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AN EMPIRICAL STUDY ON THE RELATIONSHIP BETWEEN LOGISTICS PERFORMANCE AND EDUCATION

Turkay YILDIZ

Izmir Institute of Technology, B.I.D.B., 35430, Gulbahce kampusu, Izmir, Turkey
E-mail: turkayyildiz@iyte.edu.tr

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Abstract. Logistics occupations require skills that involve blue- and white-collar activities and different levels of educational skills. With the increase in global trade and competition, the varying skills necessary for different parts of the logistics sector have attracted attention. In this regard, this empirical study examines the relationship between logistics performance indicators and education assessment scores and identifies associations. The presented results, by using canonical correlation analysis, indicate that certain education assessment scores contribute more to improving logistics performance than do other variables. The variables that influence logistics performance are also highlighted.

Keywords: logistics performance, transportation, education assessment, PISA, global competitiveness, canonical correlation.

JEL Classification: A20, I25, L25, M20.

1. Introduction

Logistics professions cover a wide range of skill levels and specialties including equipment operators and mechanics, inventory managers, supply chain managers, business information systems, and distribution frames (Sheffi 2012). To recruit labor and carry out on-the-job training, many logistics groups attract and develop workers in partnership with educational institutions that supply vocational, undergraduate, postgraduate, and professional training (Sheffi 2012).

Indeed, technological, economic, and political trends have increased demand for higher skills and reduced demand for low skills while increasing competition for quality jobs (Stewart 2012). This is one reason for paying attention to the international core skills assessments that have recently been implemented. These core skills evaluations and their results have led to a growing body of research, observation, and discussion that goes beyond the numbers and rankings to help us understand why some systems are moving forward quickly and producing more equitable performance, while others remain static and uneven. In this regard, the current research was undertaken to address the issue of developing human capital in the field of logistics, specifically for achieving higher logistics performance. In which areas, do logistics firms need help building competencies in order to improve performance? What skills should these firms be looking for in the first place? More specifically, how do education and skills influence logistics performance?

The remainder of this paper is organized as follows. Section 2 reviews the literature on logistics in general and education-related issues in particular. Section 3 introduces the data and methods used for the canonical correlation analyses of the perceptions of countries' logistics efficiencies and educational scores by using various measures drawn from the World Bank, the Global Competitiveness Index (GCI) of the World Economic Forum (WEF), and the International Institute for Management Development (IMD) database. Specifically, this section investigates the associations between logistics performance indicators and education-related scores derived from the Programme for International Student Assessment (PISA) of the OECD, the WEF, and the IMD. In addition, ridge regression analysis is performed on the logistics performance indicators and PISA education variables to find those variables that contribute most to influencing overall logistics performance. Section 4 presents and discusses the empirical findings. The study is concluded in Section 5.

2. Literature

Koenig (2011) stated that there is a growing recognition that individuals need a broad range of skills to meet the demands of the modern workplace. Gone are the days where multitudes of jobs were available that required workers to perform simple manual tasks (Koenig 2011). In this vein, Goldsby and Martichenko (2005) indicated that all forms of education continue to offer the fastest return on the investment made and that all knowledge acquired through training exercises improves firm performance.

Svensson (2007) stated that logistics educators in general have received their training in marketing, operations, and quantitative methods, but that skills in organizational behavior and psychology are also required. These skill sets suggest that current teachers are ill equipped to deal with the new managerial dimensions required for modern SCM (Svensson 2007). However, these additional dimensions must be incorporated into logistics education if the promises of SCM are to be met (Svensson 2007). Managers should also search out such educational opportunities.

The rapid expansion of national participation in studies of international achievement has been a feature of education planning over the past 25 years (Wiseman 2010). Large-scale international comparative educational assessments began more than 50 years ago with the formation of the International Association for the Evaluation of Educational Achievement (IEA) and they have since developed and diversified (Wiseman 2010). However, particularly over the past decade, renewed interest in these studies has swept public discourse. National rankings of test results are now part of common educational jargon and the number, severity, scope, complexity, and connectivity of these assessments are at a historically high level (Wiseman 2010).

Researchers have examined the connection between industry performance and education on SCM. For example, authors have explored the challenges of SCM module boards (Bak, Boulocher-Passet 2013), the development of SCM training (Bernon, Mena 2013), using SCM software in education (Campbell *et al.* 2000), the integration of production and logistics in principle, in practice, and in education (Chikan 2001), and education and training needs in logistics (Felea *et al.* 2010). Furthermore, scholars have investigated logistics and SCM doctoral training (Grant, Bourlakis 2010), SCM simulation as a tool for education (Holweg, Bicheno 2002), and SCM for education engineering students and employees (Ilie-Zudor *et al.* 2011).

Research on logistics education has also examined the current state of the art (Lutz, Birou 2013), using SCM to improve collaboration between universities (Om *et al.* 2007), and the future of logistics education (Ozment, Keller 2011). Similarly, previous studies have explored activities and education in logistics (Skrinjar *et al.* 2008), competitiveness, manufacturing, and the role of education in SCM in the forest industry (Smith 2005), the provision of education and current practitioner future needs (van Hoek, Wagner 2013), and competitiveness, manufacturing, and the role of education (Winistorfer 2005). Moreover, Zinn and Goldsby (2014) presented a study about logistics professional identity for strengthening the discipline. Wu and Huang (2013) performed a study about making on-line logistics training sustainable through e-learning. In the same vein, Sweeney *et al.* (2010) performed a study on teaching supply chain and logistics management through commercial software. Bian *et al.* (2014) performed an empirical research on the effect of workplace learning on logistics management and decision implications. Cvetic and Vasiljevic (2012) explored game-based enhancement for teaching logistics and supply chain management.

In addition, Fawcett and Rutner (2014) assessed the supply chain education and explored the challenge of retaining relevance in today's marketplace. Kovacs *et al.* (2012) explored the skills needed to be a humanitarian logistician. Thai and Yeo (2015) studied perceived competencies required for container shipping logisticians in Singapore and South Korea. Shi and Handfield (2012) explored talent management issues for multinational logistics companies in China. Wong *et al.* (2014) studied UK markets on logistics and supply chain education and jobs. Wu *et al.* (2013) provided perspectives from practitioners in Taiwan about global logistics management curriculum.

