	0.02	2.24	0.16	2.08	2.23
Median	85.62	88.06	5.20	3.77	1.93	8.96	27.99	61.56	56.10	57.08	10.13	0.28	72.00	0.14	1.33	17.11	0.68	18.59	3.31	99.01	57.34
Standard Deviation	10.99	25.69	0.70	0.46	0.99	3.77	4.95	16.29	29.11	28.89	1.96	0.31	15.72	0.06	0.56	35.02	0.15	13.24	0.96	12.29	13.22
Kurtosis	-0.22	-0.41	-1.09	-1.09	-0.27	0.11	1.25	-0.89	-0.76	-1.18	0.00	2.67	-0.49	1.06	0.01	3.59	-0.20	0.76	1.00	2.49	4.76
Skewness	-0.69	0.43	0.14	-0.28	0.55	0.05	0.25	0.30	-0.39	-0.23	0.38	1.65	-0.56	0.28	-0.09	1.77	-0.60	1.05	-0.04	0.74	-0.71
Range	39.89	107.22	2.58	1.67	3.88	16.66	24.80	57.60	99.10	97.36	8.76	1.34	60.00	0.31	2.50	142.24	0.58	59.19	4.87	58.50	80.80
Minimum	58.35	45.09	4.07	2.77	0.38	0.77	16.17	36.43	0.00	0.00	6.59	0.07	30.00	0.01	0.11	0.15	0.34	0.00	0.89	71.58	10.00
Maximum	98.24	152.31	6.65	4.44	4.27	17.43	40.97	94.03	99.10	97.36	15.36	1.41	90.00	0.32	2.60	142.39	0.92	59.19	5.76	130.09	90.80
Count	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00

Moreover, this goal has been identified as the goal that covers the Industry 4.0 scope and objectives. The detailed objectives of the SDG 9 are as follows.

UN Sustainable Development Goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation (Sustainable Development Knowledge Platform, 2019)

1. Develop quality, reliable, sustainable and resilient infrastructure
2. Promote inclusive and sustainable industrialization and, by 2030
3. Increase the access of small-scale industrial and other enterprises, in developing countries, to financial services
4. Upgrade infrastructure and retrofit industries to make them sustainable
5. Enhance scientific research, upgrade the technological capabilities of industrial sectors in all countries
6. Significantly increase access to information and communications technology and strive to provide universal and affordable access
7. Support domestic technology development, research and innovation in developing countries
8. Significantly increase access to information and communications technology and strive to provide universal and affordable access to the Internet

RESULTS

The findings of experimentation with PCA and DEA methods were explained in twofold: PCA results and DEA results. PCA method was primarily applied to mitigate or best remove the potential deteriorating (skewing) impacts of multicollinearity in the data. On the other hand, DEA was utilized to peer-to-peer benchmark the preparedness of OECD countries by creating a maturity score between 0 and 1.

Results Of PCA

When working with PCA, the motivation and necessity of using this nonparametric statistical method stems from the higher degree of multicollinearity. Initially, a correlation analysis was conducted on the raw data and results of correlations among input variables are provided in Figure 2. Strong and significant correlations were marked with yellow highlight. 63 out of 77 distinct correlations were significant and strong. which makes up more than 80% of the distinct correlations. In this context, a distinct correlation means all correlations except a variable’s correlation with itself, which is 1. In addition, results of correlations among output variables are provided in Figure 3. Ten out of 21 distinct correlations (approximately 50%) were found to be strong and significant. Considering both input and output variable sets high degree of multicollinearity, there is an absolute necessity to treat this issue before using this data for further analysis. The proposed treatment method was PCA, which is a robust dimension reduction and multicollinearity treatment approach.

