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Sürdürülebilir Kentsel Hareketliliğin İyileştirilmesi için Hibrit Bir Çerçeve: Paylaşımlı Bisiklet Sistemi İstasyon Yer Seçiminde Çok Kriterli Karar Verme ve Maksimum Kapsama Probleminin Entegrasyonu

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Anahtar Kelimeler
Sürdürülebilirlik,
Kentsel Hareketlilik,
Paylaşımlı Bisiklet,
Çok Kriterli Karar Verme (ÇKKV),
Optimizasyon

Öz: Sürdürülebilir kentsel hareketlilik çevresel etkilerin azaltılması ve ulaşım verimliliğinin artırılması açısından kritik öneme sahiptir. Paylaşımlı Bisiklet Sistemleri (PBS), istasyonların optimal konumlandırılmasına bağlı olarak etkinlik göstermektedir. Bu çalışmada, PBS istasyonlarının yer seçimi için Çok Kriterli Karar Verme (ÇKKV) ve mekânsal optimizasyon teknikleri entegre edilerek veri odaklı bir çerçeve geliştirilmiştir. Kriter ağırlıklarının belirlenmesinde IDOCRIW yöntemi ile alternatiflerin değerlendirilmesinde CoCoSo yöntemi bir arada kullanılmıştır. Bisiklet yollarına, tramvay duraklarına yakınlık, nüfus yoğunluğu ve trafik kaza oranları gibi faktörler dikkate alınarak analiz gerçekleştirilmiştir. Sonuçların doğruluğunu teyit etmek amacıyla TOPSIS, ARAS ve COPRAS yöntemleri uygulanmış ve Borda Sayım yöntemiyle sonuçlar birleştirilmiştir. Ek olarak Maksimum Kapsama Problemi kullanılarak nüfus kapsama oranı optimize edilmiştir. Seçilen üç optimal istasyon konumu, kent nüfusunun %18'ini kapsayarak yöntemin etkinliğini ortaya koymuştur. Senaryo analizleri, hizmet mesafesi eşik değerlerinin sistem performansı üzerindeki etkisini değerlendirerek planlama esnekliği konusunda içgörüler sunmaktadır. Bulgular, ÇKKV teknikleri ile mekânsal modellemenin entegrasyonu PBS'nin verimliliğini ve sürdürülebilirliğini artırdığını göstermektedir.

A Hybrid Framework for Improving Sustainable Urban Mobility: Integrating Multi-Criteria Decision-Making and Maximal Covering Location Problem for Bike-Sharing System Site Selection

Keywords
Sustainability,
Urban Mobility,
Bike-Sharing,
Multi-Criteria Decision-Making (MCDM),
Optimization

Abstract: Sustainable urban mobility plays a critical role in reducing environmental impacts and enhancing transportation efficiency. Bike-Sharing Systems (BSS) operate effectively when station locations are optimally selected. In this study, a data-driven framework integrating Multi-Criteria Decision-Making (MCDM) and spatial optimization techniques is developed to determine optimal station locations for BSS. The Integrated Determination of Objective Criteria Weights (IDOCRIW) method is employed for deriving criterion weights, while the Combined Compromise Solution (CoCoSo) method is used to evaluate alternatives. Factors such as proximity to bike lanes and tram stops, population density, and traffic accident rates are incorporated into the analysis. To validate the robustness of the results, TOPSIS, ARAS, and COPRAS methods are applied, and outcomes are consolidated using the Borda count method. Additionally, the Maximal Covering Location Problem is utilized to optimize population coverage. The three selected optimal station locations collectively cover 18% of the urban population, demonstrating the effectiveness of the proposed approach. Scenario analyses further explore the impact of service distance thresholds on system performance, offering insights into planning flexibility. The findings indicate that integrating

MCDM techniques with spatial modeling significantly enhances the efficiency and sustainability of BSS implementation.

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1. Introduction

Urban areas are recognized as hubs of economic and social activities. The United Nations (UN) predicts that by 2050, 68% of people on Earth will reside in cities [1]. Despite cities taking up only 2% of the planet's land, they use 65-75% of its energy and emit more than 75% of global CO2 emissions [2]. Urbanization represents one of the most significant societal transformations of the modern era, influencing and being influenced by various social, economic, and environmental processes [3]. The growing tendency of urbanization not only improves social advantages but also adds considerably to the economy by promoting rural development and technical improvement. However, urbanization has significant environmental consequences that can have a direct influence on the economy, public health, and living standards [4]. The transportation and fuel sectors are being burdened by the world's rapid population growth and rising demand for transportation especially in urban areas [5]. In addition to rising fuel prices, deteriorating air quality, noise pollution, increasing traffic congestion, accidents, and parking problems are among the main problems urban areas have to contend with. All stakeholders such as local authorities, transportation companies, and urban residents are impacted by these occurrences and grapple with diverse challenges [6]. The responsibilities of municipalities in combating climate change and developing policies within the sustainability framework are increasing daily. Municipalities face difficulties in formulating regulations or incentives that foster sustainable transportation networks and integrating them into urban development plans [7]. BSS have an important place among the sustainable methods adopted by municipalities as an alternative to traditional fossil fuel-dependent transportation systems. The first BSS was introduced in Amsterdam, Netherlands, in the 1960s. "White Bikes" were used by the general public all across the city. The program was dropped because the bicycles were frequently stolen and vandalized. BSS was first implemented in 1996 at Portsmouth University in England [8]. Over time, BSS has evolved and overcome obstacles by subscription systems. It allows urban residents to borrow bicycles for short-term, local journeys. This sustainable transportation mode seeks to minimize greenhouse gas emissions, dependence on fossil fuels, traffic congestion, air and noise pollution, and also travel expenses. On the other hand, it contributes to the sustainability of cities and Sustainable Development Goals with the advantages of an increase in public transport usage, accessibility, physical activity, and thus health improvement, and urban environment perception. The greenhouse gas emissions per journey of vehicles [9] and the environmental benefit of bicycle usage in terms of the environment are presented in Figure 1.