The modern workplace requires workers to have broad cognitive and affective skills (Koenig 2011), often referred to as "21st century skills." These skills include being able to solve complex problems, think critically about tasks, communicate effectively with people of different cultures, use a variety of techniques, work with others, adapt to changing environments and conditions to carry out tasks, effectively manage workload, and acquire new skills and information proactively (Koenig 2011). Skills, which relate to experience and are knowledge context-dependent, are taught in most logistics classes, which are vital for practitioners (Gammelgaard, Larson 2001). However, to achieve a level of competence in the discipline of logistics, practitioners gain knowledge depending on their degrees of organizational experience (Gammelgaard, Larson 2001).

The present study adds another dimension to the existing literature. In this regard, by using statistical methods, it provides a better understanding for policymakers. Specifically, it differs from previous works in that it investigates statistically significant relationships between logistics performance and education assessment scores.

3. Data and methods

In this study, four main types of data sources are used, all of which are drawn from the World Bank, the GCI database, and the IMD's World Competitiveness database. The first data source is on the perceptions of countries' logistics efficiencies. The second data source is the PISA survey assessment indicators. The third data source is the fifth pillar from the GCI (GCI5 hereafter), which measures higher education and training. The fourth data source is the IMD's various education scores (see Tables A17 and A18).

The Logistics Performance Index (LPI) is the first international benchmarking tool that measures the ease of trade and transport logistics by country (McLinden *et al.* 2010). The LPI is based on a global survey that the World Bank conducts every two years, covering 155 countries and completed by nearly 1,000 logistics professionals in international freight forwarders and express carriers (Arvis *et al*. 2010). Each LPI report contains a comprehensive cross-country assessment to help countries identify their challenges and opportunities in trade and transport logistics performance and disaggregates data into six categories to highlight problem areas (McLinden *et al.* 2010).

The composite LPI summarizes all areas of performance. In brief, these variables are as follows: CUST stands for the customs clearance process, INFR is the quality of trade and transport-related infrastructure, ITRN is the ease of arranging competitively priced shipments, LOGS is the quality of logistics services, TRAC is the ability to track and trace consignments, TIME is the frequency with which shipments reach the consignee within the scheduled time, and OVRL is overall logistics performance.

PISA is a triennial international survey that aims to evaluate education systems worldwide by testing the skills and knowledge of 15-year-olds. To date, students representing over 70 countries have participated in the evaluation. PISA 2012, the fifth survey program, assessed the skills of 15-year-olds in reading (READ), mathematics (MATH), and science (SCI) in 65 countries and economies. Approximately 510,000 students aged 15 years and 3 months and 16 years and 2 months participated in the evaluation, which represents about 28 million children worldwide, thereby providing evidence of the effect of the development of younger children on later school success (Wu *et al.* 2012). PISA is unique because it develops tests that are not directly related to the curriculum. These tests are designed to assess how well students at the end of compulsory education can apply their knowledge to real-life situations and be equipped to participate fully in society. The information gathered through questionnaires also provides a context that can help analysts interpret the results.

The GCI (2013–2014) measured national competitiveness by using a complex methodology involving raw data and executive opinions. The index rests on 12 pillars categorized into three groups, namely *basic requirements* (four pillars), *efficiency enhancers* (six pillars), and *innovation and sophistication factors* (two pillars). Countries are rated on a seven-point scale, with a higher score indicating more competitiveness. In this research, the fifth pillar, which concerns *higher education and training*, is taken into consideration. This pillar has three sub indicators: *quantity of education*, *quality of education*, and *on-the-job training*.

The GCI is a comprehensive database of the competitiveness of nations. Global competitiveness is an area of economic theory that analyzes the facts and policies that shape the ability of a nation to create and maintain an environment that sustains more value creation for its enterprises and more prosperity for its people. The approach of the IMD's World Competitiveness Center for global competitiveness is to analyze how nations and businesses manage all their skills to achieve greater prosperity. From this database, only education-related variables are used in this study.

It should be noted that the LPI variables (CUST, INFR, ITRN, LOGS, TRAC, TIME) introduce severe multicollinearity. Multicollinearity, which occurs when the predictors included in the linear model are highly correlated (Yan 2009), poses statistical inference problems. Therefore, to overcome this problem, by applying the factor analysis technique, six LPI variables were factor analyzed and six components extracted, each representing their respective variables, although factor analysis mainly aims to obtain a smaller number of factors that account for most of the variability. In this special case, six factors were extracted from the six variables. Together, they accounted for 100% of the variability in the original LPI data. Finally, these extracted factors were stored as Anderson–Rubin factor scores, which are uncorrelated scores with other factors. The same multicollinearity issue for the three PISA variables (MATH, READ, SCI) was also overcome by using the same technique. The factor loadings of the equamax rotation are presented in Tables A1 through A6.

Multicollinearity does not pose a problem for the GCI5 variables. The preliminary tests of these variables indicated that the variance inflation factors (VIFs) were below 5. VIF is an indicator of how the other explanatory variables affect the variance of a regression coefficient of a particular variable, given by the inverse of the square of the multiple correlation coefficient of the variable with the remaining variables (Everitt 2002). Ideally, researchers are looking for VIFs < 10 (see Table A7). The multicollinearity issue was overcome for the IMD variables by extracting factor scores and storing the extracted factors as Anderson–Rubin factor scores (see Tables A11 through A16).

3.1. Canonical correlation analysis of logistics performance indicators and PISA scores

Nearly 80 years ago, Harold Hotelling (1936) introduced canonical correlation analysis (see also Brown *et al.* 2011). Essentially, this method identifies the holistic relationship between two multivariate sets of variables, an obvious next step after factor analysis and principal component analysis made their appearance in the first decades of the twentieth century (Brown *et al.* 2011). This procedure finds the linear combinations of two sets of variables that have the highest correlation between them (see Table A8 for the linear relationship between the LPI and PISA scores).

Table 1. Chi-Square tests with successive roots removed. Rows having $p < 0.05$ are highlighted

	Canonical R	Canonical R-sqr.	Chi-sqr.	df	p	Lambda – Prime
0	0.72	0.52	56.62	18	0.00	0.33
1	0.51	0.26	18.66	10	0.04	0.69
2	0.24	0.06	2.97	4	0.56	0.94

The canonical analysis summary is that the canonical R equals 0.72, $Chi^2(57)$ equals 56.61, and p equals 0.00. In this case, three sets of linear combinations have been formed. However, only two sets are statistically significant ($p < 0.05$; Table 1 and Fig. 1). The first set, which forms the strongest correlations, has the following highly contributing variables:

$U_1 = -\mathbf{0.68{\times}MATH} - 0.55{\times}READ - 0.46{\times}SCI$

and

$L_1 = -\mathbf{0.61{\times}CUST} - 0.36{\times}INFR - 0.39{\times}ITRN - \mathbf{0.47{\times}LOGS} - 0.09{\times}TIME - 0.16{\times}TRAC$.