FIGURE 2
CORRELATION ANALYSIS OF INPUT VARIABLES

Correlations

	IU	MBS	GCI	LPI	EXPRAD	NUMRAD	WIS	INTEQ_INV	UNI	GOVEF	HES	EXPDEV	COR	LABQUAL
IU	1	.545**	.547**	.566**	.503**	.619**	-0.229	.536**	0.263	.713**	.364*	.461**	.788**	-0.236
MBS	.545**	1	.513**	.385*	.544**	.559**	-0.180	.425*	.410*	.608**	.453**	0.319	.597**	-.389*
GCI	.547**	.513**	1	.598**	.596**	.476**	-0.280	.411*	.464**	.623**	.502**	.383*	.598**	-0.196
LPI	.566**	.385*	.598**	1	.530**	.474**	-0.313	0.310	.667**	.603**	.429*	.542**	.605**	0.024
EXPRAD	.503**	.544**	.596**	.530**	1	.836**	-0.175	0.285	.496**	.388*	.432**	0.193	.417*	-0.086
NUMRAD	.619**	.559**	.476**	.474**	.836**	1	-0.086	.354*	.415*	.467**	.475**	0.297	.573**	-0.221
WIS	-0.229	-0.180	-0.280	-0.313	-0.175	-0.086	1	-0.022	-0.164	-.416*	0.266	-.628**	-0.285	-.623**
INTEQ_INV	.536**	.425*	.411*	0.310	0.285	.354*	-0.022	1	0.190	.607**	.588**	-0.103	.512**	-.506**
UNI	0.263	.410*	.464**	.667**	.496**	.415*	-0.164	0.190	1	.448**	.603**	0.266	.438**	-0.008
GOVEF	.713**	.608**	.623**	.603**	.388*	.467**	-.416*	.607**	.448**	1	.480**	.615**	.880**	-0.151
HES	.364*	.453**	.502**	.429*	.432**	.475**	0.266	.588**	.603**	.480**	1	-.337*	.640**	-.624**
EXPDEV	.461**	0.319	.383*	.542**	0.193	0.297	-.628**	-0.103	0.266	.615**	-.337*	1	.582**	.814**
COR	.788**	.597**	.598**	.605**	.417*	.573**	-0.285	.512**	.438**	.880**	.640**	.582**	1	-0.199
LABQUAL	-0.236	-.389*	-0.196	0.024	-0.086	-0.221	-.623**	-.506**	-0.008	-0.151	-.624**	.814**	-0.199	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

FIGURE 3
CORRELATION ANALYSIS OF OUTPUT VARIABLES

Correlations

		J	PA	CYSEC	CLOUD	ICT_EMP	NEWENT	GMCI
J	Pearson Correlation	1	.450**	0.272	.501**	.638**	-0.026	-0.099
PA	Pearson Correlation	.450**	1	.447**	.367*	.436**	0.067	0.301
CYSEC	Pearson Correlation	0.272	.447**	1	0.170	.357*	0.159	0.292
CLOUD	Pearson Correlation	.501**	.367*	0.170	1	.452**	0.150	0.134
ICT_EMP	Pearson Correlation	.638**	.436**	.357*	.452**	1	-.382*	-0.106
NEWENT	Pearson Correlation	-0.026	0.067	0.159	0.150	-.382*	1	.390*
GMCI	Pearson Correlation	-0.099	0.301	0.292	0.134	-0.106	.390*	1

**. Correlation is significant at the 0.01 level (2-tailed).

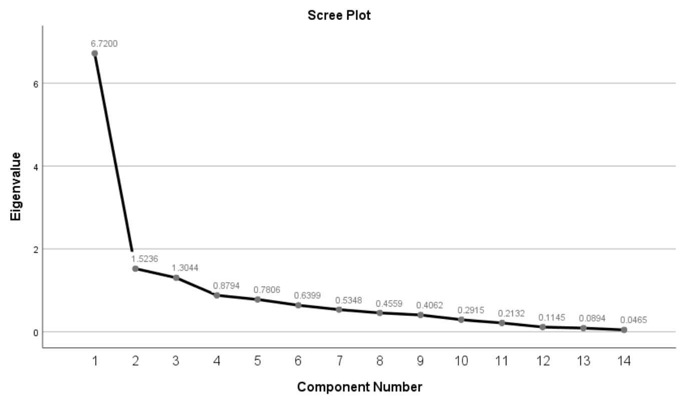
*. Correlation is significant at the 0.05 level (2-tailed).