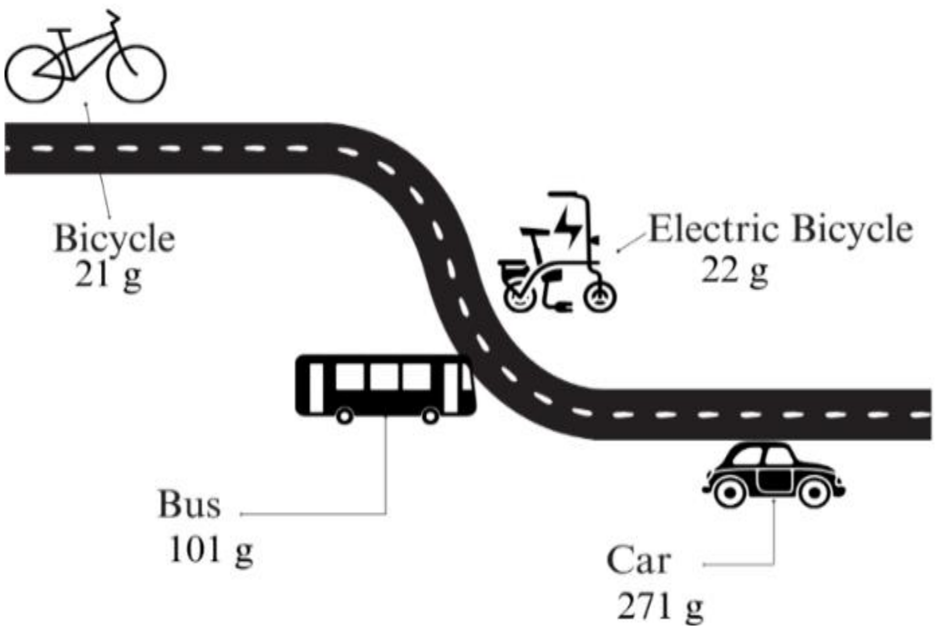

Figure. 1. The Greenhouse Gas Emissions per Journey of Vehicles

BSS make it possible for urban residents to utilize bicycles as an eco-friendly and healthful form of transportation [5, 10, 11, 12, 13]. BSS is widely recognized as a pivotal factor contributing significantly to the efficacy of transit-oriented development within urban communities. Its pivotal role is manifested in the augmentation of travel options, the promotion of public transit connectivity, and the facilitation of recreational opportunities [14].

Furthermore, BSS is mobility options that enhance transportation networks when assessing first- and last-mile solutions [15, 16]. Researchers focus on last-mile and urban freight transport, which have become increasingly important in recent years [17]. The goals of the first- and last-mile solutions are to promote transit use, close the distance between transit hubs, and urge people to abandon using automobiles in favor of environmentally cleaner modes of transportation. This replacement is viable in cities with powerful BSS networks [18]. BSS enhances short-distance travel and readily connects to other transportation systems, allowing individual trips to smoothly integrate numerous modes of transportation [19]. Evaluating BSS is a critical aspect of improving urban mobility and multimodal transportation. A multitude of criteria should be considered when determining the sites of stations for a successful BSS. Stations, for example, should be positioned close to transport stops to supplement transit [20]. For urban residents looking for a low-carbon way to commute short distances and local authorities, BSS has become popular [21]. According to a study done in Shanghai, BSS has resulted in 8358 tons of fuel savings. As a result, there is a reduction in carbon dioxide and nitrogen oxide gas emissions leading to an improvement in air quality [22].

The application of MCDM methods in the site selection process for BSS significantly enhances the decision-making quality by determining the appropriate sites based on a balanced consideration of factors such as accessibility, demand, safety, and proximity to key sites of the city, leading to improved user satisfaction and system sustainability. In this study, BSS, which provides environmentally friendly transportation opportunities and constitutes a component of smart transportation systems designed to address challenges arising from urbanization, is investigated. Firstly, a data-driven MCDM framework has been proposed to identify the appropriate sites for BSS, and to demonstrate how the suggested methodology can be applied, a case study has been carried out. The criteria's weights have been determined using the Integrated Determination of Objective Criteria Weights (IDOCRIW) method and the Combined Compromise Solution (CoCoSo) method has been used for the evaluation and ranking of the alternative sites. After the weights are collected individually using the Entropy and CILOS procedures, a single weight is calculated using the IDOCRIW methodology. The weights computed by IDOCRIW will indicate a change in the criteria values, but the relevance of the criteria will diminish if the losses are greater than the other criteria [23]. The CoCoSo method used for evaluating the alternative BSS sites combines basic additive weighting with the exponentially weighted product model. This strategy is excellent for ranking or selecting options. In the literature, several MCDM strategies have been used to handle a variety of challenging decision problems. Different MCDM methods produce different performance evaluations because of the methodologies' different mathematical calculation manners. Explaining these rating discrepancies and clarifying the ranks derived from the methodologies are therefore imperative [24]. In this study, the findings obtained from the adopted methodology have been compared with the outcomes derived from the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Additive Ratio Assessment (ARAS), and Complex Proportional Assessment (COPRAS) methods. TOPSIS is based on the idea that the selected choice should have the shortest distance from the positive ideal solution and the farthest distance from the negative one [25]. On the other hand, ARAS is such a sensitive tool, that even small changes to the data can have an impact on the results. The key feature of this model lies in its capability to treat maximum and minimum criteria separately, thereby preventing inconsistency and enabling more precise, contradiction-free outcomes [26]. One of the main benefits of COPRAS is its ability to handle relevant and irrelevant factors independently, which gets around an issue with the ARAS technique. Furthermore, it is feasible to obtain both metrics that are qualitative and quantitative using the COPRAS technique since it can compute both maximization and minimization criteria [27]. Besides the comparison of the CoCoSo results with TOPSIS, ARAS, and COPRAS, a combined ranking is obtained by utilizing the rankings of the mentioned methods via the Borda Count method, which is a data fusion technique. As a final step, a mathematical model has been formulated for the Maximal Covering Location Problem (MCLP). The alternative sites that ranked according to their performance within the framework of the criteria considered and their weights are considered potential bike-sharing stations at this stage. Thanks to MCLP, station sites are optimized to serve the maximum population. The model introduces a novel approach to literature by incorporating already existing bike-sharing stations into the analysis. As a result of the model, the population coverage of the newly established stations has been maximized, offering valuable insights for enhancing the efficiency and impact of the BSS station. The study's structure has been set up as follows: Section 2 presents the material and method, Section 3 outlines the results, and Section 4 provides the discussion and conclusion.

2. Material and Method

The study first adopts a comprehensive approach implementing the IDOCRIW and CoCoSo methods to determine the appropriate sites for BSS station. A data-driven methodology is employed for determining criterion values and conducting the performance ranking of alternative sites. The data used in the analysis are obtained from the Geographic Information System (GIS). The framework adopted in the study is given in Figure 2.

