JOURNAL OF MARITIME LOGISTICS
Universiti Malaysia Terengganu

Journal of Maritime Logistics is an international multidisciplinary journal. It collects and publishes scholarly articles on topics related to the maritime industry. It provides the results of the latest research and analysis on foreland, seaports and the hinterland. It also explores substantial topics, including logistics, policies, operations, management and navigation related to three main agenda — ocean activities, seaports and the hinterland.

eISSN: 2805-5195 Journal homepage: https://journal.umt.edu.my/index.php/jml/index

ASSESSING A COUNTRY'S SECTOR-SPECIFIC LOGISTICS PERFORMANCE: THE CASE OF INDIA'S MARINE-PRODUCT SECTOR

Satyendra Nath Chakrabartty[1], and Deepankar Sinha[2]
[1]Indian Ports Association & Indian Maritime University. [2]Indian Institute of Foreign Trade, Kolkata Campus

To cite this article: Satyendra Nath Chakrabartty and Deepankar Sinha (2022): Assessing a Country's Sector-specific Logistics Performance: The case of India's Marine-product Sector, Journal of Maritime Logistics

DOI: https://doi.org/10.46754/jml.2022.12.004

Journal of Maritime Logistics
https://journal.umt.edu.my/index.php/jml

ASSESSING A COUNTRY'S SECTOR-SPECIFIC LOGISTICS PERFORMANCE: THE CASE OF INDIA'S MARINE-PRODUCTS SECTOR

Satyendra Nath Chakrabartty[1] and Deepankar Sinha[2]

[1]Indian Ports Association & Indian Maritime University. [2]Indian Institute of Foreign Trade, Kolkata Campus

ABSTRACT

Country-wise Logistics Performance Index (LPI) is insufficient to guide changing policies for different sectors with varied logistics requirements and perspectives. Each perspective has various measures, and hence a battery of scales is mandated to measure the performance for an individual sector like marine, agriculture, and similar. For the marine-product sector of India, scores are transformed and combined to follow normal distributions enabling parametric analysis. A method of sector-specific logistics performance index (LPI-S) is proposed addressing multi-dimensional, multi-scale response categories satisfying the desired properties of an index. An empirical illustration is given to assess LPI-S for the marine-product sector in India, combining responses of 141 Indian marine exporters in a battery with nine dimensions. The proposed method generates continuous, monotonic data, and distributions of dimension/battery scores are normal. The LPI-S scores have better arithmetic aggregation admissibility, even if lengths of dimensions are different. In addition, it identifies critical dimensions, detects changes by longitudinal data, and dimension-wise elasticity reflecting the sensitivity of the dimension from snap-shot data. Irrespective of dimensions and types of data, the proposed methodology uses the sensitivity of a dimension on LPI-S to help policy makings separately for individual categories to improve logistics efficiency. The study identified eight crucial dimensions associated with marine product logistics. The sensitivity of these dimensions in the descending order of importance were - Information system, Regulatory process, Safety & Security issues, Timeliness and Completeness efficiency, Sustainability in logistics, Operating conditions, Logistics facility pricing, Quality of Logistic services, Transportation Networks and Logistics infrastructure. Such ordering of dimensions help in deciding policy priorities.

Keywords: Logistics performance index, sector-specific logistics performance index, battery of scales, elasticity, marine sector.

Introduction

Logistics issues, like the Suez Canal blockade and container crises, are intriguing. Such events have varied impacts on different cargo types; e.g, delays have a higher impact on perishables than other cargo. Competitiveness of goods reduce with an increase in freight as it affects the total-landed cost. A country producing higher-quality products at a lower price, coupled with convenient and cheaper transport, has a competitive advantage in the international market and vice-versa (Devlin & Yee, 2005). Inefficient logistics affect countries and firms by reducing exports and turnovers (Hausman *et al.,* 2005).

The logistics performance index (LPI) by the World Bank is reckoned as a yardstick for policymakers in transport and logistics (Göçer *et al.,* 2021; Rezaei *et al.,* 2018). The LPI impacts a country's global trade (Gani, 2017; Coto-Millán *et al.,* 2013) and is a valuable tool for policymaking. Researchers discussed the uses of LPI and ways to improve by avoiding its drawbacks

*Corresponding author: chakrabarttysatyendra3139@gmail.com

(Chakrabartty, 2020; Marti *et al.,* 2017; Marti *et al.,* 2014). However, none of these studies differentiate logistics performance for different cargo types, such as marine products. It does not explicitly say what improvements are required for improving logistics of marine products or Over-Dimensional Cargo (ODC) or similar.

Thus, to develop competitive advantages and meet exigencies, governments must focus on significant sectors, assess the sector-wise current logistics system, optimize sub-systems, remove bottlenecks, and improve through policies and initiatives (Jhawar *et al.,* 2017). A well-defined sector-specific Logistics Performance Index (LPI-S) of a country considering unique value chains and challenges will help the government frame regulations and make policy changes towards the trade procedures for the specific sector.

Logistics requirements and Key Performance Indicators (KPIs) vary significantly for sectors like agricultural products, chemicals, marine products, engineering goods, gems, jewelers, and similar (NCAER, 2019). Table 1 illustrates the differences in logistics requirements across cargo types. Thus, Understanding and measurement of LPI-S for enhanced competitiveness are essential for an economy.

Perishable cargo requires pre-cooling centers, temperature-controlled warehouses, and reefer containers. A slight fluctuation of temperature and humidity can cause deterioration of these cargoes (Ji *et al.,* 2017); over-dimensioned shipment requires roads and bridges to have adequate turning radius and load-bearing capacity (Rievaj *et al.,* 2018). Cape-sized Bulk-vessels need appropriate port facilities to accommodate and serve them. Thus, the performance of a sector depends on factors like infrastructure, quality of logistics services and cost, operating environment, safety and security, sustainability, and regulatory processes (Dua & Sinha, 2019).

The country-level LPI by World Bank (Arvis *et al.,* 2016) measures logistics competence in six dimensions without differentiating between cargoes. Thus, LPI cannot distinguish between competencies related to different cargo types. Hence, there is a need for a sector-specific logistics index (LPI-S). The paper provides an assumption-free single index measure of LPI-S through a multi-stage method to convert ordinal, discrete scores of a Likert item to continuous, monotonic scores following Normal distribution. Dimension scores are taken as the sum of such transformed item scores, and the LPI-S score (or Battery score) is the sum of the dimension scores. The proposed method satisfying the desired properties of an index is illustrated with data obtained for marine products, using a suitably designed questionnaire with nine dimensions. Similar approach has been employed in developing indices (Chakrabartty, 2022).