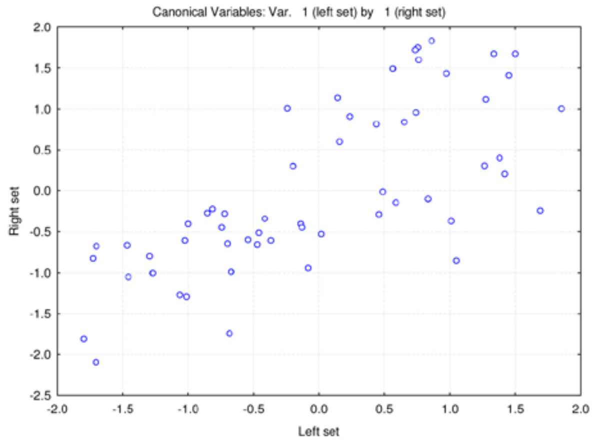
In addition, the second set of linear combinations, the next strongest correlation among all combinations that are uncorrelated with the first set, has the following highlighted highly contributing variables:

$U_2 = -0.43{\times}MATH + \mathbf{0.83{\times}READ} - 0.38{\times}SCI$

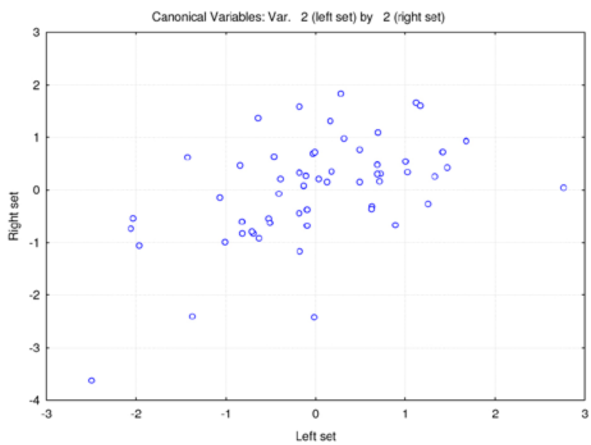
and

$L_2 = -0.07{\times}CUST + 0.45{\times}INFR - 0.25{\times}ITRN - 0.30{\times}LOGS + \mathbf{0.95{\times}TIME} + \mathbf{0.67{\times}TRAC}$,

where the variables have first been standardized by subtracting their means and dividing by their standard deviations. Table 1 and Figure 1 show the estimated correlations between each set of canonical variables. Since two of the p values are less than 0.05, those sets have statistically significant correlations at the 95% confidence level.



(a)



(b)

Fig. 1. (a) PISA (right set root 1) versus LPI (left set root 1) and
(b) PISA (right set root 2) versus LPI (left set root 2)

Other ways of dealing with complex sets of multivariate data are structural equation modeling and confirmatory factor analysis (Brown *et al.* 2011). These powerful developments in the factor analytic tradition, which have arrived over the past three decades or so, constitute a computational general case of which factor analysis and canonical correlation analysis are special cases (Brown *et al.* 2011). Whereas principal component analysis, canonical correlation analysis, and some factor analyses can improve the holistic understanding of complex data and provide a better visible apprehension of one's data, structural equation models allow researchers to test specific scientific models against complex empirical data (Brown *et al.* 2011).

3.2. Ridge regression for logistics performance indicators versus raw PISA scores

Ridge regression is one of the remedies to treat severe multicollinearity in least squares estimations (Yan 2009). One approach to dealing with multicollinearity is thus to apply the ridge regression (Lesaffre, Lawson 2012). The method of ridge regression suggested by Hoerl in 1962 and systematically developed by Hoerl and Kennard (1970a, 1970b) can significantly improve the mean squared error of the least squares estimator when the columns of the matrix vector design are multicollinear (Tong *et al.* 2011).

The R-Squared statistic indicates that the model as fitted explains 46.32% of the variability in OVRL. The adjusted R-Squared statistic, which is more suitable for comparing models with different numbers of independent variables, is 43.28%. The standard error of the estimate shows the standard deviation of the residuals to be 0.35. The mean absolute error of 0.28 is the average value of the residuals. The Durbin–Watson statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in the data.

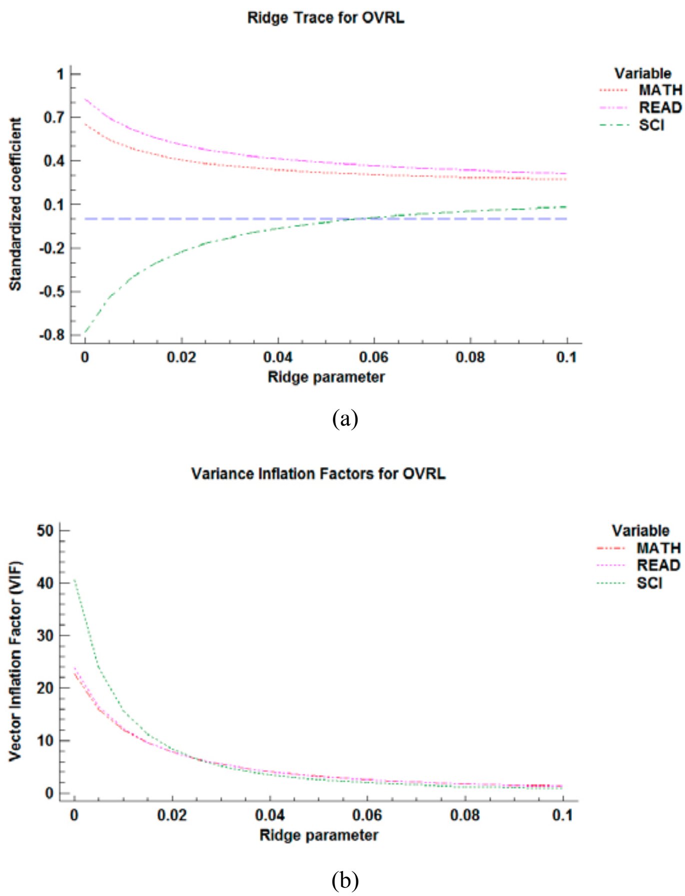


Fig. 2. (a) Ridge trace for OVRL and (b) VIFs for OVRL

Figure 2a shows the standardized regression coefficients for the values of the ridge parameter between 0.0 and 0.1. These are the coefficients of the regression model when the variables are expressed in standardized form. As the ridge parameter increases from 0, the coefficients often change dramatically at first and then become relatively stable. A good value for the ridge parameter is the smallest value after which the estimates change slowly. This is admittedly subjective, but the ridge trace helps researchers make a good choice.