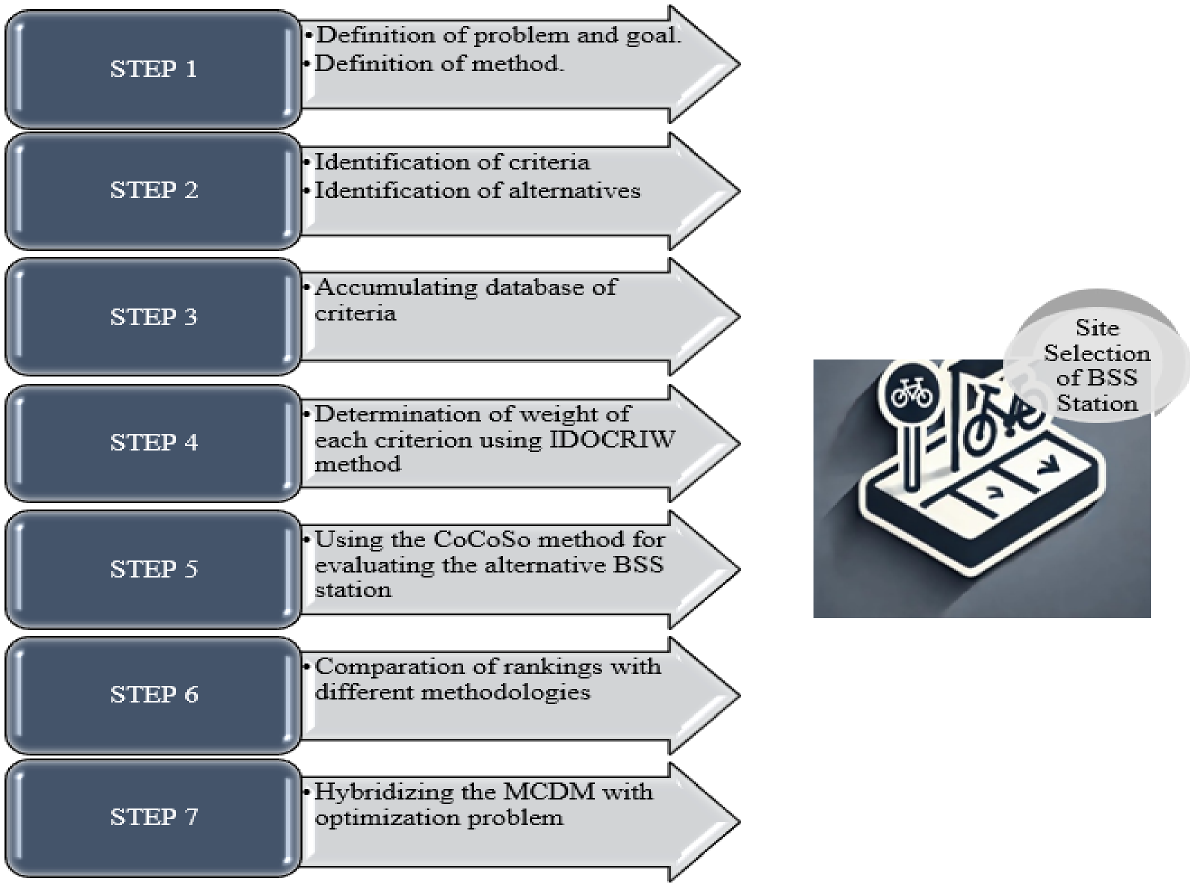

Figure 2. The Framework of the Study

2.1. Literature Review

Although BSS has been established for over fifty years, in the last fifteen years, it has become much more prominent in literature and practice. BSS, recognized for its environmental sustainability and contribution to a healthy transportation infrastructure, is currently operational in 1590 cities across 92 countries. The majority of these systems are concentrated in China, North America, and Europe [28]. Recent studies have attempted to improve the outcomes of BSS efforts via the use of diverse scientific approaches such as mathematical models and MCDM techniques. This section focuses on the literature related to the site selection problem of BSS. Table 1 shows the studies that have approached site selection problems for BSS using mathematical modeling and/or an MCDM approach.

Table 1. Studies examining the BSS station site selection

References	Problem	Methods
Luo-ke [29]	Determining the ideal sites for stations.	AHP
Lin and Yang [30]	Developing an optimization model for station locations.	Network Optimization
García-Palomares et al. [31]	Formulating optimization model for BSS.	GIS-MCLP
Martinez et al. [32]	Determining the ideal sites for stations.	MILP
Romero et al. [33]	Optimizing the location of docking stations in a public bicycle system for economic and social efficiency.	Genetic Algorithm
Ghandehari et al. [34]	Determining the ideal sites for stations.	AHP, SAW, and GIS
Lin et al. [35]	Determining the number and location of stations.	A Hub Location Inventory Model

Deng et al [36]	Determining the ideal sites for stations.	AHP
Frade and Ribeiro [37]	Determining the ideal sites for stations.	MCLP
Lopez Gonzalezz [38]	Determining the ideal sites for stations.	Location-Allocation Models and Spatial Analysis
Pan and Dou [39]	Estimating prospective bike demand and developing an optimization model for station sites.	Network Optimization
Ciancio et al. [40]	Developing an optimization model for station locations.	Stochastic MC
Çetinkaya [41]	Determining the ideal sites for stations.	F-AHP and TOPSIS
Park and Sohn [42]	Determining the ideal sites for stations.	P-Median and MCLP Model
Kabak et al. [43]	Assessing the current state of BSS and locating prospective station locations by comparing them to existing stations.	GIS and MOORA
Mete et al. [44]	Determining the ideal sites for stations.	MC, P-center and P-median
Chen et al. [45]	Developing an optimization model for station locations.	Tabu Search and Agent-based Modeling
Gehrke and Welch [46]	Selecting station area types based on variation.	Latent Class Cluster Analysis
Hu et al. [47]	Adding a new station, deleting an existing station, and redistributing the existing bike stations.	The Potential Path Area and MCLP
Jahanshahi et al. [48]	Evaluation of existing BSS and identification of potential new ones.	GIS, AHP, and VIKOR
Shu et al. [49]	Determination of optimum distances between building entrance-exit points and stations.	Questionnaire, Logistic Model, and Non-linear Regression Model
Eren [50]	Analysis of existing stations based on land use types and station location selection.	AHP, VIKOR, and GIS
Lee et al. [51]	Determining the ideal sites for stations.	MLR and MOORA
Salih-Elamin and Al-Deek [52]	Finding the optimal locations of BSS and maximizing BSS demand coverage.	MCLP, TOPSIS, and AHP
Alkılınç et al. [53]	Determining the ideal sites for stations.	GIS and AHP
Eren and Katanalp [18]	Selecting station sites depending on land use.	FL-Based GIS, AHP, VIKOR, and P-VIKOR Method
Guler and Yomralıoğlu [54]	Determining the ideal sites for stations.	BWM and GIS
Öztaşcı et al. [55]	Cost-benefit analysis.	Questionnaire
Bahadori et al. [56]	Determining the ideal sites for stations.	AHP, TOPSIS, and GIS
Ebrahimi et al. [20]	Mapping the spatial distribution of bike-sharing stations.	GIS, Target Market Share Maximize Coverage and Minimize Facility
Mix et al. [57]	Determining the demand for BSS trips and the optimal ts of stations.	Maximum Demand Coverage Models
Qian et al. [58]	Determining the ideal sites for stations.	Mathematical Model and Genetic Algorithm
Chai et al. [59]	Determining the ideal sites for stations.	AHP

Note: AHP (Analytical Hierarchy Process), BWM (Best Worst Method), GIS (Geographical Information Systems), FL-Based (Fuzzy Logic Based), F-AHP (Fuzzy Analytical Hierarchy Process), MC (Maximal Covering), MCLP (Maximal Covering Location Problem), MILP (Mixed-Integer Linear Programming), MLR (Multiple Linear Regression), MOORA (Multi Objective Optimization By Ratio Analysis), SAW (Simple Additive Weighting), P-VIKOR (Psychometric-Vlsekriterijumska Optimizacija I Kompromisno Resenje), GIS (Geographical Information System).