The rest of the paper is organized as follows: The following section reviews the literature describes the proposed methodology and associated properties. Section 3 describes the methodology employed in this research work. Section 4 gives an empirical illustration of LPI-S of the marine-product sector in India followed by discussion of the results and policy implications in Section 5. Section 6 concludes the study.

Literature Review

Integration of logistics is positively correlated with a firm's or a sector's competitiveness (Mellat-Parast and Spillan, 2014). Researchers observed a positive relationship between world trade with key logistical indicators (Beysenbaev, 2018; Gani, 2017). However, logistics processes constantly adapt and change, implying a change in volume of business with logistics development and vice-versa (Duˇsko & Boˇzica, 2016).

Better management of logistics operations aiming at effective administration of the flow of goods can improve trade and distribution of cargo across geographical borders (Christopher, 2016; Schönsleben, 2018). Dimensions chosen by researchers vary in terms of concepts and definition, number of items (scale length), and number of response categories (scale width). Factor Analysis (FA) of Likert items using Pearson correlations or Polychoric correlations violates the assumption of at least interval-level measurement. It may result in over-dimensionalization (van der Eijk and Rose, 2015). Bradburn *et al.* (2004) observed that variations in scale length alone might introduce systematic bias in the distribution of sample statistics since scales with higher lengths have higher mean and variance. Thus, usual summative scores of Likert items with different scale lengths, different score ranges, and different contributions to the LPI-S scores may give misleading and biased results. Multivariate logistics, different levels of efficiency across sectors, non-uniform transparency of transactions, level of service, reliability, ordinal measurements, etc., make it challenging to have an Index of LPI-S satisfying desired measurement properties. Measuring multi-dimensional LPI-S involves several theoretical and measurement issues for meaningful comparisons over time and space and comparing LPI-S for different sectors.

The battery of Likert scales is used for surveys in other areas, like Economic indicators (OECD, 2002), Index of Economic Freedom (Johnston and Sheehy, 1995), etc. However, the number and format of items, factors, and aggregation methods are different for different approaches. Ordinal data emerging from Likert-type items and scales to assess various efficiencies of logistics performance have the following major limitations:

i) Ambiguities: Perceptions of response categories like never, rarely, sometimes, often andalways could differ for different individuals (Lee & Soutar, 2010). Gu *et al.* (1995) raised the question, “How often is often?”

ii) No rule to decide on the length and width of a scale. Mean is more influenced by the number of levels than the underlying variable (Lim, 2008). There is no optimal width (Chakrabartty, 2021). Dawes (2007) observed distorted results due to different scale formats. Reliability, validity, and discriminating power are lower for 2-point, 3-point, 4-point scales than scales with higher levels (Preston *et al.,* 2000).

iii) Likert data are not additive due to unequal and unknown distance between levels (Ferrando, 2003; Wu, 2007). If successive response categories are marked by ordered positive numerical values a, b, c, d, and e, the equidistant property for arithmetic aggregation demands satisfaction of the following condition:

$$(b-a)=\frac{1}{2}(c-a)=\frac{1}{3}(d-a)=\frac{1}{4}(e-a) \qquad (1)$$

Violation of (1) implies unequal/unknown distance between response categories and does not enable meaningful computation of mean and standard deviation (SD). Hand (1996) opined that mean and SD are in error as the successive intervals on the scale are unequal or non-equidistant. Statistical analysis may go wrong when mean and SD are not meaningful (Bastien *et al.,* 2001). Thus, normalization of scores of an indicator as the first step of PCA involving mean and SD may not be meaningful for ordinal data.

iv) Equal weights to items can be criticized for different item-total correlations, factor loadings, and substitution effect (poor score in one dimension can be compensated by higher scores in other dimensions) and may mislead results (Ray, 2008).

v) Summative scores result in tied scores as different responses to different items can generate identical aggregate scores for several respondents. Thus, the scale fails to discriminate individuals with the same score.

vi) Assumptions of regression, Principal Component Analysis (PCA), etc. are not satisfied by ordinal Likert scores, which are often skewed with outliers (Harwell & Gatti, 2001)

vii) Observed correlation may be significantly lower than the population correlation if continuous variables are categorized, say, into 5-point items (Flora *et al.,* 2012). It may affect the factor structure based on the observed correlations.

viii) Unknown probability density function (pdf) of summated scores does not allow meaningful comparisons of different dimensions and aggregated scores, estimating population parameters. Correlation and regression between two variables assume a continuous and normal distribution of error scores (predicted values minus actual dependent variable values).

If item scores $X_1 X_2, \ldots X_m$ are not independent and each $X_i \sim N(\mu_i, \sigma_i^2)$

then by convolution property

$\sum_{i=1}^{m} X_i \sim Normal$ with mean $\sum_{i=1}^{m} \mu_i$ and SD =

$$\sqrt{\sum \sigma_i^2 + 2\sum_{i \neq j} Cov(X_i, X_j)} \quad (2)$$

The problem of finding probability distribution of $(X_1 + X_2)$ becomes complicated if X_1 and X_2 are not continuous or if one is continuous and the other is discrete or $X_1 X_2$ follows two different distributions. Further, distribution of a random vector

$X = (X_1, X_2, \ldots, X_m)^T$ with fixed marginal distributions $F_1 F_2, \ldots, F_m$ and varying dependence structure, the asymptotic distribution of X_i has no universal solution (Wang, 2014).

Empirical accuracy depends on accuracy of measurement and authors have expressed concerns regarding the correctness of data collection in surveys (Rüschendorf, 2013; Zahedian & Saba, 2016). For a review of measurement errors in surveys, see Bound *et al.* (2000). Without testing the above said assumptions and the admissibility of operations like addition, the validity of parametric analyses of Likert-type data is unclear.

Methodology

Proposed Approach:

The study included development of a questionnaire based on relevant dimensions of marine product logistics. The dimensions and the questions were prepared after collating the criteria used for developing similar indices, namely, Logistics Performance Index (LPI) (World Bank, 2018), Logistic Ease Across Different States in India (LEADS, 2019), Liner Shipping Connectivity Index (LSCI) (UNCTAD, 2019), Port Liner Shipping Connectivity Index (PLSCI) (UNCTAD, 2019b), Enabling Trade Index (WEF, 2016) and Services Trade Restrictiveness Index (OECD, 2019). The criteria were brainstormed with exporters under Marine Product Export Development Authority (MPEDA, India) and relevant ones were included. Marine products are perishable in nature and have shorter shelf life. Nine crucial dimensions were identified. Figure 1 illustrates the salient features of the questionnaire.