Figure 2b shows the VIFs for each of the coefficients in the regression model. VIFs measure the degree to which the variance of the estimated coefficients is inflated relative to the case when all the independent variables are uncorrelated. As before, as the ridge parameter increases from 0, the VIFs often decrease dramatically at first and then become relatively stable. A good value for the ridge parameter is also the smallest value after which the VIFs change slowly. This is admittedly subjective, but the plot of the VIFs again helps us make a good choice.

This procedure aims to estimate the regression coefficients when the independent variables are strongly correlated. By allowing for a small amount of bias, the precision of these estimates can often be greatly increased. In this case, the fitted regression model is:

OVRL = 0.3593 + **0.0025×MATH** + **0.0032×READ** + 0.0008×SCI.

Table 2. Model results when the ridge parameter is 0.1

Parameter	Estimate	VIFs
Constant	0.3593	
MATH	0.0025	1.32968
READ	0.0032	1.30215
SCI	0.0008	0.911942

3.3. Canonical correlation analysis of logistics performance indicators and GCI5 scores

As noted earlier, this procedure finds the linear combinations of two sets of variables that have the highest correlation between them (see Table A9 for the linear relationship between the LPI and GCI5). The canonical analysis summary is that the canonical R equals 0.87, Chi²(18) equals 189.45, and p equals 0.00.

Table 3. Chi-Square tests with successive roots removed. Rows having $p < 0.05$ are highlighted

	Canonical R	Canonical R-sqr.	Chi-sqr.	df	p	Lambda – Prime
0	0.87	0.75	189.45	18	0.00	0.21
1	0.30	0.09	19.61	10	0.03	0.85
2	0.25	0.06	7.71	4	0.10	0.94

In this case, three sets of linear combinations have been formed. However, only two sets are statistically significant ($p < 0.05$; Table 3 and Fig. 3). The first set forms the strongest correlations (R^2 equals 0.75). In detail, the first set of linear combinations with the highlighted highly contributing variables is:

U_3 = +0.43×F_TIME + 0.31×F_ITRN + 0.42×F_CUST + 0.35×F_INFR **+ 0.50×F_TRAC** + 0.37×F_LOGS

and

L_3 = +0.37×[Quantity of education] – 0.01×[Quality of education] **+ 0.76×[On-the-job training]**.

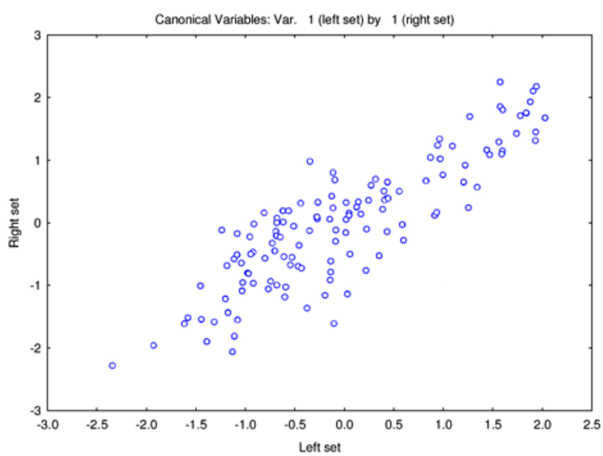
The second set of linear combinations, which has the next strongest correlation (R^2 equals 0.09) among all combinations that are uncorrelated with the first set, has the following contributing variables:

U_4 = –0.25×F_TIME + 0.17×F_ITRN **– 0.76×F_CUST + 0.51×F_INFR** + 0.20×F_TRAC + 0.27×F_LOGS

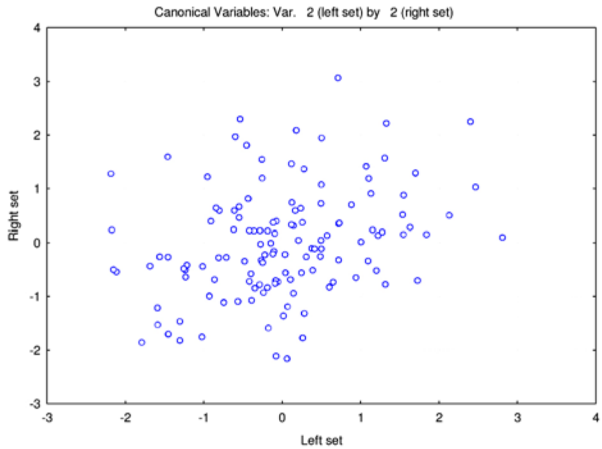
and

L_4 = +0.72×[Quantity of education] **– 2.01×[Quality of education]** + 1.23×[On-the-job training],

where the variables have first been standardized by subtracting their means and dividing by their standard deviations. Table 3 and Figure 3 show the estimated correlations between each set of canonical variables. Since two of the p values are less than 0.05, those sets have statistically significant correlations at the 95% confidence level.



(a)



(b)

Fig. 3. (a) GCI5 (right set root 1) versus LPI (left set root 1) and (b) GCI5 (right set root 2) versus LPI (left set root 2)

3.4. Canonical correlation analysis of logistics performance indicators and IMD scores

Again, this procedure finds the linear combinations of two sets of variables that have the highest correlations between them (see Table 4 for the linear relationship between the LPI and the IMD's education assessment pillar). The canonical analysis summary is that the canonical R equals 0.98, $Chi^2(96)$ equals 135.18, and p equals 0.00.