As indicated in Table 1, there are many studies in the literature that address the problem of site selection for BSS station with different approaches, especially in recent years. Due to the challenges in obtaining complete data, nearly all of the studies addressing the site selection problem of BSS station with the MCDM methodology are typically evaluated by subjective methods based on expert opinion. In this study, a data-driven MCDM approach (IDOCRIW and CoCoSo) has been used. There are studies in the literature that use the IDOCRIW and CoCoSo methods in a hybrid manner in different fields. For example, Eslami et al. [61], used the IDOCRIW and CoCoSo process to establish the optimum plan for mitigating the negative consequences of dam building based on the results of environmental impact assessments. Luo et al.[29], evaluated tourist attraction centers in China based on internet reviews. In this study, BSS station sites evaluated using IDOCRIW and CoCoSo methods provide input to the mathematical model and a framework hybridizing MCDM-MCLP is proposed to optimize the best sites to serve the most population. To the best of the authors' knowledge, there is no such study in the literature and it is hoped that the results obtained will contribute to local authorities making effective use of their scarce resources to serve more residents, increasing the demand for bike-sharing by urban residents thus reducing the carbon footprint of urban mobility, and raising the socio-economic development levels in urban areas.

This study aims to provide a comprehensive and multidimensional contribution to the existing literature on BSS. First and foremost, the set of evaluation criteria has been restructured in line with recent scholarly approaches, incorporating spatially explicit and data-driven indicators. Unlike many previous studies that rely heavily on subjective weighting techniques, this research adopts the IDOCRIW method, which is rarely employed in combination within the MCDM literature. Through the integration of the Entropy and CILOS methods, objective and balanced criterion weights are obtained [29]. This integrated approach not only enhances the accuracy and reliability of the analysis but also supports the construction of a highly reproducible evaluation framework.
For the ranking of alternatives, the CoCoSo method is selected due to its consistent performance in previous studies. By combining the classical WSM and WPM approaches through a triple aggregation strategy, CoCoSo enhances the robustness of the decision-support process [73].
This study also addresses a significant gap in the literature by incorporating user safety into the decision-making framework. As emphasized in the literature, user safety is frequently evaluated based on expert opinions or other subjective assessment methods. In contrast, this study offers a novel contribution by incorporating traffic accident data as a direct, objective, and spatially explicit risk indicator, thereby enhancing the methodological rigor of the safety analysis. By utilizing accident statistics at the neighborhood level for each candidate location, user safety is modeled through objective and quantifiable indicators. This represents one of the first attempts in the literature to analyze spatial safety factors through a holistic and systematic approach.

Finally, the widely used Maximal Covering Location Model is innovatively adapted to the station location problem. In this model, the spatial configuration of the existing 70 BSS stations is taken into account, and the coverage areas of new proposed stations are evaluated in relation to these reference points. This application ensures that the decision-making process is fully integrated with the urban spatial context, significantly enhancing the practical relevance and real-world applicability of the proposed framework.

Taken together, these contributions not only introduce methodological innovations to the literature but also serve as a valuable reference for practitioners and policymakers seeking to develop spatial intelligence-based decision support systems for sustainable urban transportation planning.

2.2. IDOCRIW Method

The IDOCRIW method was introduced by Zavadskas and Podvezko [62]. This approach integrates the salient aspects of the Entropy [63] and the CILOS (Method of Criterion Impact Loss) methods [62] to assess data structure. The entropy method is extensively applied for ascertaining criteria weights, representing the comparative advantage of one alternative over another at equivalent standard values. Meanwhile, the CILOS method is employed to determine the relative impact loss experienced by an alternative criterion when another criterion is identified as superior. This method is linked to the evaluation of the probability of significance loss for each criterion when assigning maximum or minimum values to one of the criteria [62]. The IDOCRIW method addresses the limitations of the entropy method while retaining the advantages of the CILOS method. Through the synthesis of these two techniques, the potential for excessively large or small differences in weights is mitigated, resulting in a highly accurate comprehensive weight. The IDOCRIW approach has been used for determining the criteria weights by the following steps.

2.2.1. Entropy Method

Shannon proposed the Entropy technique in 1948 as "a statistical parameter that measures, in a sense, how much information is produced on average for each letter of a text in the language" [63]. Most multi-criteria decision analysis (MCDA) issues necessitate the formulation of criteria weights to demonstrate the relative importance of each criterion concerning other factors impacting option alternatives and results. Without relying on subjective information from experts or decision-makers, entropy weights can evaluate the amount of relevant information provided by the index based on attribute value discrepancies. The fundamental advantage of the Entropy methodology over subjective-based weighing methods is that it removes human influence from the weighting process, allowing criteria weights to be established objectively [64, 65].

The initial decision matrix is constructed as follows:

$$X = [x_{ij}]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} (i = 1,2,\dots,m;\ j = 1,2,\dots,n) \quad (1)$$

The decision matrix $[x_{ij}]_{m\times n}$ constitutes the initial step of the evaluation process. This matrix encompasses m alternatives and n criteria. Each element x_{ij} in the decision matrix represents the performance score of the i^{th} alternative with respect to the j^{th} criterion. This value serves as a fundamental data component that enables the evaluation and comparison of alternatives based on each criterion.

Due to the differing units of measurement across the various criteria in the decision matrix, normalization is required prior to proceeding with the analysis. The normalization process ensures that all criteria are brought onto a comparable scale, thereby facilitating a consistent and meaningful evaluation.

The normalization of the decision matrix is performed using Eq. (2).

$$r_{ij} \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \quad (2)$$

In the equation, r_{ij}represents the normalized value of the i^{th} alternative with respect to the j^{th} criterion. This process ensures comparability of each alternative in relation to the corresponding criterion.

The entropy degree is calculated using Eq. (3).

$$E_j = -\frac{1}{ln_n}\sum_{i=1}^{n} r_{ij} ln(r_{ij}) \ \ j = 1,2,\dots,m; 0 \le E_j \le 1 \quad (3)$$

The degree of differences, represented by, d_j is calculated by applying Eq. (4).

$$d_j = 1 - E_j \quad (4)$$

The entropy weight w_j is calculated using Eq. (5).

$$W_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, \sum_{j}^{m} w_j = 1 \quad (5)$$

The degree of non-homogeneity in data is reflected by Entropy weights. Homogeneous data has zero weight, which doesn't significantly influence evaluation. The largest weight corresponds to the criterion with the highest weight ratio [62]. Entropy weight establishes the importance of the criteria in the decision-making process; a lower Entropy number indicates a higher Entropy-based weight, implying that more information can be derived from the given criterion [69].