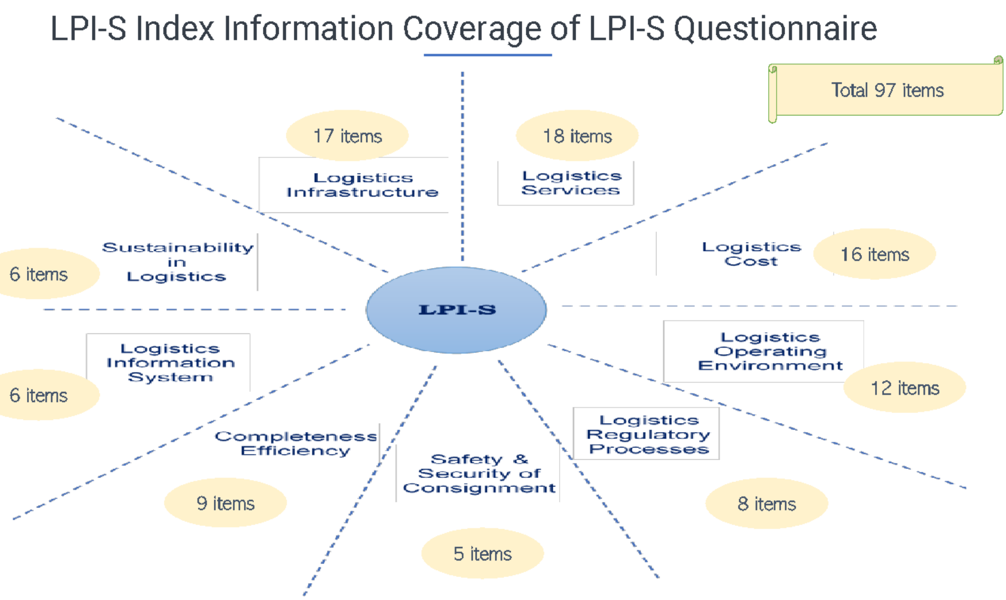

Figure 1: The Dimensions of LPI-S Questionnaire

Responses were collected from 150 Indian exporters of marine products from different coastal states. All exporters were approached through online mode. The marine products from India included shrimp, prawns, lobsters, tuna and similar (MPEDA).

Proposed Method for Index Development

Let X_{ij} denote score of the *i*-th individual in the *j*-th item, taking values 1, 2, 3… *K for* a *K*-point item. For *K*= 5, the equidistant property is ensured if the scores are taken as a weighted sum such that W_1, $2W_2$, $3W_3$, $4W_4$ and $5W_5$ forms an arithmetic progression. Transformations given below can achieve this property:

I: Convert raw sores of an item *(X)* to continuous equidistant scores (*E*) by weighted sum. Here, data-driven weights to different response categories of different items are obtained by the following steps.

For a 5-point item with sample size *n,* find initial weights $\omega_{ij} = \frac{f_{ij}}{n}$

Arrange the $\omega_{ij}'s$ in

increasing order and denote them as $\omega_{i1}, \omega_{i2}, \omega_{i3}, \omega_{i4} and\ \omega_{i5}$.

Find intermediate weights

$$W_{i3} = \frac{\omega_{i1}+2\alpha}{3}; W_{i4} = \frac{\omega_{i1}+3\alpha}{4} \text{and } W_{i5} = \frac{\omega_{i1}+4\alpha}{5} \text{ where } \alpha = \frac{5f_{max}-f_{min}}{4n}$$

Obtain final weights $W_{ij(Final)} = \frac{W_{ij}}{\sum_{j=1}^{5} W_{ij}}$.

Here, $\sum_{j=1}^{5} \quad W_{ij(Final)}$ = 1 for *i*-th item and $jW_{(j)(Final)} - (j-1)W_{(j-1)(Final)}$ = Constant $\forall$ $j = 2, 3, 4, 5$.

Thus, *E*-scores (as weighted sum) is continuous, equidistant, and monotonic with better admissibility of addition. If $f_{ij} = 0$ for a particular *j*-th level of an item, the method fails and can be taken as a zero value for scoring Likert items as a weighted sum.

II. Standardize equidistant scores (*E*) by $Z_{ij} = \frac{E_{ij}-E}{SD(E)} \backsim N(0,1)$.

Scale score as sum of standardized item-scores follows normal with mean zero and SD

$$= \sqrt{\sum \quad Z_i^2 + 2\sum_{i \neq j} \quad Cov(Z_i, Z_j)}.$$

III. To avoid negative values, convert the *Z*-scores to *Y*-scores following normal distribution $Y \in [1, 10]$

and by the linear transformation:

$$Y = (10-1)\left[\frac{Z_{ij} - Min(Z_{ij})}{Max(Z_{ij}) - Min(Z_{ij})}\right] + 1 \qquad (3)$$

The score of *i*-th dimension (D_i) is the sum of item-wise *Y*-score. D_i ~ normal with parameters depending on mean, variances, and covariances. *LPI-S* scores or battery scores are taken as

$$Y_{Scale} = \sum_{i=1}^{d} \quad D_i$$

which also follows normal, where *d* denotes the number of dimensions.

Benefits of the Proposed Method

Significant benefits of the proposed method considering frequencies of Item-Response-categories without involving assumptions of continuous nature or linearity or normality for the observed variables or the underlying variables being measured are as follows:

- *E*-scores are continuous (weighted sums are taken as expected values), monotonic (endorsement of (*j*+1)-th response category instead of the *j*-th category of an item increases *E*-score), and equidistant (satisfies equidistant criteria -1).
- Mean and variance of *E*-scores get reduced.
- *E*-scores and *Y*-scores avoid equal importance to items and levels and ensure better admissibility of arithmetic aggregation.
- *LPI-S* scores (Y_{Scale}) with practically no tied scores can discriminate respondents with equal *X*-scores and assigns unique ranks to individuals.

- Normality of *LPI-S* scores facilitates meaningful comparisons, ranking and parametric analysis, including estimation and statistical hypothesis testing.
- Easy computation of contribution of *i*-th dimension D_i to Y_{Scale}.
- Meaningful comparison of scales of different lengths and different formats.
- Progress/decline of *LPI-S* at successive time-periods can be assessed by

$$\frac{LPI-S_{t_2}}{LPI-S_{t_1}} \text{ or by}$$

$$\frac{LPI-S_{t_2}-LPI-S_{t_1}}{LPI-S_{t_1}} \times 100$$

reflecting ability of *LPI-S* to detect changes, i.e., responsiveness. Progress can be positive or negative if

$$Y_{t_2} > Y_{t_1} \text{ or } Y_{t_2} < Y_{t_1}$$

respectively. Significance of progress/ decline can be tested statistically since the ratio of two normally distributed variable follows χ^2 distribution.