Since the correlation results necessitated integration of PCA, PCA experiments were conducted on SPSS 2221 software. Results of PCA experiments were provided in Figures 4 and 5. Figure 4 indicates results of KMO, Bartlet's test and Principle Component (PCA) loadings of input data, whereas Figure 5 depicts the results of PCA analysis on the output data. Since both input and output data will be needed for DEA analysis, PCA transformation was applied to each separately. KMO and Bartlett's tests carried out in a PCA indicate the suitability of the sample data for structure detection. A KMO value greater than 0.5 is generally assumed as cutoff for PCA validation and indicates that PCA could be effectively used (Lamichane, 2021). On the other hand, the Bartlett's test of sphericity test is conducted on the correlation matrix to verify how close it is to the identity matrix. The closer the correlation matrix is to the identity matrix, the more the variable indicators are uncorrelated. For a valid PCA application, Bartlett's test p value is expected to be less than 0.05 (Park et al., 2016).

According to the results, 3 PCs were created from 14 input variables; thus the data was reduced by 11 dimensions (Fig. 4). The total variance loadings 3 newly created PCs were around 68%. Besides, the scree plot indicates that the eigen value of the 4th PC goes below 1, therefore having 3 PCs is ideal for this transformation. In terms of output data, 2 PCS were produced which account for 59% of the variation with eigen values of 2.8359 and 1.3317. The 3rd and following PCs provided eigen values less than 1, thus excluded from the transformation. The results of KMO and Bartlett's tests indicate that the data set is adequately sampled as both KMO values were greater than 0.6 and that PCA of the data is appropriate as the p values are less-0.05 and significant. All in all, PCA transformed both the input and output data, by doing so the multicollinearity has been removed. Next section provides the results of the next iteration, Data Envelopment Analysis (DEA).

FIGURE 4
KMO & BARTLETT'S TEST(A), SCREE PLOT(B), AND PRINCIPAL COMPONENTS(C) OF INPUT DATA

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin		0.771
Bartlett's Test of Sphericity	Approx. Chi-Square	312.683
	df	91
	Sig.	0.000



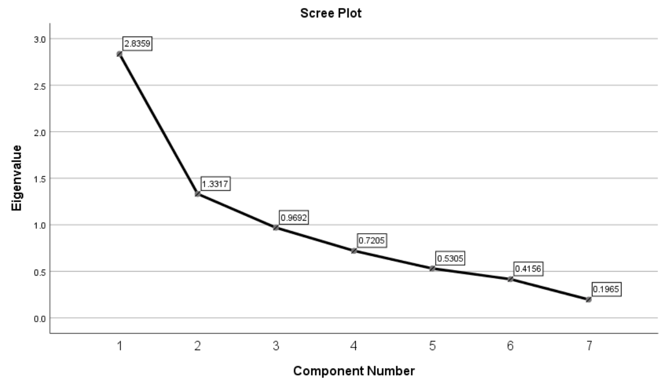
Total Variance Explained

Component	Initial Eigenvalues			Loadings			Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.720	48.000	48.000	6.720	48.000	48.000	4.176	29.830	29.830
2	1.524	10.883	58.883	1.524	10.883	58.883	3.628	25.917	55.747
3	1.304	9.317	68.201	1.304	9.317	68.201	1.743	12.453	68.201
4	0.879	6.282	74.482						
5	0.781	5.576	80.058						
6	0.640	4.571	84.629						
7	0.535	3.820	88.448						
8	0.456	3.257	91.705						
9	0.406	2.901	94.606						
10	0.291	2.082	96.688						
11	0.213	1.523	98.211						
12	0.115	0.818	99.029						
13	0.089	0.639	99.668						
14	0.046	0.332	100.000						

Extraction Method: Principal Component Analysis.