Table 4. Chi-Square tests with successive roots removed. Rows having $p < 0.05$ are highlighted

	Canonical R	Canonical R-sqr.	Chi-sqr.	df	p	Lambda – Prime
0	0.98	0.97	135.18	96	0.01	0.00
1	0.95	0.90	82.76	75	0.25	0.00
2	0.87	0.75	46.64	56	0.81	0.05

In this case, some sets of linear combinations have been formed. However, only one set of linear combinations is statistically significant ($p < 0.05$; Table 4 and Fig. 4). The first set forms the strongest correlations (R^2 equals 0.97) and this has the following highly contributing variables:

U_5 = **–0.45×[Student mobility outbound]** – 0.13×[Educational assessment, Science]

–0.11×[Language skills] – 0.10×[Pupil-teacher ratio (primary education)]

–0.03×[Secondary school enrollment (%)] – 0.02×[Total public expenditure on education]

+0.02×[Management education] + 0.03×[Educational assessment, Mathematics]

+0.17×[English proficiency - TOEFL] + 0.19×[Student mobility inbound]

+0.22×[Higher education achievement (%)] + 0.24×[Pupil-teacher ratio (secondary education)]

+0.31×[Educational system] + 0.33×[Illiteracy (%)]

+0.41×[University education] + 0.55×[Science in schools]

and

L_5 = –0.22×F_INFR–0.12×F_TIME + 0.17×F_LOGS + 0.18×F_ITRN **+ 0.46×F_CUST + 0.82×F_TRAC**,
where the variables have first been standardized by subtracting their means and dividing by their standard deviations. Table 4 and Figure 4 show the estimated correlations between each set of canonical variables. Since two of the p values are less than 0.05, those sets have statistically significant correlations at the 95% confidence level.

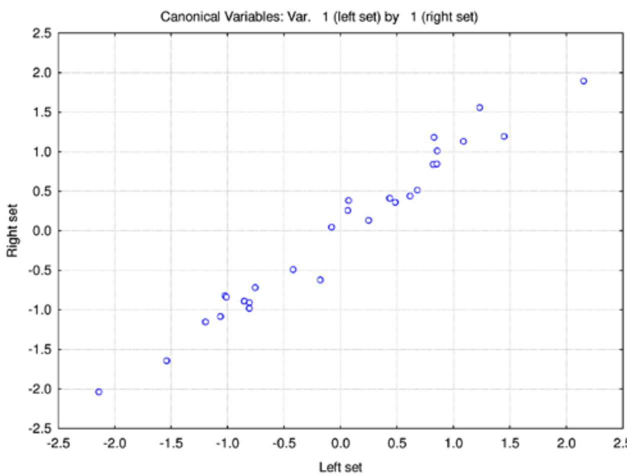


Fig. 4. IMD scores (left set root 1) versus LPI (right set root 1)

4. Research findings and highlighted discussions

The first canonical correlation, U_1 and L_1, is moderately strong with a magnitude of 0.72 and statistically significant at $p < 0.05$ (see Table 1 and Fig. 1a). There are primarily relationships between the logistics performance variables of LOGS and CUST, on the one hand, and the education assessment variable of MATH with some contribution from READ and SCI, on the other. This finding implies that *the quality of logistics services* and *customs clearance process* are related to the education assessment variables of the *mathematics* skill, with some contribution from the *reading* and *science* skills.

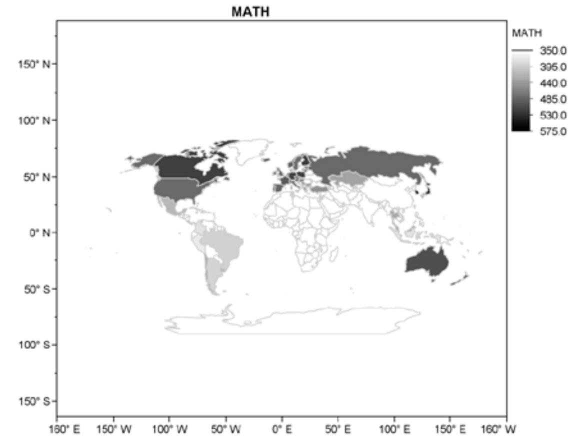
The second canonical correlation, U_2 and L_2, is less strong with a magnitude of 0.51 and statistically significant at $p < 0.05$ (Table 1 and Fig. 1b). We see relationships between the logistics performance variables of TIME and TRAC and the education assessment variable of READ with some contribution from MATH and SCI. The implication here is that *the frequency with which shipments reach the consignee within the scheduled time* and *the ability to track and trace consignments* are related to the education assessment variable of the *reading* skill with some contribution from the *mathematics* and *science* skills.

The ridge regression model for the dependent variable of OVRL versus the PISA variables shows the contributions of the independent variables. The R-Squared statistic indicates that the model as fitted explains 46.32% of the variability in OVRL. The adjusted R-Squared statistic, which is more suitable for comparing models with different numbers of independent variables, is 43.28% and is moderately strong (Table 2). As the fitted ridge regression model explains, the MATH and READ variables highly contribute to overall logistics performance with a smaller coefficient of SCI.

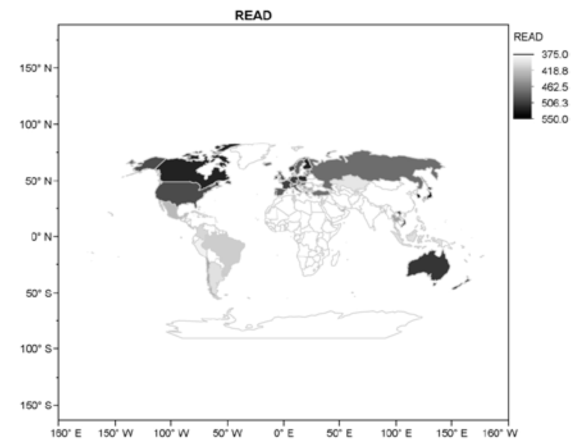
For GCI5 versus the LPI variables, the first canonical correlation, U_3 and L_3, is moderately strong with a magnitude of 0.87 and statistically significant at $p < 0.05$ (Table 3 and Fig. 3a). There seems to be a relationship between all logistics performance variables (as their coefficients are close to each other) and the education assessment variable of *On-the-job training* with some contribution from *Quantity of education.* Primarily, TRAC and the variable *On-the-job training* are canonically correlated with the highest coefficient. This finding implies that *the ability to track and trace consignments* is primarily related to the education assessment variable of the *On-the-job training* with some contribution from *Quantity of education. Quality of education* has almost no effect in this first canonical correlation.

The second canonical correlation of GCI5 versus the LPI variables, U_4 and L_4, is less strong with a magnitude of 0.51 and statistically significant at $p < 0.05$ (Table 3 and Fig. 3b). There is a relationship between CUST and INFR and the education assessment variable of *Quality of education* with some contribution from *On-the-job training* and *Quantity of education*. The primary implication here is that *the customs clearance process* and *quality of trade and transport-related infrastructure* are related to the *Quality of education* with some contribution from *On-the-job training* and *Quantity of education*.