- Effect of small change in *i*-th dimension (D_i) to scale score Y_{Scale} can be quantified in terms of elasticity, i.e., change of Y_{Scale} due to slight change in D_i. The dimensions can be ranked based on such dimension-wise elasticity. Elasticity studies in economics, reliability engineering, often consider model like

$logQ_{jt} = \alpha_j + \beta_j logP_{jt}$ where Q_{jt}: quantity demanded of *j*-th industry at time *t* and P_{jt}: price index of the economy (Sinha, 1994). However, logarithmic transformations are not required for normally distributed *Y*-scores to fit the regression equation of the form

$Y_{Scale} = \alpha_i + \beta_i D_i + \varepsilon_i$ where β_i =

$$\frac{LPI-S_{t_2}-LPI-S_{t_1}}{LPI-S_{t_1}} \times 100$$

The coefficient β_i reflects the impact of a unit change in the independent variable (*i*-th dimension) on the dependent variable (Y_{Scale}) However, these coefficients are not elasticities. The elasticity of the independent variable P for regression of Q on P can be written as

$$\frac{\frac{\Delta Q}{Q}}{\frac{\Delta P}{P}} = \frac{\Delta Q}{\Delta P}\frac{P}{Q} = \beta . \frac{P}{Q} \text{ where } \beta$$

where is the slope of regression line

$$Q = \alpha + \beta P.$$

Thus, elasticity is

$$e = \beta \frac{\underline{p}}{\underline{q}} \times 100 \text{ where } \underline{p} \text{ and } \underline{q}$$

where are the mean values of independent and dependent variables respectively. The dimensions of *LPI-S* can be arranged in increasing order where dimensions with high elasticity are the *"Stars" or "Cash Cow"* with strong potentials, and the dimensions with lower elasticity are the areas with a chance to become "*Stars*." Policymakers can decide appropriate corrective actions accordingly

- Critical areas requiring corrective actions or changes in policies/strategies are those dimensions for which

$$Y_{t_2} > Y_{t_1}$$

- Integration of

  $Y_{i\text{-th dimension}}$ and $Y_{j\text{-th dimension}}$

  can be done by finding equivalent scores Y_i^0 and Y_j^0 such that

$$\int_{-\infty}^{Y_i^0} f(X)dx = \int_{-\infty}^{Y_j^0} g(Y)dy \quad (4)$$

where $f(X)$ and $g(Y)$ up to denotes respectively the pdf of

$$Y_{i\text{-th dimension}} \sim N(\mu_1, \sigma\ )$$

and

$$Y_{i\text{-th dimension}} \sim N(\mu_1, \sigma_2^2).$$

Equation (4) ensures that area under $f(X)$ up to Y_i^0 = area under $g(Y)$ up to Y_j^0.
For a given value of Y_i^0, the equivalent score Y_j^0 can be found by solving (4) using the Normal Probability table. Note that if Y_i^0 is equivalent to Y_j^0 then Y_j^0. Moreover, equating is not forecasting; thus, equivalent scores are different from predicted values by regressing $Y_{i\text{-th dimension}}$ on $Y_{j\text{-th dimension}}$ (Livingston, 2004). The correlation between such equivalent scores will be close to perfect.

Reliability using Cronbach's alpha is not proper if the battery has several independent factors. Chakrabartty (2020b) proposed to find battery reliability $(r_{tt(Battery)})$ by

$$r_{tt(Battery)} = \frac{\sum_{i=1}^{K} r_{tt_i} S_{Y_i}^{\ 2} + \sum_{i\neq j=1}^{K} \sum_{j=1}^{K} 2Cov(Y_i, Y_j)}{\sum_{i=1}^{K} S_{Y_i}^{\ 2} + \sum_{i\neq j=1}^{K} \sum_{j=1}^{K} 2Cov(Y_i, Y_j)} \quad (5)$$

where r_{tt_i}: reliability of the *i*-th dimension in terms of correlation between Y_i and *LPI-S* score (in line with item–total correlation), $S_{Y_i}^{\ 2}$: variance of Y_i and battery score is equal to sum of dimension scores.

However, before applying the parametric technique, additional assumptions for such methods need to be verified. For example, correlation and linearity are taken as synonymous. But, correlation between *X* and *f(X)* could be very high even if f*(X)* is a non-linear function of *X,* like *X* takes integers values in [1, 30], r_{X,X^2} = 0.97, r_{X,X^3} = 0.92. Thus, a correlation may not indicate linearity. Linearity may be tested by fitting a regression line of the form $X^2 = \alpha + \beta X + \epsilon$ and finding normality of ϵ-scores and low value of SD of error score by

$$S_\epsilon = \sqrt{\frac{1}{n}\sum (Y_i - \hat{Y}_i)^2} = S_Y\sqrt{1-r^2}$$

indicating acceptance of linearity. In the instant case, the assumption of normal distribution of error score $\boldsymbol{\epsilon} = (\boldsymbol{Y} - \hat{\boldsymbol{Y}})$ is violated. This is just an example to show the effect of violation of assumptions of a parametric technique may give wrong results, despite apparent robustness of correlation which is believed to be synonymous with linearity.

Results and Discussion

Empirical illustration: Data on a specially designed questionnaire to assess sector-specific LPI was obtained from 141 Indian marine exporters. The 97 items of the questionnaire were distributed across nine dimensions, having similarities with LPI dimensions (World Bank) and mega-trends identified by the World Economic Forum (WEF 2017). Each scale consisted of 5-point items, but the number of items per scale differed. Details are shown in Table 2.

Thus, the questionnaire is, in fact, a battery of nine Likert scales with the following limitations:

- The number of dimensions items influences the test score, maximum being 18 and minimum being 5. Therefore, dimensions with a higher number of items and higher score range contribute more to the Battery score, i.e., LPI-S scores.
- While the maximum possible score of D_6 is 30, the same for D_2 is 90.
- A poor score in say D_2 can be compensated by high scores in other dimensions. Thus, summative item scores may mislead results.