FIGURE 5
KMO & BARTLETT'S TEST(A), SCREE PLOT(B), AND PRINCIPAL COMPONENTS(C) OF OUTPUT DATA

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin		0.647
Bartlett's Test of Sphericity	Approx. Chi-Square	66.878
	df	21
	Sig.	0.000



Total Variance Explained

Component	Initial Eigenvalues			Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.836	40.513	40.513	2.836	40.513	40.513	2.616	37.365	37.365
2	1.332	19.025	59.538	1.332	19.025	59.538	1.552	22.173	59.538
3	0.969	13.846	73.384						
4	0.720	10.292	83.676						
5	0.531	7.579	91.255						
6	0.416	5.937	97.192						
7	0.197	2.808	100.000						

Extraction Method: Principal Component Analysis.

Results of DEA

DEA resulted in the maturity scores of OECD countries, which were depicted in Figure 6. The top five countries with the highest I4.0 maturity scores were found to be United States, Sweden, Finland, Switzerland, and Japan. In contrast, Mexico, Latvia, Chile, Turkey and Slovak Republic were found to have the lowest I4.0 maturity scores. The descriptive statistics of I4.0 maturity scores were provided in Table 3. The average I4.0 maturity was found to be 0.57, with a quite high standard deviation value of 0.3. The I4.0 maturity ranges between OECD countries significantly as the range was found to be 0.99. This brings the importance of SDG 17: Partnerships for the goals. The 2030 Agenda urges "a revitalized and enhanced global partnership that brings together Governments, civil society, the private sector, the United Nations system and other actors, mobilizing all available resources" (Lamichane, 2021). Both skewness and kurtosis values of the maturity results indicate that there is a slight skew towards higher maturity scores in the data, and overall the results indicate a normal balanced histogram as supported with the box plot.

FIGURE 6
INDUSTRY 4.0 MATURITY SCORES OF OECD COUNTRIES

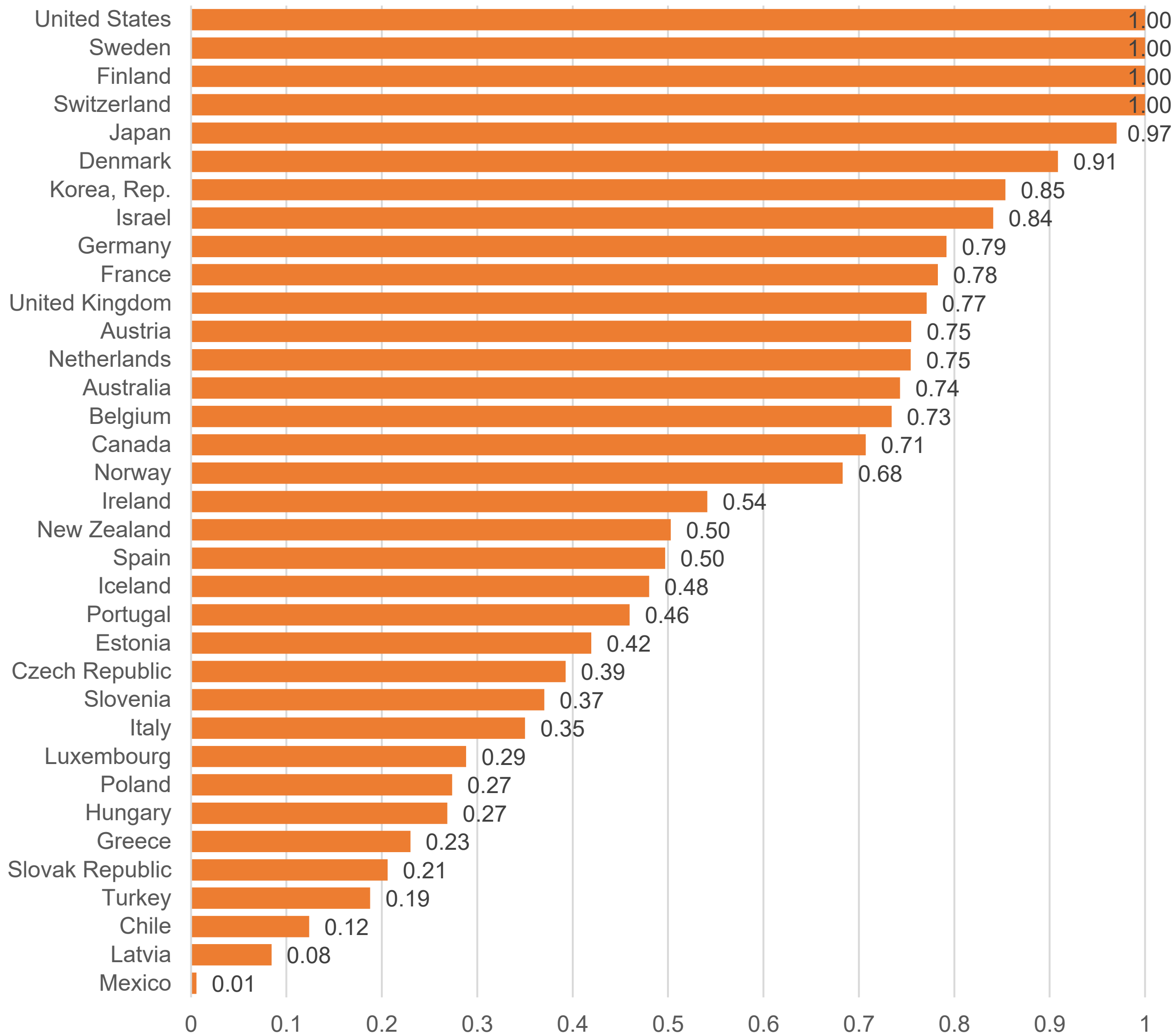
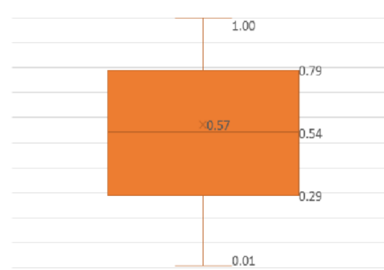