For the IMD versus the LPI variables, the canonical correlation, U_5 and L_5, is strong with a magnitude of 0.98 and statistically significant at $p < 0.05$ (Table 4 and Fig. 4). CUST and TRAC are related to science education in schools and university education with some contribution from illiteracy (percentage) and the educational system. This finding implies that the *ability to track and trace consignments* and *customs clearance process* are related to the education assessment variables of *Science education in schools* and *university education* with some contribution from *illiteracy (percentage)* and the *educational system*.


MATH
MATH
350.0
395.0
440.0
485.0
530.0
575.0
150° N
100° N
50° N
0° N
50° S
100° S
150° S
160° E
150° W
100° W
50° W
0° E
50° E
100° E
150° E
160° W

(a)


READ
READ
375.0
418.8
462.5
506.3
550.0
150° N
100° N
50° N
0° N
50° S
100° S
150° S
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150° W
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0° E
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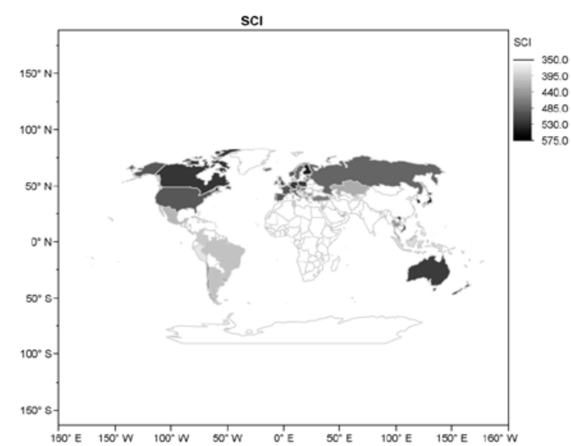
100° E
150° E
160° W

(b)


SCI
SCI
350.0
395.0
440.0
485.0
530.0
575.0
150° N
100° N
50° N
0° N
50° S
100° S
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150° W
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50° W
0° E
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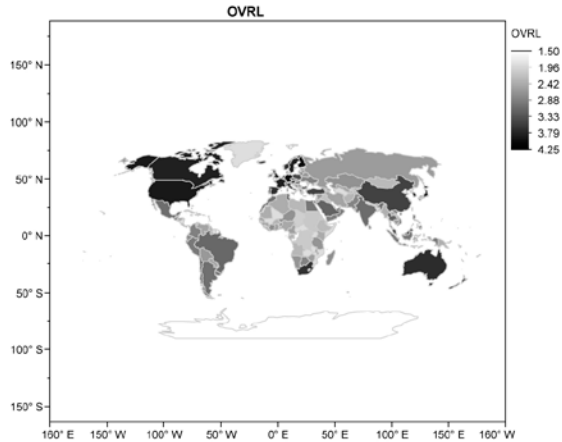
100° E
150° E
160° W

(c)

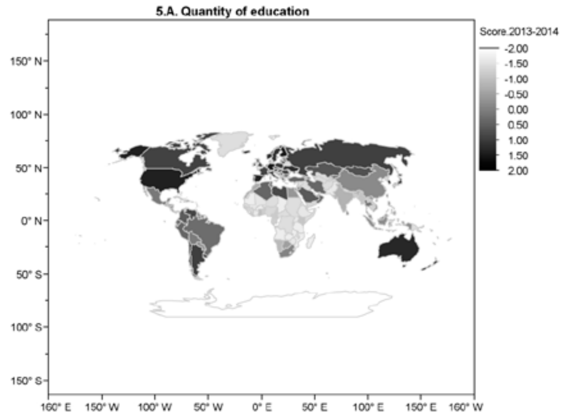


(d)

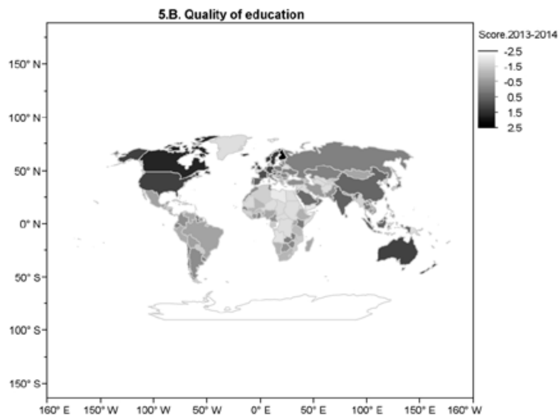
Fig. 4. In each figure, the countries with darker (lighter) grays indicate good (poor) performance. White regions/countries: unavailable data. (a) MATH scores, (b) READ scores, (c) SCI scores, and (d) overall logistics performance (OVRL)

All countries are trying to get people out of poverty and respond to increasing public pressure to provide more economic opportunities for the next generation through the expansion of education (Stewart 2012). Countries with high performance and rapid improvement are also carefully designed as learning systems, constantly checking and updating in order to determine if the education system is preparing their students for the knowledge economy in this rapidly changing world (Stewart 2012). However, during the past two decades, countries have focused on the expansion of education as the key driver to maximizing individual well-being, reducing poverty, and stimulating economic growth (Stewart 2012) (see Figs 4, 5, and 6).

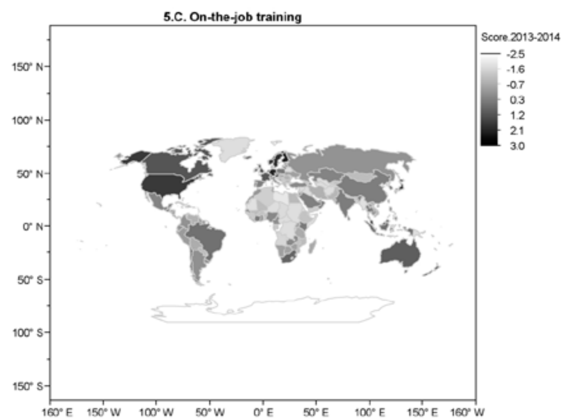
The design, management, and constant renewal of logistics systems and the supply chain demand considerable sophistication and analytical knowledge (Sheffi 2012). The analysis of logistics systems makes extensive use of mathematics, particularly operations research methods that aim to optimize the flow of goods, people, and goods subject to the constraints of cost, time, capacity, and uncertainty (Sheffi 2012). Even though a worker can physically move a box, intellectual muscle remains necessary in order to determine which of the thousands of boxes to put in which truck to transport each item (Sheffi 2012). Because tasks such as designing a network of distribution centers, planning travel modes, and optimizing inventory in the face of an uncertain future need technical sophistication, companies require logistics managers and engineers with university and postgraduate training (Sheffi 2012).