Weights for Equidistant Scores

As an example, weights to the response categories of each of the 8 items under the dimension "Regulatory process" (D_5) are given in Table 3.-

Observations

E-score of an item as weighted sum, i.e.

$$\sum_{i=1}^{5} i.W_i(Final)$$

is continuous, monotonic and equidistant since

$5W_{5(Final)} - 4W_{4(Final)} = 4W_{4(Final)} - 3W_{3(Final)}$
$= 3W_{3(Final)} - 2W_{2(Final)} = 2W_{2(Final)} - W_{1(Final)}$
=constant > 0

Similarly, final weights were calculated for each item under each dimension to convert item-wise raw scores (*X*) to equidistant scores (*E*). *E*-score of a dimension was the sum of item-wise *E*-scores. Score ranges of dimension scores under *X, E,* and *Y* are shown in Table 4. -

Tied scores

E-scores or *Y*-score had no tied scores. For example, *E*-scores and *Y*-scores of the seven persons (illustrative), each with *X*= 23 in D_8 are shown in Table 5.

Observations

- For two different persons *i* and *j*, $E_i \neq E_i$ and $Y_i \neq Y_j$ even if $X_i = X_j = 23$
- *E*-scores and *Y*-scores give unique ranks to the individuals
- For the set of persons with a tied score, *X*-score with zero variance failed to discriminate those persons.
- $\underline{E} \neq \underline{Y} \neq \underline{X}$; SD (*E*)=0.66 and SD(*Y*) = 4.14 for the 7-persons with X= 23.

Descriptive statistics

Descriptive statistics for dimensions and scale scores are shown in Table 6.

Observations

- Dimensions with a higher number of items exhibited a higher mean for *X*-scores, unlike *E*-scores and *Y*-scores
- Scores of dimensions with different scale lengths were converted to fixed score-range and following normal distributions with different values of parameters.
- *E*-scores reduced considerably mean and variance and made the data more homogeneous.
- It is known that if $X \sim N(\mu_X, \sigma_X^2)$ and $Y \sim N(\mu_Y, \sigma_Y^2)$ then $(X+Y) \sim N(\mu_X, + \mu_Y, \sigma_X^2 + \sigma_Y^2 2 + \sigma_{XY}$.
  Here, $Var(Battery) >$ Sum of variances of the 9-dimensions for *X*, *E*, and *Y*, implying positive correlations between pair of dimensions.
- Distributions of item-wise *X*-scores or *E*-scores are not known and vary across dimensions. However, dimension wise, Y-scores follow Normal distribution for each item. Besides, *LPI-S* scores
  $= Y_{Scale} = \sum_{i=1}^{d} D_i$
  also follow a normal distribution, and the parameters can be estimated from the data.

CV indicates the extent of variability in relation to the mean. Thus, a lower value of CV is desirable. Theoretically defined test reliability

$$r_{tt} = \frac{S_T^2}{S_X^2} = \frac{\frac{S_T^2}{\bar{T}^2}}{\frac{S_X^2}{\bar{X}^2}} = \frac{CV_T^2}{CV_X^2} \Rightarrow CV_X^2 = \frac{CV_T^2}{r_{tt}}$$

where CV_X and CV_T denote respectively CV for observed scores and for true scores. Equation (6) gives a negative relationship

between CV_X^2 and r_{tt}

(as per definition) $\Rightarrow$ lower the CV, the higher the test reliability. Verification of r_{tt} this requires the computation of as per theoretical definition, which is beyond the scope of the paper. For the battery

$$CV_Y < CV_E.$$

Thus, theoretically defined test reliability for *Y*-scores may exceed the same for *E*-score.

Correlations and Reliability

Inter-dimension correlations and correlation between dimension and battery are shown in Table 7.

Observations

- Dimensions were positively correlated.
- Maximum correlation (0.783) was observed between D_1
  and D_2 .
  The minimum correlation of 0.283 was between D_7
  and D_8 .
- r_{EY}
  will be almost perfect since *Y* is obtained from *E* through linear transformations.
  However, *E* obtained from *X* by weighted sum may show
  $r_{EX} < 1$.
- Correlation between a dimension and the battery may be taken as the reliability of the dimension, in line with item-total correlation. Dimension reliability ranged between 0.587 (for D_8) to 0.880 (for D_2)

- Battery reliability as per (5) was

$$\frac{3365.42199+14965.2371}{4221.7709+14965.2371} = 0.955$$

Distributions

Table 8 gives the distribution of dimension-wise *D*-scores and LPI-S scores.

Number of Factors

PCA was done to find the dimension-wise number of independent factors. Results are shown in Table 9.

Observations

- The number of independent factors did not change much for raw scores (X) and *D*-scores primarily because standardized X and Y values are almost similar and can be reflected by high values of r_{XD}
- However, factor loadings for *X* and *D* were different for each dimension, implying new factors created by PCA with the original variables in a linear combination fashion with *X*-scores were different from those created with *D*-scores for each dimension.

Elasticity

Elasticity of *i*-th dimension was

$$\beta\left[\frac{Mean\ of\ D_i}{Mean\ of\ LPI-S}\right] \times 100 \text{ where } \beta$$

is the slope of regression equation

$$LPI\text{-}S = \alpha + \beta D_i.$$

Dimension-wise elasticity and β coefficients are shown in Table 10.

Observations

- Values of elasticity did not vary much, the highest being 0.0534 for D_8 and lowest being 0.01655 for D_1.
- A slight increase in D_8 is likely to increase the *LPI-S* maximum.
- Low elasticity values indicate no dimension impacts more than the other. Hence, policy needs to be framed to improve each dimension to enhance *LPI-S* of the marine-product sector.

The proposed scoring generates continuous, monotonic data following normal distribution of dimension scores and LPI-*S* score, even if lengths of dimensions are different. Thus, it provides better admissibility of arithmetic aggregation.

Normality of *LPI-S* score helps drawing inferences on the population rather than sample-based observations and undertakes parametric analysis.

A high correlation between *Y*-scores and raw scores indicates an undisturbed data structure.

The zigzag pattern of the progress path of *LPI-S* from longitudinal data helps to find the time-period of improvement or deterioration. Therefore, it is possible to test the hypothesis

$$H_0: Progress_{(t+1) over\ t} = 0, \text{ i.e.,}$$

whether improvement was significant. Similarly, one can test hypothesis like

$$H_0: \overline{D_i} = \overline{D_j} \text{ or } H_0: \mu_{LPI_i} = \mu_{LPI_i} \text{ or } = H_0: \mu_{LPI(t_i)} = \mu_{LPI(t_j)}$$

Integration of two *LPI-S's* can be achieved by finding equivalent scores from the distributions of *LPI-S*$_i$ and *LPI-S*$_j$

The elasticity of dimensions shows the potentiality of dimensions to influence *LPI-S*. For example, in the study of the marine-product sector in India, the relative importance of the nine dimensions in terms of elasticity are:

Information system (D_8) > Regulatory process (D_5)> Safety & Security issues

Timeliness (D_6) > & Completeness efficiency (D_7) > Sustainability in logistics (D_9)> Operating conditions (D_4) > Logistics facility pricing (D_3) > Quality of Logistic services (D_2) > Transportation Networks & Logistics infrastructure (D_1). Such ordering of dimensions may help in deciding priorities.