TABLE 3
DESCRIPTIVE STATISTICS OF MATURITY SCORES

Mean	0.57	Range	0.99
Standard Error	0.05	Minimum	0.01
Median	0.54	Maximum	1.00
Standard Deviation	0.30	Sum	19.98
Sample Variance	0.09	Count	35.00
Kurtosis	-1.20	Confidence Level (95.0%)	0.10
Skewness	-0.14		



DISCUSSION, CONCLUSION, AND FUTURE WORK

A non-parametric efficiency assessment (PCA+DEA) approach is proposed to assess the OECD countries' preparedness for Industry 4.0 adoption from macro-economic perspective. It was found that PCA is a robust approach that should be used to deal with dataset with high multicollinearity to produce a composite index of multiple variables of interest. PCA's outputs were used as the input data for DEA and min-max normalization with scaling was crucial for the success of using such methods back-to-back. Results indicated that US, Sweden, and Finland were found to be the best 3 countries, and Mexico, Latvia, and Chile were found to be the worst 3 in terms of readiness for Industry 4.0 adoption. This study shows a conceptual framework to adapt in assessing I4.0 maturity of countries. The literature of I4.0 maturity assessment has been growing significantly in the last couple of years, but majority of the works do not take into account the significantly high degree of multi collinearity in sustainability datasets. Especially, when working with UN SDGs, most of the these goals use similar sustainability indicators that are prone to have high correlations. Therefore, correlation mitigation is crucial to produce scientifically reliable and statistically good quality results. Potential future research directions are provided as follows. Current research left investigating the relationship(s) between the input & output variables and the Industry 4.0 maturity scores. For instance, Lasso, Ridge, Stepwise regression and machine learning algorithms such as Random Forest, Neural Networks, Support Vector Machines and deep learning could be integrated to the results of the current study. Furthermore, scope of the study could be extended to include other countries who are not part of OECD, but when doing so, a clustering approach will be needed since developing and developed countries have significant differences on various indicators, which could result in either overrated maturity scores for developed countries or underrated maturity scores for the developed countries as a result of discrepancies in data between the two major groups.

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