In the next step, the CILOS methodology is applied. This method provides a complementary approach for determining the corresponding weights of the criteria. The CILOS approach aims to calculate objective weights that contribute to the decision-making process by evaluating the relative influence loss of alternative criteria. A detailed procedure of the CILOS method is presented in the following section.

2.2.2. CILOS Method

In the method proposed by Čereška et al., one of the remaining criteria involves assessing the loss of each criterion until the optimum is reached [70]. The CILOS approach is utilized, considering the effect loss of each criterion when one of the other criteria reaches the maximum or minimum value. The stages of the CILOS method, as outlined by Zavadskas and Podvezko [62], are as follows: The first step is transforming minimized criteria into maximizing criteria using Eq. (6).

$$\tilde{r}_{ij} = \frac{min_i r_{ij}}{r_{ij}} \tag{6}$$

The new matrix is indicated by; $X = \|x_{ij}\|$.
Eq. (7) is used to identify the highest value within each criterion column. This operation is intended to determine the maximum value for each criterion in the matrix, which will subsequently serve as a reference point in the following calculations.

$$x_j = max_i x_{ij} = x_{kij} \tag{7}$$

The 'B' matrix is constructed by selecting thex_{kij} values from the X matrix that correspond to the maximum values of the i^{th} criterion. As a result of this process, a square 'B' matrix consisting of k_i rows are obtained, as presented in Eq. (8).

$$B = \|b_{ij}\|, \; b_{ii} = x_i, b_{ij} = x_{kij} \tag{8}$$

The 'P' matrix represents the relative impact loss of each criterion. The calculation is performed using Eq. (9).

$$P = \|p_{ij}\|, p_{ij} = \frac{x_j - b_{ij}}{x_j} = \frac{b_{ii} - b_{ij}}{b_{ii}}, \qquad P_{ij} = 0; i, j = 1, 2, \ldots, m \tag{9}$$

The 'F' matrix, which defines the criterion weights, is constructed using Eq. (10).

$$F = \begin{bmatrix} -\sum_{i=1}^{m} P_{i1} & P_{12} & \cdots & P_{1m} \\ P_{21} & -\sum_{i=1}^{m} P_{i2} & \cdots & P_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ P_{m1} & P_{m2} & \cdots & -\sum_{i=1}^{m} P_{im} \end{bmatrix}_{m \times m} \tag{10}$$

To determine the CILOS weights, a system of linear equations is solved using Eq. (11).

$$F \times q_j = 0 \tag{11}$$

The criterion weights q_j are calculated from the defined homogeneous linear system of equations presented by Ali et al. [66].
The "impact loss" criteria technique solves the Entropy method's drawbacks. When the criteria value changes only slightly, the members p_{ij} of the matrix P, which indicates the relative loss of criterion influence, tend to approach zero. In contrast, the associated criterion weights rise dramatically, having a considerable impact on the entire evaluation.

When one criterion remains constant across all options the relative losses for that criterion, as well as its overall loss, become zero. As a result of a whole column of elements in matrix P being reduced to zero, the linear system of equations loses importance.

Drawing on the concept of distinct impact weights merging into a unified overall weight [68, 71] it becomes feasible to establish a connection between the Entropy weights W_j and the weights q_j derived from the CILOS method. This connection serves to associate them with shared ultimate criteria aimed at evaluating the weight array structure ω_j- Eq. (12).

$$\omega_j = \frac{q_j W_j}{\sum_{j=1}^{m} q_j W_j} \tag{12}$$

These weights will emphasize the separation of specific criterion values but their significance will be decreased due to greater loss in other criteria. The estimated weights of Entropy and criterion loss of impact are combined into aggregated weights, which are then used in multi-criteria assessment, option ranking, and selecting the optimal alternative [70].

2.3. CoCoSo Method

A particular MCDM ranking model, known as the CoCoSo approach, was proposed in 2019 by Yazdani et al., [72]. It is based on the combination of three score aggregation functions that have been compromised [73, 74]. Given its high dependability in calculating the right compromise score utilizing an integrated framework, CoCoSo has been used in a variety of sectors, including sustainability and performance evaluation. The method is based on an integrated basic additive weighting and an exponentially weighted product model [72].

Formulating the initial decision (Xij) matrix based on real data as follows:

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \qquad i = 1,2, \dots, m \qquad j = 1, 2, \dots, n \tag{13}$$

The normalization process varies according to the type of criteria. For benefit criteria, normalization is performed using Eq. (14), while for cost-type criteria, Eq. (15) is applied. In this way, all criteria are transformed into a comparable scale, ensuring consistency throughout the evaluation process.

$$x_{ij} = \frac{x_{ij} - x_{ij}^{-}}{x_{ij}^{+} - x_{ij}^{-}} \tag{14}$$

$$x_{ij}^{-} = \frac{\min(x_{ij})}{1 \le i \le n}, x_{ij}^{+} = \frac{\max(x_{ij})}{1 \le i \le n}$$

$$x_{ij} = \frac{x_{ij}^{+} - x_{ij}}{x_{ij}^{+} - x_{ij}^{-}} \tag{15}$$

The sum of the weighted comparability sequence and the sum of the power weight of comparability sequences for each choice, as Si and Pi, respectively are calculated by Eqs. (16-17).

$$S_i = \sum_{j=1}^{n} (w_j x_{ij}), \tag{16}$$

$$P_i = \sum_{j=1}^{n} (x_{ij}) a^{w_j}, \tag{17}$$

The following aggregation procedures are used to calculate the relative weights of the options. In this step, relative weights for additional alternatives are generated using three evaluation score methodologies (Eqs. (18-20)).

$$\varphi_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)}, \tag{18}$$

$$\varphi_{ib} = \frac{S_i}{\underset{i}{min} S_i} + \frac{P_i}{\underset{i}{min} P_i}, \tag{19}$$

$$\varphi_{ic} = \frac{\lambda(S_i)+(1-\lambda)(P_i)}{\left(\lambda^{\underset{i}{max} S_i} + (1-\lambda)^{\underset{i}{max} P_i}\right)};\ 0 \leq \lambda \leq 1 \tag{20}$$

Eq. (18) corresponds to the Weighted Sum Method (WSM) and the Weighted Product Model (WPM). Eq. (19) illustrates the aggregated relative scores obtained from both WSM and WPM in comparison to the optimal solution. Eq. (20) introduces a balanced compromise between the results derived from these two methods.
Finally, the performance scores of the alternatives are calculated by applying Equation (21).

$$\varphi_i = (\varphi_{ia}\varphi_{ib}\varphi_{ic})^{\frac{1}{3}} + \frac{1}{3}(\varphi_{ia} + \varphi_{ib} + \varphi_{ic}). \tag{21}$$

Consequently, the alternatives are ranked based on their performance scores, with a higher performance score being preferable.

