

IC-SHARE 2024

International Conference on Sharing Economy and
Contemporary Business Models: Theory and Practice

May 10th-11th, 2024 Belgrade





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**Proceedings of the first International conference on
sharing economy and contemporary business models:
Theory and practice**

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Belgrade, 2024



PUBLISHER

University of Belgrade – Faculty of Organizational Sciences
Jove Ilića 154, Belgrade, Serbia

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PRINTING Newpress, Smederevo

ISBN: 978-86-7680-469-6

Circulation: 50

YEAR 2024

CONFERENCE ORGANIZER University of Belgrade – Faculty of Organizational Sciences

CIP - Каталогизација у публикацији
Народна библиотека Србије, Београд

005(082)

330(082)

INTERNATIONAL conference on sharing economy and contemporary business models: theory and practice (1 ; 2024 ; Belgrade)

Proceedings of the first International conference on sharing economy and contemporary business models: theory and practice, Belgrade, May 10-11, 2024 / editors Milica Maričić, Veljko Jeremić, Nikola Zornić. - Belgrade : University, Faculty of organizational sciences, 2024 (Smederevo : Newpress). - 184 str. : graf. prikazi, tabele ; 24 cm

Tiraž 50. - Napomene i bibliografske reference uz tekst. - Bibliografija uz svaki rad.

ISBN 978-86-7680-469-6

а) Менаџмент -- Зборници

б) Економија -- Зборници

COBISS.SR-ID 153385225

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Sharing Economy Index: How Can it Be Altered?

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Abstract. *Sharing economy is defined as a business model in which individuals (providers) share an unused resource with others (consumers) for a predefined period and price via online platform. Since the model first emerged in the 2000s, it quickly spread in industries such as transport, tourism, apparel, working space, and others. With it, the need of decision-makers and practitioners for a metric and ranking system, emerged. To this day, several metrics have been devised. The composite index which is the focus of this study is the Sharing Economy Index (SEI) 2023, published by Consumer Choice Center. The interest of the paper is to observe and scrutinise the current weighting scheme of the index by applying the statistical multivariate analysis Ivanovic distance (I-distance) and Composite I-distance Indicator (CIDI) methodology. The results show that the SEI structure should be in four pillars, with the most importance awarded to E-Scooters indicator. This paper attempts to draw attention to the field of composite indicators in the field of sharing economy and their methodological aspects.*

Keywords. *Sharing economy Index, Ivanovic distance, composite indicator, weighting scheme, CIDI*

1 Introduction

Intense digitalisation, the Internet, and the development of ICT lead to the development of new business models such as e-commerce (e.g. Amazon), Subscription-based models (e.g. Netflix), Digital content creation and monetisation (e.g. Youtube), Blockchain and cryptocurrency-based models (e.g. NFTs), and sharing economy (e.g. Airbnb, Uber). The business model which attracts a lot of attention among various stakeholders is the sharing economy. According to Puschmann and Alt (2016) “*contrary to the traditional market model, which is based on ownership, the “Sharing Economy” is built on using and sharing of products and services among others*”. As the sharing economy is on the rise (Zervas et al., 2017), there is a need to provide a metric which will allow ranking of different entities (cities, regions, countries) based on the level of its adoption. Useful metrics of such a complex, multidimensional, and interdisciplinary phenomenon are composite indicators. OECD (2004) defines composite indicators as quantitative measures that combine multiple individual indicators or dimensions into a single, aggregated index.

Although composite indicators are very useful metrics, one should consider some of their methodological issues. Namely, the methodological steps of indicator selection process, weighting scheme determination, and aggregation method of composite indices have faced widespread criticism for their subjectivity (Greco et al., 2018). The step that attracts scholars' and practitioners' attention is individual indicator weighting. The allocation of weights to indicators is a crucial aspect of composite index development, giving rise to uncertainty and debate throughout the process (Becker et al., 2017). Therefore, particular attention should be paid to this phase when constructing a composite index. The assignment of weights may rely on statistical methods, expert methods, or their combination (Maricic et al., 2019; OECD, 2004). However, data-driven weighting schemes are seen as objective and more reliable than expert-driven ones (Banerjee, 2018).

Among several composite indicators in the field of sharing economy, the index which attracted our attention was the Sharing Economy Index (SEI) published by the Consumer Choice Center (Consumer

Choice Center, 2024). Although the SEI is comprehensive in sense it covers as many as nine aspects of sharing economy market, its methodology could be more comprehensive in the statistical aspect. The issue of the SEI we aim to tackle is the weighting scheme. In the current form, the weighting scheme is equal and the aggregation method is the simple sum. We are interested in exploring whether the equal weighting scheme is appropriate and, if not, how it should be changed. To scrutinise the SEI, we will apply the Ivanovic distance (I-distance) method (Ivanovic, 1963).

The paper is structured as follows. In the second section, we provide an overview of the currently devised composite indicators in the sharing economy. The third chapter presents the methodological aspects of the Sharing Economy Index and the applied I-distance method. In the chapter that follows, we present the results. The final section comprises the discussion and concluding remarks.