(a)

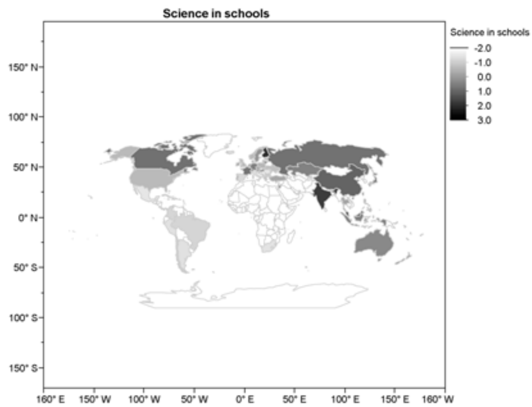


(b)

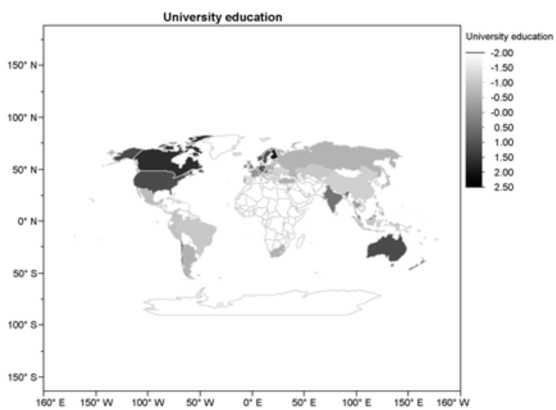


(c)

Fig. 5. (a) Quantity of education scores, (b) Quality of education scores, and (c) On-the-job training scores



(a)



(b)

Fig. 6. (a) Science in schools and (b) University education
(source: the IMD World Competitiveness database (60 countries))

Globalization poses challenges for everyone. Every education system in the world is struggling to some extent to deal with the rapid pace of change (Stewart 2012). In addition, countries are facing similar challenges. For example, internal and international migration have created more widespread heterogeneous societies everywhere, imposing new demands on teachers as they respond to students and families from diverse cultural and linguistic backgrounds (Stewart 2012).

5. Conclusions

In this empirical study, the relationship between logistics performance indicators and educational assessment scores are examined and their associations are identified. The presented results indicated that certain educational assessment indicators, as evidenced by the canonical correlation analyses, contribute much more to improving logistics performance than do other variables.

Logistics performance depends on many factors, as supply chains are complex systems with complex processes. Supply chain organizations are challenged to improve efficiency in the face of increasing complexity and global competition. Therefore, it became necessary to determine the relationship and recognize the relevant indicators that contribute to high logistics performance. It is evidenced by the analysis that certain variables in indicators contribute much more to logistics performance than other variables. In this regard, it is essential for policymakers in the logistics field to take account of those variables that have higher contributions in canonical correlations. By taking into consideration the education assessment indicators, the main areas for improvement of the logistics performance include focusing more on the highlighted indicators to have an opportunity to significantly improve outcomes.

Indeed, this research has one main limitation, as it does not directly assess the group of skills required to improve logistics performance. It rather investigated the canonical correlations between logistics performance and selected educational assessment scores, which is an indirect measurement of contribution. However, as the assessment scores suggest, countries that provide better education opportunities are also those that improve logistics performance. Further research should nevertheless aim to investigate those skills directly related to the logistics industry that can improve logistics performance. Such research would shed light on the primary skills needed in the logistics sector.

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APPENDIX

Factor analysis of LPI and PISA scores
Retrieval of LPI Factors:

The *Kaiser–Meyer–Olkin* measure indicates sampling adequacy, which is 0.938. Since this value is above 0.6, it indicates that sampling is adequate. *Bartlett's test of sphericity* is a test of the null hypothesis of whether the correlation matrix is an identity matrix, which would indicate that the factor model is inappropriate. Since its P-value is 0.00, which is below the 0.05 threshold, the null hypothesis is rejected. This implies that the model is appropriate for factor analysis.

Table A1. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.938
Bartlett's Test of Sphericity	Approx. Chi-Square	1625.877
	df	15
	Sig.	0.000

Table A2. Total variance explained. Extraction method: Principal Component Analysis

Component	Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %
1	1.035	17.250	17.250
2	1.024	17.072	34.322
3	1.007	16.790	51.112
4	0.985	16.417	67.529
5	0.984	16.401	83.930
6	0.964	16.070	100.000

Table A3. Rotated component matrixa

	1	2	3	4	5	6
TIME	0.692					
ITRN		0.677				
CUST			0.642			
INFR				0.614		
TRAC					0.616	
LOGS						0.575

Extraction Method: Principal Component Analysis.
Rotation Method: Equamax with Kaiser Normalization.
a. Rotation converged in 59 iterations.

Retrieval of PISA Factors:

The *Kaiser–Meyer–Olkin* measure indicates sampling adequacy, which is 0.761. Since this value is above 0.6, it indicates that sampling is adequate. *Bartlett's test of sphericity* is a test of the null hypothesis of whether the correlation matrix is an identity matrix, which would indicate that the factor model is inappropriate. Since its P-value is 0.00, which is below the 0.05 threshold, the null hypothesis is rejected. This implies that the model is appropriate for factor analysis.

Table A4. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.761
Bartlett's Test of Sphericity	Approx. Chi-Square	353.298
	df	3
	Sig.	0.000

Table A5. Total variance explained. Extraction method: Principal Component Analysis

Component	Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %
1	1.016	33.857	33.857
2	1.008	33.592	67.449
3	0.977	32.551	100.000

Table A6. Rotated component matrixa

	Component		
	1	2	3
MATH	0.699		
READ		0.691	
SCI			0.656

Extraction Method: Principal Component Analysis.
Rotation Method: Equamax with Kaiser Normalization.
a. Rotation converged in 36 iterations.