3. Results

In this section, IDOCRIW and CoCoSo methods, whose methodology has been given in the previous section, are used to determine criteria weights and evaluate alternatives for the problem of site selection for BSS station, which are important for sustainable mobility in urban centers. A comprehensive set of criteria has been determined based on synthesizing insights from both expert opinions (working for Kayseri Transportation Inc., a subsidiary of Kayseri Metropolitan Municipality) and the existing literature. Seventeen criteria that form the basis for the sustainability of the city's transportation systems by selecting the most appropriate station sites are given in Table 2.

Table 2. Considered Criteria and Their Relationship with Literature

Criteria	Definition	[75]	[76]	[77]	[37]	[41]	[11]	[48]	[78]	[53]	[56]	[18]	[79]	[80]	[?]
Cri_1	Proximity to Bus Stop	Δ	Δ	Δ					Δ	Δ	Δ	Δ	Δ		Δ
Cri_2	Proximity to Tram Stop			Δ	Δ		Δ	Δ	Δ	Δ	Δ	Δ	Δ		Δ
Cri_3	Proximity to the Existing Stops							Δ					Δ		Δ
Cri_4	Proximity to Important Junction							Δ							Δ
Cri_5	Proximity to University and High School	Δ	Δ	Δ		Δ	Δ	Δ	Δ	Δ		Δ	Δ	Δ	Δ
Cri_6	Proximity to Student Residence									Δ					Δ
Cri_7	Proximity to Library														Δ
Cri_8	Proximity to Hospital											Δ			Δ
Cri_9	Proximity to City Hall											Δ			Δ

Cri_10	Young Population				Δ									Δ
Cri_11	Proximity to Green Areas	Δ				Δ		Δ	Δ		Δ	Δ		Δ
Cri_12	Proximity to Historical and Touristic Areas		Δ	Δ	Δ	Δ	Δ		Δ	Δ	Δ	Δ	Δ	Δ
Cri_13	Proximity to Cinema													Δ
Cri_14	Proximity to Shopping Mall				Δ	Δ		Δ				Δ	Δ	Δ
Cri_15	Proximity to Restaurant	Δ											Δ	Δ
Cri_16	Proximity to Bike Lane	Δ			Δ	Δ	Δ			Δ	Δ	Δ	Δ	Δ
Cri_17	The number of traffic accidents													Δ

⊕: Current Paper.

3.1. Criterion Weighting

In this section, the weight values of performance criteria considered for determining the best sites for BSS station with the perspective of sustainability have been calculated using the IDOCRIW method.

The decision matrix (DM) comprising the alternatives and criteria is presented in Table 3.

Table 3. The DM for the Entropy Method

Criteria/ Alternative	Cri_1	Cri_2	Cri_3	Cri_4	Cri_5	Cri_6	Cri_7	Cri_8	Cri_9
Alt_1	110	140	1800	480	1700	600	1450	45	8000
Alt_2	35	20	507	45	180	300	900	670	1110
Alt_3	130	220	120	120	55	90	380	360	250
Alt_4	110	1600	880	170	210	250	700	350	1220
Alt_5	75	600	550	110	370	1110	920	550	2495
Alt_6	135	1100	620	290	430	1300	480	375	745
Alt_7	60	20	915	880	235	890	1380	1255	3055
Alt_8	130	40	860	600	520	290	950	890	780
Alt_9	100	80	860	555	450	710	715	750	2965
Alt_10	120	40	470	150	580	490	1500	300	1750

Criteria/ Alternative	Cri_10	Cri_11	Cri_12	Cri_13	Cri_14	Cri_15	Cri_16	Cri_17
Alt_1	632	1335	1340	2005	1040	125	7040	128
Alt_2	1666	25	1010	2180	1200	300	30	14
Alt_3	1040	140	20	910	250	50	65	49
Alt_4	3451	180	560	1415	1420	25	35	28
Alt_5	2009	30	690	3240	2660	770	304	34
Alt_6	1692	485	415	1045	1030	130	260	15
Alt_7	4177	245	1595	1685	1120	470	200	61
Alt_8	835	320	280	5265	4555	60	1500	7
Alt_9	14150	685	2545	2900	2510	900	680	72
Alt_10	14148	555	1235	4484	4240	180	1590	70

The normalized DM calculated through Eq. (2) is presented in Table 4.

Table 4. The Entropy Method Normalized DM

Criteria/ Alternative	Cri_1	Cri_2	Cri_3	Cri_4	Cri_5	Cri_6	Cri_7	Cri_8	Cri_9
Alt_1	0.11	0.04	0.24	0.14	0.36	0.10	0.15	0.01	0.36
Alt_2	0.03	0.01	0.07	0.01	0.04	0.05	0.10	0.12	0.05

Alt_3	0.13	0.06	0.02	0.04	0.01	0.01	0.04	0.06	0.01
Alt_4	0.11	0.41	0.12	0.05	0.04	0.04	0.07	0.06	0.05
Alt_5	0.07	0.16	0.07	0.03	0.08	0.18	0.10	0.10	0.11
Alt_6	0.13	0.28	0.08	0.09	0.09	0.22	0.05	0.07	0.03
Alt_7	0.06	0.01	0.12	0.26	0.05	0.15	0.15	0.23	0.14
Alt_8	0.13	0.01	0.11	0.18	0.11	0.05	0.10	0.16	0.03
Alt_9	0.10	0.02	0.11	0.16	0.10	0.12	0.08	0.14	0.13
Alt_10	0.12	0.01	0.06	0.04	0.12	0.08	0.16	0.05	0.08
Criteria/ Alternative	**Cri_10**	**Cri_11**	**Cri_12**	**Cri_13**	**Cri_14**	**Cri_15**	**Cri_16**	**Cri_17**	
Alt_1	0.01	0.33	0.14	0.08	0.05	0.04	0.60	0.27	
Alt_2	0.04	0.01	0.10	0.09	0.06	0.10	0.00	0.03	
Alt_3	0.02	0.04	0.00	0.04	0.01	0.02	0.01	0.10	
Alt_4	0.08	0.05	0.06	0.06	0.07	0.01	0.00	0.06	
Alt_5	0.05	0.01	0.07	0.13	0.13	0.26	0.03	0.07	
Alt_6	0.04	0.12	0.04	0.04	0.05	0.04	0.02	0.03	
Alt_7	0.10	0.06	0.16	0.07	0.06	0.16	0.02	0.13	
Alt_8	0.02	0.08	0.03	0.21	0.23	0.02	0.13	0.01	
Alt_9	0.32	0.17	0.26	0.12	0.13	0.30	0.06	0.15	
Alt_10	0.32	0.14	0.13	0.18	0.21	0.06	0.14	0.15	

E_j values obtained through Eq. (3) and the Entropy values W_j of the criteria calculated with Eqs. (4-5) are shown in Table 5.