2 Composite indicators on the topic of sharing economy

Composite indicators on the topic of sharing the economy can be divided into two groups: those proposed by organisations and those proposed by scholars. MSCI ACWI IMI Sharing Economy Index is developed by MSCI corporation to show the performance of businesses involved in the creation of new goods and services encompassing sharing economy. Due to the ambiguous transparency of the methodology used, no further information is available. Another noteworthy example was Timbro Sharing Economy Index developed by the Swedish think tank Timbro in 2018. The goal of the index is to measure the amount of global activity in the sharing economy. Their research methodology consisted of a three-phased data acquisition process, which combined both an Internet traffic indicator and scraped data about the number of active suppliers on a service. Giovanini (2021) underscored the utilisation of regression analysis for the development of a sharing economy index that ranked 175 countries based on a vast amount of available internet traffic data. As presented, different approaches to creating composite indices in the sharing economy have been suggested in the literature so far.

3 Sharing Economy Index (SEI)– Methodology and scrutinisation

The Consumer Choice Center, as a global consumer advocacy group, is devoted to providing reports for consumers of different services (nightlife, air travel, betting), as well as indices on lifestyle choices, smart policies, science, healthcare. The Sharing Economy Index (SEI) is just one of the many indices this center publishes. Some of them include European railway station index, Nightlife index, Pandemic resilience index, and Fan friendly stadium index (Consumer Choice Center, 2024).

The Sharing Economy Index (SEI) was first published in 2020 when it ranked 52 cities using seven indicators. Each year, the index methodology is improved, and the list of cities covered is increased. In the year 2023, for which the data is available, the SEI ranked 60 cities worldwide using nine indicators: Ride-hailing (availability and accessibility) (40 points), Carpooling (10 points), Professional car sharing (30 points), Ultra-fast delivery apps (10 points), Peer-to-peer lending (availability and accessibility) (20 points), Gym sharing (10 points), Library sharing (10 points), Flat sharing (availability and accessibility) (20 points), and E-scooters (10 points). The points are awarded based on whether or not a particular sharing service is available and based on which conditions. The weighting scheme is equal weighting while the aggregation method is simple sum. The SEI is calculated as the sum of the nine variables. Therefore, the maximum number of points a city can accumulate is 160. According to the 2023 ranking, Vilnius (Lithuania) tops the list with 155 points, followed by Buenos Aires (Argentina) with 145 points and Madrid (Spain) and Belgrade (Serbia) who share the third place with 140 points.

3.1 Ivanovic distance (I-distance) method

To assess the equal weighting scheme suggested by the index creators, we will employ the Ivanovic distance (Ivanovic, 1963). The Ivanovic distance is a statistical multivariate method which calculates the mutual distances between the entities being processed, whereupon they are compared to one another to create a rank (Jeremic et al., 2011). The distances in the I-distance represent the distance of an observed entity from the fixed, referent entity (Maricic et al., 2019). Most commonly, the fixed entity is a fictive entity which has the minimal measured values of each indicator. Therefore, the higher the value

of the calculated I-distance, the better the entity performs. The formula by which the I-distance is computed is (Jeremic et al., 2011)

$$D^2(r, s) = \sum_{i=1}^k \frac{d_i^2(r, s)}{\sigma_i^2} \prod_{j=1}^{i-1} (1 - r_{ji, 12, \dots, j-1}^2) \quad (1)$$

Where $d_i(r, s)$ is the distance between the values of the indicator X_i for entities e_r and e_s , σ_i^2 is the variance of the indicator X_i , while $r_{ji, 12, \dots, j-1}^2$ is the coefficient of partial determination between indicators i and j .

What additionally makes the I-distance method stand out is the fact that besides just providing ranks, it can be used to propose data-driven weights. The process of assigning I-distance derived weights is referred to as the Composite I-distance Indicator (CIDI) methodology (Dobrota et al., 2016). To obtain objectively assigned weights, the initial step involves calculating the correlation coefficients between each indicator and the I-distance value. Subsequently, the next phase involves computing new weights for each indicator by dividing the correlation coefficient with the I-distance value by the sum of all correlations. The resultant sum of weights equals 1, establishing a new and appropriate weighting system.

4 Results

Before the application of I-distance and CIDI on SEI 2023, we present the descriptive statistics of the nine SEI indicators (Table 1). As can be seen, indicators are not measured on the same scales; some are on the scale from 0 to 40, while some are from 0 to 10. The indicator with the largest standard deviation is *Ride-hailing*, 10.481. This result indicates that the cities differ in performance. Although the median is quite high, 30, there are cities which visibly underperform. Interestingly, for the indicator *Professional car-sharing*, the minimal measured value is 20, which might signal that all observed cities have embraced a form of car sharing services. Looking at the four indicators measured on a scale from 0 to 10, the indicator with the smallest mean is *Ultra-fast delivery* (7.670), while the indicator with the highest mean is *E-scooters* (9.330). This could indicate that cities have widely adopted e-scooters.