The proposed *LPI-S* score of the marine-product sector in India followed $(641.8731, 138.90249$ (superscript: $2))$, which is the convolution of normally distributed scores of the chosen nine dimensions. The dimension D_8 affected LPI-*S* the most, implying the information system needs greater attention. Discussions with stakeholders indicate that getting an export clearance certificate from MPEDA (a body under the Government of India) is cumbersome with only online upload (of scanned copies) facilities, but scrutiny is done manually. More so, the information systems of the Customs, ports, and other agencies are not fully integrated as they operate in silos. Following this dimension, the next ones are the regulatory aspects, and safety and security. Stakeholders reported lack of right-sized fishing vessels (especially for tuna catches and their processing onboard), lack of communication system leading to loss of life and business, fishing storing facilities at jetties, and transportation to packaging centers. All these dimensions require government intervention and policy initiatives.

The existing policies do not stress the quality of fishing on high seas. Most fishing vessels are less than 500 GRT (gross-registered-tonnage), not requiring IMO (International Maritime Organization) interventions. Thus, policies on high seas fishing need to address all dimensions - infrastructure, communication, sustainability, regularity, safety, and security.

Conclusion and Implication

The paper gives *LPI-S* scoring, avoiding limitations of summative ordinal scores, and facilitates analysis under a parametric setup for meaningful comparisons. Furthermore, the approach makes no assumptions regarding continuous nature, linearity, normality for the observed or underlying variables. Thus, researchers and policymakers can benefit from the proposed method by converting discrete ordinal scores to normally distributed *LPI-S* scores. The desired properties of this approach also include identifying critical dimensions, detecting changes by longitudinal data, and dimension-wise elasticity showing changes in snap-shot data.

Thus, the proposed scoring of a battery consisting of several Likert scales is an improvement of the existing methods. *LPI-S* for other sectors can be measured through the proposed approach. The exercise reveals the changes required in the policies related to the marine-product business in India. Future studies could be undertaken to find the relationship between the *LPI-S* score of a sector and its revealed comparative advantage (RCA).

Disclosure statement

No potential conflict of interest was reported by the author(s).

APPENDIX

Table 1: Illustrative logistics requirements across cargo types

Cargo Types	Packaging	Warehousing	Material-handling Equipment	Transportation
Non-perishable break-bulk cargo	Cartons, Pallets, Drums, Barrels, ISO – Non-reefer-Containers	Closed warehouse and Open container yard for marine containers	Forklifts Container handling cranes	Covered carriers, trailers for containers, general cargo ships, or container vessels.
Perishable break-bulk cargo	Cartons, Pallets in Reefer-Containers	Temperature controlled warehouse before container stuffing	Forklifts, Container handling cranes	Reefer carriers
Dry-Bulk Cargo	Loose storage with no packaging	Open yards or large closed warehouse	Shovels, conveyors, grabs	Open-top trucks, dry-bulk carriers
Liquid-Bulk Cargo	Loose storage with no packaging	Storage tanks	Pipelines	Tankers, Liquid -carriers
ODC	No packaging or waterproof wrappings	Open yard or High-cube containers	Cranes or Ro-Ro facilities	Low chassis, multi-axel trucks, general-cargo vessels, RO-RO carriers

Table 2: Number of dimensions and items

Sl. No.	Dimensions	No. of Items (5-point)
1	Transportation Networks & Logistics infrastructure (D_1)	17
2	Quality of Logistic services (D_2)	18
3	Logistics facility pricing (D_3)	16
4	Operating conditions (D_4)	12
5	Regulatory process (D_5)	8
6	Safety & Security issues (D_6)	5
7	Completeness efficiency (D_7)	9
8	Information system (D_8)	6
9	Sustainability in logistics (D_9)	6
Total	**Nine dimensions**	**97 items**

Table 3: Weights to response categories of Items of D_5

Item	RC-1	RC-2	RC-3	RC-4	RC-5	Common Difference
1	0.178699	0.198301	0.204835	0.208102	0.210062	0.217903
2	0.023056	0.185888	0.240165	0.267304	0.283587	0.34872
3	0.165112	0.197218	0.207919	0.21327	0.216481	0.22932
4	0.03319	0.186696	0.237865	0.263449	0.2788	0.34020
5	0.05909	0.188762	0.231986	0.253597	0.266565	0.31843
6	0.185249	0.198824	0.203348	0.205611	0.20696	0.2124
7	0.353113	0.212211	0.165244	0.141761	0.127671	0.07131
8	0.402371	0.21614	0.154053	0.123025	0.104402	0.0299

Legend: RC- j ⇒ j-th Response category for j=1,2,3,4,5
Common difference = $jW_j - (j-1)W_{j-1}$ *= 2,3,4,5*

Table 4: Score range of dimension score

Dimension & No. of items	Raw score (X)		Equidista score (E)		Y-score in [1.10] following normal	
	Max	Min	Max	Min	Max	Min
1 (17 items)	83	18	20.41422	4.365158	163.6292	46.31525
2 (18 items)	90	18	21.71896	4.376015	176.88073	44.135917
3 (16 items)	80	16	20.93897	3.836177	159.3084	38.61204
4 (12 items)	56	12	14.26819	2.530405	110.9961	28.97711
5 (8 items)	40	8	11.42616	1.285645	78.44095	13.68314
6 (5 items)	25	5	6.392169	0.682729	43.62263	6.767187
7 (9 items)	45	9	11.10969	1.826699	85.48226	19.20658
8 (6-items)	30	6	8.754545	0.768877	60.00	8.379065
9 (6 items)	30	6	8.555144	1.192141	60.00	11.82744

Table 5: Zero ties in E-score and *Y*-score in [1, 10]

Raw score in D_8							**Equidistant score (*E*)**	***Y*-score (*Y*)**
Item 1	**Item 2**	**Item 3**	**Item 4**	**Item 5**	**Item 6**	**Total (X)**		
4	4	4	5	5	1	23	6.775746	46.36868
4	4	4	4	4	3	23	6.401906	44.33398
3	5	4	4	4	3	23	5.749481	40.2746
5	5	4	2	4	3	23	5.704404	39.89433
5	5	4	4	2	3	23	4.756106	33.89678
4	3	4	5	5	2	23	6.254644	43.05705
3	4	4	4	4	4	23	6.300156	44.15853
Mean						23	5.991778	41.71199
SD						0	0.6602	4.13928