Table 5. Entropy Values and Criterion Weights

Criteria	**Cri_1**	**Cri_2**	**Cri_3**	**Cri_4**	**Cri_5**	**Cri_6**	**Cri_7**	**Cri_8**	**Cri_9**
E_j	0.98	0.66	0.94	0.87	0.86	0.91	0.96	0.92	0.84
Criteria	**Cri_10**	**Cri_11**	**Cri_12**	**Cri_13**	**Cri_14**	**Cri_15**	**Cri_16**	**Cri_17**	
E_j	0.77	0.82	0.88	0.94	0.90	0.80	0.57	0.89	
Criteria	**Cri_1**	**Cri_2**	**Cri_3**	**Cri_4**	**Cri_5**	**Cri_6**	**Cri_7**	**Cri_8**	**Cri_9**
W_j	0.01	0.14	0.03	0.05	0.06	0.04	0.01	0.03	0.06
Criteria	**Cri_10**	**Cri_11**	**Cri_12**	**Cri_13**	**Cri_14**	**Cri_15**	**Cri_16**	**Cri_17**	
W_j	0.09	0.07	0.05	0.03	0.04	0.08	0.17	0.05	

The CILOS weights that are used in obtaining IDOCRIW weights, for the cost-oriented Cri_17 criterion in the DM shown in Table 3, are transformed to the benefit direction through Eq. (7), and the results are presented in Table 6.

Table 6. CILOS Benefit-Oriented DM

Criteria/ Alternative	**Cri_1**	**Cri_2**	**Cri_3**	**Cri_4**	**Cri_5**	**Cri_6**	**Cri_7**	**Cri_8**	**Cri_9**
Alt_1	110	140	1800	480	1700	600	1450	45	8000
Alt_2	35	20	507	45	180	300	900	670	1110
Alt_3	130	220	120	120	55	90	380	360	250
Alt_4	110	1600	880	170	210	250	700	350	1220
Alt_5	75	600	550	110	370	1110	920	550	2495
Alt_6	135	1100	620	290	430	1300	480	375	745
Alt_7	60	20	915	880	235	890	1380	1255	3055
Alt_8	130	40	860	600	520	290	950	890	780
Alt_9	100	80	860	555	450	710	715	750	2965
Alt_10	120	40	470	150	580	490	1500	300	1750
Criteria/	**Cri_10**	**Cri_11**	**Cri_12**	**Cri_13**	**Cri_14**	**Cri_15**	**Cri_16**	**Cri_17**	
Alt_1	632	1335	1340	2005	1040	125	7040	0.05	
Alt_2	1666	25	1010	2180	1200	300	30	0.50	
Alt_3	1040	140	20	910	250	50	65	0.14	
Alt_4	3451	180	560	1415	1420	25	35	0.25	
Alt_5	2009	30	690	3240	2660	770	304	0.21	
Alt_6	1692	485	415	1045	1030	130	260	0.47	
Alt_7	4177	245	1595	1685	1120	470	200	0.11	
Alt_8	835	320	280	5265	4555	60	1500	1.00	
Alt_9	14150	685	2545	2900	2510	900	680	0.10	

Alt_10	14148	555	1235	4484	4240	180	1590	0.10

The results obtained from the normalization process are presented in Table 7.

Table 7. The Normalized DM of CILOS Method

Criteria/ Alternative	Cri_1	Cri_2	Cri_3	Cri_4	Cri_5	Cri_6	Cri_7	Cri_8	Cri_9
Alt_1	0.11	0.04	0.24	0.14	0.36	0.10	0.15	0.01	0.36
Alt_2	0.03	0.01	0.07	0.01	0.04	0.05	0.10	0.12	0.05
Alt_3	0.13	0.06	0.02	0.04	0.01	0.01	0.04	0.06	0.01
Alt_4	0.11	0.41	0.12	0.05	0.04	0.04	0.07	0.06	0.05
Alt_5	0.07	0.16	0.07	0.03	0.08	0.18	0.10	0.10	0.11
Alt_6	0.13	0.28	0.08	0.09	0.09	0.22	0.05	0.07	0.03
Alt_7	0.06	0.01	0.12	0.26	0.05	0.15	0.15	0.23	0.14
Alt_8	0.13	0.01	0.11	0.18	0.11	0.05	0.10	0.16	0.03
Alt_9	0.10	0.02	0.11	0.16	0.10	0.12	0.08	0.14	0.13
Alt_10	0.12	0.01	0.06	0.04	0.12	0.08	0.16	0.05	0.08
Criteria/ Alternative	**Cri_10**	**Cri_11**	**Cri_12**	**Cri_13**	**Cri_14**	**Cri_15**	**Cri_16**	**Cri_17**	
Alt_1	0.01	0.33	0.14	0.08	0.05	0.04	0.60	0.02	
Alt_2	0.04	0.01	0.10	0.09	0.06	0.10	0.00	0.17	
Alt_3	0.02	0.04	0.00	0.04	0.01	0.02	0.01	0.05	
Alt_4	0.08	0.05	0.06	0.06	0.07	0.01	0.00	0.09	
Alt_5	0.05	0.01	0.07	0.13	0.13	0.26	0.03	0.07	
Alt_6	0.04	0.12	0.04	0.04	0.05	0.04	0.02	0.16	
Alt_7	0.10	0.06	0.16	0.07	0.06	0.16	0.02	0.04	
Alt_8	0.02	0.08	0.03	0.21	0.23	0.02	0.13	0.34	
Alt_9	0.32	0.17	0.26	0.12	0.13	0.30	0.06	0.03	
Alt_10	0.32	0.14	0.13	0.18	0.21	0.06	0.14	0.03	

IDOCRIW weights are determined, and the criteria weights results are summarized in Table 8.

Table 8. Weight of Each Criterion

Criteria	Cri_1	Cri_2	Cri_3	Cri_4	Cri_5	Cri_6	Cri_7	Cri_8	Cri_9
Weight	0.036	0.127	0.032	0.074	0.053	0.048	0.028	0.035	0.056
Criteria	**Cri_10**	**Cri_11**	**Cri_12**	**Cri_13**	**Cri_14**	**Cri_15**	**Cri_16**	**Cri_17**	
Weight	0.074	0.072	0.051	0.029	0.042	0.063	0.134	0.036	

According to the IDOCRIW, the order of importance of criteria has been determined as C16> C2 > C10 > C4 > C11 > C15 > C9 > C5 > C12 > C6 > C14 > C17 > C1 > C8 > C3 > C13 > C7.
While the most important weight among the criteria is attributed to the "proximity to the bike lane", "proximity to the tram stop" ranks second. Although bicycle use is a healthy and environmental transportation mode, integrating BSS with other public transport systems and allowing transit use in order to provide advantages in terms of speed plays a very important role in the transportation planning of cities. According to the results of criteria weights, the fact that shared bicycles are mostly preferred by the young and educated population around the world is also valid for Kayseri province. The criterion with the least importance weight has been identified as "proximity to libraries" and "proximity to cinemas".