Table 1. Descriptive statistics of the nine SEI indicators (Source: Authors' work)

	Ride-hailing	Carpooling	Prof. car sharing	Ultra-fast delivery	P2P lending	Gym sharing	Library sharing	Flat sharing	E-scooters
Mean	26.250	8.830	28.170	7.670	12.670	8.50	8.17	10.120	9.330
Std	10.481	3.237	3.902	4.265	5.856	3.601	3.902	4.434	2.515
Me	30.000	10.000	30.000	10.000	15.000	10.000	10.000	10.000	10.00
Min	0	0	20	0	0	0	0	5	0
Max	40	10	30	10	20	10	10	20	10

In the next step, we applied the I-distance method. We used the quadratic I-distance and the minimal entity as the referent. The initial application of the I-distance indicated negative correlation coefficients of indicators with the I-distance value. Such a result is a signal that the underlying structure of the SEI should be altered as well. Principal component analysis (PCA) with Varimax rotation was employed to propose a novel structure. The pretests showed that the data is suitable for the analysis (KMO=0.554, Bartlett's test=133.416, $p<0.001$). PCA suggested a four-component structure which explains 73.046% of variability. The new suggested structure is the following: Micromobility (E-scooters), Lifestyle (Gym sharing, Prof. car sharing, Ultra-fast delivery, Library sharing), Long-term sharing activities (Carpooling, P2P lending) and Short-term sharing activities (Flat sharing, Ride-hailing). To obtain the I-distance weights, the CIDI methodology was applied in two folds: first to obtain weights within the pillar, and second to determine the weights among pillars. The obtained weights are presented in Table 2. Looking at the weights within pillars, in pillars with two indicators, the weights are almost equal. However, in the



pillar Lifestyle, there are some differences. The most important indicator within the pillar is Gym sharing (0.316), while the least important is Library sharing (0.188). Analysing the pillar weight, again slight difference in the importance can be noted. What is also useful to observe are the total indicator weights. The individually most important indicator for the ranking process is E-scooters, followed by P2P lending and Carpooling.

Table 2. I-distance derived weights of the nine SEI indicators (Source: Authors' work)

Pillar	Micromobility	Lifestyle				Long-term sharing activities		Short-term sharing activities	
Indicator	E-scooters	Gym sharing	Prof. car sharing	Ultra-fast delivery	Library sharing	Carpooling	P2P lending	Flat sharing	Ride-hailing
Indicator weight	1	0.316	0.285	0.211	0.188	0.464	0.536	0.521	0.479
Pillar weight	0.226	0.247				0.293		0.234	
Total weight	0.226	0.078	0.070	0.052	0.046	0.136	0.157	0.122	0.112

Due to limited space, we will not present the full I-distance rankings herein. However, the results are available on request from the corresponding author. The top and bottom ten ranked cities based on the I-distance rank compared to the official SEI rank are presented in Table 3. Vilnius and Buenos Aires top the list in both rankings, Belgrade and Madrid stayed on close 3rd and 4th ranks. According to the I-distance, the Hague and Mexico City found their place in top 10, moving from 14th and 18th place respectively. Looking at the bottom of the list, no drastic changes occurred, except for Shanghai who dropped from 50th to 55th place.

Table 3. Top and bottom ten ranked cities based on the I-distance rank compared to the official SEI rank (Source: Authors' work)

SEI	SEI rank	I-dist SEI	I-dist rank	City	SEI	SEI rank	I-dist SEI	I-dist rank	City
155	1	16.951	1	Vilnius	100	49	11.701	51	San Jose
145	2	16.311	2	Buenos Aires	95	52	10.203	52	Nicosia
140	4	15.701	3	Belgrade	87	55	9.933	53	Valletta
140	3	15.220	4	Madrid	84	56	9.725	54	Tokyo
136	5	14.732	5	London	100	50	9.298	55	Shanghai
135	6	14.660	6	Barcelona	91	53	9.014	56	Copenhagen
135	10	14.660	7	Helsinki	90	54	8.717	57	Istanbul
135	14	14.611	8	Hague	80	57	8.372	58	Luxembourg
130	18	14.580	9	Mexico City	73	59	7.956	59	Ljubljana
135	9	14.435	10	Stockholm	71	60	7.712	60	Athens

5 Discussion and conclusion

This study aimed to assess the methodological choices of the SEI related to the index structure and weighting scheme. The application of I-distance and CIDI showed that the SEI should be restructured and that equal weighting is not an adequate weighting approach. The directions of future research could encompass the application of other statistical methods to assess the SEI, such as the Benefit of the Doubt (Rogge, 2018), a combination of BoD and I-distance (Maricic & Jeremic, 2023), or even ultrametric composite indicator (Cavicchia et al., 2024).

We hope our study will serve as validation for the methodology and results of the SEI and as a source of guidance for potential methodological improvements to this metric. Additionally, this research could have the potential to initiate innovative approaches in evaluating sharing economy acceptance, with potential implications for decision-makers on the city level in the future.

Acknowledgement

This research was supported by the Science Fund of the Republic of Serbia, Grant no. 7523041, Setting foundation for capacity building of sharing community in Serbia - PANACEA.

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