Table 6: Descriptive statistics of dimension scores and test scores

Description	Raw score (X)	Equidistant scores (E)	Y- score in [1, 10]
Dimension 1			
Mean	49.34752	12.40143	102.9616
Variance	251.3284	17.21526	929.4857
CV	0.321259	0.334568	0.296105
Dimension 2			
Mean	54.49645	13.87242	114.01041
Variance	230.3375	15.49181	981.30216
CV	0.278493	0.283726	0.2747621
Dimension 3			
Mean	55.74468	14.14989	110.7808
Variance	208.9201	15.77749	784.2875
CV	0.259291	0.280715	0.525275
Dimension 4			
Mean	38.78014	10.00401	80.75354
Variance	121.9727	9.800964	558.7744
CV	0.284788	0.312939	0.292723
Dimension 5			
Mean	30.4539	8.325787	58.48492
Variance	37.13536	4.606667	190.4051
CV	0.200102	0.257791	0.235937
Dimension 6			
Mean	17.46809	4.527963	31.03346
Variance	23.77933	2.171864	126.7705
CV	0.279161	0.325472	0.304244
Dimension 7			
Mean	30.24113	7.612496	58.65428
Variance	57.94144	4.924058	289.1016
CV	0.251708	0.291497	0.289885
Dimension 8			
Mean	24.42553	6.533623	45.34496
Variance	23.63191	2.952451	122.3088
CV	0.199024	0.262989	0.243893
Dimension 9			
Mean	21.2695	5.575473	40.45701
Variance	58.48399	5.59517	239.3352
CV	0.359552	0.424253	0.382393
Battery/LPI-S Score (Total of all nine Dimensions)			
Mean	322.227	83.0031	641.8731
Variance	4828.405	372.3993	19293. 903
CV	0.215645	0.232493	0.216402

Table 7: Correlation matrix of *Y*-scores between Dimensions and Battery

	D-1	D-2	D -3	D-4	D - 5	D - 6	D - 7	D - 8	D - 9	Battery
D-1	1	0.783	0.697	0.635	0.469	0.379	0.355	0.329	0.359	0.832
D-2		1	0.730	0.694	0.499	0.432	0.389	0.442	0.444	0.880
D-3			1	0.646	0.510	0.382	0.398	0.484	0.472	0.851
D-4				1	0.502	0.472	0.440	0.316	0.493	0.812
D-5					1	0.447	0.398	0.591	0.497	0.691
D-6						1	0.514	0.407	0.441	0.608
D-7							1	0.283	0.408	0.593
D-8								1	0.493	0.587
D-9									1	0.644

Table 8: Distribution of dimension scores and Battery scores

Dimension	Distribution of *D*-scores
1	$N(102.96161, 30.48747^2)$
2	$N(114.01041, 31.325743^2)$
3	$N(110.7808, 28.00513^2)$
4	$N(80.75354, 23.63841^2)$
5	$N(58.48492, 13.79874^2)$
6	$N(30.42562, 11.25924^2)$
7	$N(58.65428, 17.00299^2)$
8	$N(40.45701, 15.47046^2)$
9	$N(641.8731, 138.90249^2)$
LPI-S (Y_{Scale})	

Table 9: Number of independent factors

Dimension	Number of Independent factors		Cumulative Variance Explained (%)		Correlation between X and Y
	X	***Y***	***X***	***Y***	r_{XY}
Dimension 1	4	4	69.402	66.072	0.958
Dimension 2	4	4	64.054	61.172	0.956
Dimension 3	4	5	63.589	63.226	0.951
Dimension 4	3	3	67.497	61.965	0.951
Dimension 5	1	2	45.29	56.056	0.962
Dimension 6	1	1	57.723	55.563	0.788
Dimension 7	2	2	64.485	65.568	0.842
Dimension 8	1	1	52.195	48.741	0.925
Dimension 9	1	1	75.497	71.057	0.968

Table 10: Elasticity of dimension

Dimension	β coefficients	Elasticity	Rank in Terms of Elasticity (potentiality to influence LPI-S)
1	0.00103	0.01655	IX
2	0.00097	0.01732	VIII
3	0.00121	0.02094	VII
4	0.00170	0.02140	VI
5	0.00506	0.04606	II
6	0.00623	0.02953	III
7	0.00291	0.02663	IV
8	0.00756	0.05340	I
9	0.00405	0.02549	V

References

Arvis, J. F., Saslavsky, D., Ojala, L., Shepherd, B., Busch, C., Raj, A., & Naula, T. (2016). *Connecting to compete: Trade logistics in the global economy.* Washington DC: World Bank

Bastien, C. H., Vallieres, A., & Morin, C. M. (2001). Validation of the insomnia severity index as an outcome measure for insomnia research. *Sleep Medicine*, *2*(4), 297–307.

Beysenbaev, R. (2018). The importance of country-level logistics efficiency assessment to the development of international trade. *British Journal for Social and Economic Research*, *3*(6), 13–20.

Bound, J., Brown, Ch., & Mathiowetz, N. (2000). *Measurement Error in Survey Data* (Report No. 00-450). Population Studies Center at the Institute for Social Research University of Michigan

Bradburn, N. M., Sudman, S., & Wansink, B. (2004). *Asking questions: The definitive guide to questionnaire design—for market research, political polls, and social and health questionnaires*. San Francisco: Jossey-Bass

Chakrabartty, S. N. (2020a). Logistics Performance Index: Methodological Issues. *Foreign Trade Review*, *55*(4), 466-477. https://doi.org/10.1177/0015732520947860

Chakrabartty, S. N. (2020b). Reliability of Test Battery. *Methodological Innovation*. *13*(2), 1-8.

Chakrabartty, S. N. (2021). Optimum number of response categories. *Current Psychology*. https://doi.org/10.1007/s12144-021-01866-6

Chakrabartty, S. N. (2022). Understanding national level logistics costs: Methodological approach. *Journal of Asian Economic Integration*, 195-207. https://doi.org/10.1177/26316846221107419

Christopher, M. (2016). *Logistics & supply chain management*. UK: Pearson

Coto-Millán, P., Agüeros, M., Casares-Hontañón. P., & Pesquera, M. Á. (2013) Impact of logistics performance on world economic growth (2007–2012). *World Review of Intermodal Transportation Research*, *4*(4), 300-310.