Table A7. VIFs and coefficients[a] of fifth pillar of GCI variables

Model	Standardized coefficients	t	Collinearity statistics	
	Beta		Tolerance	VIF
(Constant)		2.662		
5.A. Quantity of education	0.298	4.997	0.595	1.681
5.B. Quality of education	–0.033	–0.349	0.236	4.231
5.C. On-the-job training	0.686	7.821	0.274	3.646

a. Dependent Variable: OVRL.

The test of the existence of linear relationships for LPI and PISA, LPI and GCI's 5th pillar, LPI and IMD's pillar:

Four multivariate statistics calculated to test the null hypothesis that the canonical correlations are zero that there are no linear relationships between LPI and PISA, and LPI and GCI's fifth pillar variables. Since p values are less than 0.05 in the Pillais (the Pillai's trace), Hotellings (the Hotelling-Lawley trace) and Wilks (the Wilks' lambda) tests, the null hypothesis is rejected. Therefore, the alternative hypothesis that there are linear relationships between LPI and PISA, and LPI and GCI's fifth pillar variables is accepted. The Roys (the Roy's greatest root) test behaves differently from the other three tests. In cases where the remaining three are not statistically significant and Roy's is statistically significant, the effect considered not to be statistically significant (See Table A8 and A9). For LPI and IMD's variables, Hotellings' p is below the 0.05 threshold, thus there is an existence of linear relationships (See Table A10).

Table A8. Between LPI and PISA. "Effect ... within cells" regression.
Multivariate tests of significance (S = 3, M = 1, N = 23)

Test Name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F
Pillais	0.85	3.27	18	150.00	0.00
Hotellings	1.53	3.95	18	140.00	0.00
Wilks	0.33	3.64	18	136.25	0.00
Roys	0.52	–	–	–	–

Table A9. Between LPI and GCI's fifth pillar. "Effect ... within cells" regression.
Multivariate tests of significance (S = 3, M = 1, N = 59)

Test name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F
Pillais	0.90	8.74	18	366.00	0.00
Hotellings	3.14	20.73	18	356.00	0.00
Wilks	0.21	13.67	18	339.90	0.00
Roys	0.75	–	–	–	–

Table A10. Between LPI and IMD's pillar. "Effect ... within cells" regression.
Multivariate tests of significance (S = 6, M = 4 1/2, N = 2)

Test name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F
Pillais	3.75	1.14	96	66.00	0.29
Hotellings	43.32	1.96	96	26.00	0.03
Wilks	0.00	1.56	96	40.81	0.06
Roys	0.97	–	–	–	–

Factor analysis of LPI and IMD's scores
Retrieval of IMD Factors:

Table A11. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.6
Bartlett's Test of Sphericity	Approx. Chi-Square	426.165
	df	120
	Sig.	0.000

Table A12. Total variance explained. Extraction method:
Principal Component Analysis

Component	Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %
1	1.151	7.194	7.194
2	1.129	7.058	14.252
3	1.102	6.890	21.142
4	1.084	6.778	27.920
5	1.082	6.764	34.684
6	1.059	6.620	41.304
7	1.022	6.389	47.693
8	1.019	6.371	54.064
9	0.981	6.129	60.194
10	0.975	6.093	66.286
11	0.950	5.937	72.223
12	0.933	5.828	78.052
13	0.899	5.616	83.668
14	0.878	5.487	89.155
15	0.870	5.437	94.592
16	0.865	5.408	100

Extraction Method: Principal Component Analysis.

Table A13. Rotated component matrix[a]

Components:	1	2	3	4	5	6	7	8
84. Science in schools	0.885							
78. Student mobility inbound		0.93						
79. Student mobility outbound			0.972					
74. Pupil-teacher ratio (primary education)				0.916				
77. Higher education achievement (%					0.884			
75. Pupil-teacher ratio (secondary						0.874		
76. Secondary school enrollment (%)							0.793	
82. English proficiency – TOEFL								0.808
Components:	9	10	11	12	13	14	15	16
72. Total public expenditure on education	0.777							
88. Language skills		0.74						
81. Educational assessment Science			0.674					
80. Educational assessment Mathematics				0.662				
87. Illiteracy (%)					–0.73			
86. Management education						0.589		
83. Educational system							0.584	
85. University education								0.566

Extraction Method: Principal Component Analysis.
Rotation Method: Equamax with Kaiser Normalization.
a. Rotation converged in 61 iterations.

Retrieval of LPI Factors:

Table A14. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.934
Bartlett's Test of Sphericity	Approx. Chi-Square	600.078
	df	15
	Sig.	0.000

Table A15. Total variance explained. Extraction method: Principal Component Analysis

Component	Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %
1	1.050	17.492	17.492
2	1.028	17.129	34.621
3	0.997	16.622	51.243
4	0.988	16.473	67.716
5	0.973	16.208	83.924
6	0.965	16.076	100

Extraction Method: Principal Component Analysis.

Table A16. Rotated component matrix[a]

	1	2	3	4	5	6
TIME	0.715					
ITRN		0.683				
CUST			0.630			
TRAC				0.616		
INFR					0.587	
LOGS						0.576

Extraction Method: Principal Component Analysis.
Rotation Method: Equamax with Kaiser Normalization.
a. Rotation converged in 71 iterations.

Table A17. WEF: "Twelve pillars of economic competitiveness".
Highlighted row variable is used.

1 – "Basic requirements" Institutions
2 – Infrastructure
3 – Macroeconomic stability
4 – Health and primary education
5 – "Efficiency enhancers" Higher education and training
6 – Goods market efficiency
7 – Labour market efficiency
8 – Financial market sophistication
9 – Technological readiness
10 – Market size "Innovation and sophistication factors"
11 – Business sophistication
12 – Innovation

Table A18. IMD: Four categories with several sub-categories. Highlighted row variable is used

Economic performance:
Domestic economy
International trade
International investment
Employment
Prices
Government efficiency:
Public Finance
Fiscal policy
Institutional framework
Business legislation
Societal framework

End of Table A18.

Business efficiency:
Productivity and efficiency
Labour market
Finance
Management practices
Attitudes and values
Infrastructure:
Basic infrastructure
Technological infrastructure
Scientific infrastructure
Health and environment
Education

Turkay YILDIZ is a researcher at Izmir Institute of Technology. He received his PhD from the Institute of Marine Sciences and Technology, Dokuz Eylul University, Izmir, Turkey. He received his Master's Degree in Logistics Management from Izmir University of Economics. He has a number of peer reviewed publications and conference presentations at various countries in such fields as transportation, logistics and supply chains. He also has various levels of expertise in the applications of Information Technology.