Dawes, J. G. (2002). Five-point vs eleven-point scales: Does it make a difference to data characteristics? *Australasian Journal of Market Research*, *10*(1), 39–47.

Devlin, J., & Yee, P. (2005). Trade logistics in developing countries: The case of the Middle East and North Africa. *The World Economy*, *28*, 435–456.

Dua, A., & Sinha, D. (2019). Quality of multimodal freight transportation: A systematic literature review. *World Review of Intermodal Transportation Research*, *8*(2), 167-194.

Duˇsko, P., & Boˇzica, R. (2016) The impact of transport on international trade development. *Acta Economica Et Turistica*, 2(1), 13–28

Ferrando, P. J. (2003) A kernel density analysis of continuous typical-response scales. *Educational and Psychological Measurement*, *63*, 809-824

Flora, D. B., & Curran , P. J. (2004) An empirical evaluation of alternative methods of estimation for confirmatory factor analysis with ordinal data, *Psychological Methods*, 9(4), 466–491. https://doi.org/10.1037/1082-989X.9.4.466

Gani, A. (2017) The logistics performance effect in international trade. *The Asian Journal of Shipping and Logistics*, *33*(4), 279–288.

Göçer, A., Özpeynirci, Ö., & Semiz, M. (2021) Logistics performance index-driven policy development: An application to Turkey. *Transport Policy*.

Gu, Peter & Wen, Q. & Wu, D. (1995) How often is often? Reference ambiguities of the Likert-scale in language learning strategy research. *Occasional Papers in English Language Teaching*, *5*, 19-35.

Hand, D. J. (1996) Statistics and the theory of measurement*, Journal of the Royal Statistical Society Series A*, *159*(3), 445-492. https://doi.org/10.2307/2983326

Harwell, M. R. & Gatti, G, G. (2001) Rescaling ordinal data to interval data in educational research. *Review of Educational Research, 71*(1), 105–131. https://doi.org/10.3102/00346543071001105

Hausman, W., Lee, H. L. & Subramanian, U. (2005) *Global logistic indicators, supply chain metrics and bilateral trade patterns*. Washington D.C: World Bank Policy Research Working Paper 3773,

Jhawar, A., Garg, S. K., & Khera, S. N. (2017) Improving logistics performance through investments and policy intervention: A causal loop model. *International Journal of Productivity and Quality Management*, *20*(3), 363–391.

Ji, Y., Yang, H., & Chen, M. (2017) Logistics network configuration for fresh agricultural products. In *2017 29th Chinese Control and Decision Conference (CCDC)* (pp. 5724-5727). IEEE.

Johnston, B. T. & Sheehy, T. P., (1995) *The Index of Economic Freedom*. Washington: Heritage Foundation, pp. ix-21

Lee, J. A. & Soutar, G. N. (2010). Is Schwartz's value survey an interval scale, and does it really matter? *Journal of Cross-Cultural Psychology*, *41*, 76-86

Lim, Hock-Eam (2008) The use of different happiness rating scales: Bias and comparison problem? *Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement*, *87*, 259–267

Livingston, S. A. (2004) *Equating test scores (without IRT).* Princeton, NJ: ETS.

Martí, L., Martín, J. C., & Puertas, R. (2017) A DEA-logistics performance index. *Journal of applied economics*, *20*(1), 169-192.

Martí, L., Puertas, R., & García, L. (2014) The importance of the Logistics Performance Index in international trade. *Applied economics*, *46*(24), 2982-2992.

Mellat-Parast, M. & Spillan, J. E. (2014) Logistics and supply chain process integration as a source of competitive advantage, *International Journal of Logistics Management,* 25(2), 289-314.

Ministry of Commerce and Industry Government of India. (2019). Logistics Ease Across Different States (LEADS). https://commerce.gov.in/wp-content/uploads/2020/08/MOC_637051086790146385_LEAD_Report-2.pdf

OECD. (2002). *An Update of the OECD Composite Leading Indicators*. Short-term economic Statistics division, Statistics Directorate/OECD, https://www.oecd.org/sdd/leading-indicators/2410332.pdf

OECD. (2020). *OECD Services Trade Restrictiveness Index: Policy trends up to 2020*. https://www.oecd.org/trade/topics/services-trade/documents/oecd-stri-policy-trends-up-to-2020.pdf

Pohit S., Gupta. D. B., Pratap. D., Alawadhi. A., Sayal. L., Malik. S. (2019). *Analysis of India's Logistics Costs*. National Council of Applied Economic Research (NCAER). https://www.ncaer.org/publication/analysis-of-india039s-logistics-costs, accessed on 10.11.2022.

Preston, Carolyn C., & Colman, A. M. (2000). Optimal number of response categories in rating scales: Reliability, validity, discriminating power, and respondent preferences, *Acta Psychologica*, *104*, 1-15

Ray, A. K. (2008). Measurement of social development: An international comparison. *Social Indicators Research, 86*(1), 1–46.

Rezaei, J., Van R., W. S., & Tavasszy, L. (2018) Measuring the relative importance of the logistics performance index indicators using Best Worst Method. *Transport Policy*, *68*, 158-169.

Rievaj, V., Vrábel, J., Synák, F., & Bartuška, L. (2018). The effects of vehicle load on driving characteristics. *Advances in Science and Technology. Research Journal*, *12*(1), 142-149. https://doi.org/10.12913/22998624/80896

Rüschendorf, L. (2013). *Mathematical Risk Analysis.Dependence, Risk Bounds, Optimal Allocations and Portfolios*. Heidelberg: Springer. MR-3051756

Schönsleben, P. (2018). *Integral logistics management: Operations and supply chain management within and across companies* (4th ed.). Auerbach–Taylor & Francis.

The World Bank. (2018). *International LPI*. https://lpi.worldbank.org/international/global

Van Der Eijk, C., & Rose, J. (2015) Risky business: Factor analysis of survey data - assessing the probability of incorrect dimensionalisation. *PloS one*, *10*(3), e0118900. https://doi.org/10.1371/journal.pone.0118900

Wang, R. (2014). Sum of arbitrarily dependent random variables. *Electronic Journal of Probability*, *19*(84), 1 - 18.

World Economic Forum. (2016) *The global enabling trade report 2016*. https://www.weforum.org/reports/the-global-enabling-trade-report-2016/

Wu, C. H. (2007). An empirical study on the transformation of likert scale data to numerical scores, *Applied Mathematical Sciences, 1*(58), 2851 – 2862.

Zahedian, A. & Saba, R. A. (2016) Measurement Error Estimation Methods in Survey Methodology. *Applications and Applied Mathematics*. *11*(1), 97-114.