3.2. Ranking of Alternatives

The normalization of the DM is shown in Table 9.

Table 9. The CoCoSo Normalized DM

Criteria/ Alternative	Cri_1	Cri_2	Cri_3	Cri_4	Cri_5	Cri_6	Cri_7	Cri_8	Cri_9
Alt_1	0.75	0.08	1.00	0.52	1.00	0.42	0.96	0.00	1.00
Alt_2	0.00	0.00	0.00	0.00	0.08	0.17	0.46	0.52	0.11
Alt_3	0.95	0.13	0.45	0.09	0.00	0.00	0.00	0.26	0.00
Alt_4	0.75	1.00	0.26	0.15	0.09	0.13	0.29	0.25	0.13

Alt_5	0.40	0.37	0.30	0.08	0.19	0.84	0.48	0.42	0.29
Alt_6	1.00	0.68	0.47	0.29	0.23	1.00	0.09	0.27	0.06
Alt_7	0.25	0.00	0.44	1.00	0.11	0.66	0.89	1.00	0.36
Alt_8	0.95	0.01	0.44	0.66	0.28	0.17	0.51	0.70	0.07
Alt_9	0.65	0.04	0.21	0.61	0.24	0.51	0.30	0.58	0.35
Alt_10	0.85	0.01	0.21	0.13	0.32	0.33	1.00	0.21	0.19

Criteria/ Alternative	**Cri_10**	**Cri_11**	**Cri_12**	**Cri_13**	**Cri_14**	**Cri_15**	**Cri_16**	**Cri_17**
Alt_1	0.00	1.00	0.52	0.25	0.18	0.11	1.00	0.00
Alt_2	0.08	0.00	0.39	0.29	0.22	0.31	0.00	0.94
Alt_3	0.03	0.09	0.00	0.00	0.00	0.03	0.00	0.65
Alt_4	0.21	0.12	0.21	0.12	0.27	0.00	0.00	0.83
Alt_5	0.10	0.00	0.27	0.54	0.56	0.85	0.04	0.78
Alt_6	0.08	0.35	0.16	0.03	0.18	0.12	0.03	0.93
Alt_7	0.26	0.17	0.62	0.18	0.20	0.51	0.02	0.55
Alt_8	0.02	0.23	0.10	1.00	1.00	0.04	0.21	1.00
Alt_9	1.00	0.50	1.00	0.46	0.52	1.00	0.09	0.46
Alt_10	1.00	0.40	0.48	0.82	0.93	0.18	0.22	0.48

CoCoSo performance scores φ_i are given in Table 10.

Table 10. Results of CoCoSo Method

	S_i	P_i	k_{ia}	k_{ib}	k_{ic}	k_i
Alt_1	0.52	13.35	0.10	6.09	0.84	2.51
Alt_2	0.15	10.23	0.07	2.50	0.63	1.11
Alt_3	0.12	8.41	0.06	2.00	0.52	0.88
Alt_4	0.29	14.33	0.10	4.21	0.89	1.86
Alt_5	0.32	15.45	0.11	4.61	0.96	2.06
Alt_6	0.33	15.51	0.11	4.70	0.96	2.09
Alt_7	0.35	14.92	0.11	4.81	0.93	2.11
Alt_8	0.33	15.33	0.11	4.65	0.95	2.07
Alt_9	0.46	15.94	0.12	5.86	1.00	2.55
Alt_10	0.38	15.70	0.11	5.15	0.98	2.27

Table 10 shows the performance rankings of alternative sites for BSS station. It can be observed that the performance of the A9 (15 Temmuz), A1 (Şehir Hastanesi), and A10 (Mevlana) are significantly better than the others. The alternatives with the lowest performance levels are obtained as A2 (Koçak) and A3 (Medrese). It is noteworthy that each of the first three sites is characterized by a young population and is located in university districts also close to tram stops, the furthest being 140 meters.

3.3. Comparative Analysis

Alternative sites of BSS station have been also evaluated using the TOPSIS, ARAS, and COPRAS methods in this section. The fundamental principle underpinning the TOPSIS posits that the selected alternative should exhibit the shortest distance to the positive ideal solution and, concurrently, the greatest distance from the negative ideal solution. The TOPSIS method stands as one of the earliest MCDM techniques in the literature and it remains one of the most frequently employed methods to date. ARAS is a sort of MCDM tool that does not involve any advanced computation procedures and is in charge of ranking a small number of choices, each of which must be evaluated concurrently against a range of decision criteria. The main benefit of using the ARAS approach is that the degree of alternative utility is evaluated by comparing the variation to the ideally optimum one, which helps to prioritize the alternatives. So, the evaluation and ranking of options are relatively convenient when this approach is used [82]. COPRAS posits that the significance and utility level of the examined alternatives are directly and proportionately dependent on a set of criteria that effectively characterize them, along with the values and weights assigned to these criteria [83]. Results from the three methods are compared with the results of the CoCoSo method and it has been observed that the performed framework and the rankings are consistent. The performance rankings of alternative sites for BSS station obtained from different methodologies are presented in Table 11.

Table 11. Alternative Ranking Scores Derived by Different Methods

Method / Alternative	CoCoSo	TOPSIS	ARAS	COPRAS
Alt_1	2.51	0.566	0.568	100
Alt_2	1.11	0.145	0.147	23.424
Alt_3	0.88	0.108	0.095	15.323
Alt_4	1.86	0.379	0.294	49.376
Alt_5	2.06	0.274	0.288	47.017
Alt_6	2.09	0.333	0.307	50.931
Alt_7	2.11	0.276	0.300	47.783
Alt_8	2.07	0.261	0.300	49.326
Alt_9	2.55	0.358	0.420	68.315
Alt_10	2.27	0.308	0.340	56.303

In this section, the Borda count method [84] has also been implemented in order to obtain an integrated ranking list. The integrated results are presented in Table 12.

Table 12. Borda Count Results

Alternative	Total	Final Rank
Alt_1	35	1
Alt_2	4	9
Alt_3	0	10
Alt_4	18	5
Alt_5	10	8
Alt_6	23	4
Alt_7	17	6
Alt_8	16	7
Alt_9	32	2
Alt_10	26	3

The results obtained from the Borda count method have been used to assess the overall performance of the alternatives across different criteria [86]. According to this method, Alt_1 has achieved the highest score indicating that it is the most suitable alternative when all criteria are considered. It has been followed by Alt_9 with a score of 32, demonstrating a performance comparable, making it a strong contender as well. Alt_10 and Alt_6 have ranked highly with scores of 26 and 23, respectively, suggesting robust performance. Alt_4 and Alt_7 have both reflected average performance while they are strong in certain criteria, they are less preferred overall compared to other alternatives. Alt_8 and Alt_5 have been positioned lower in the ranking, indicating weaker performance relative to the other options. Finally, Alt_2 and Alt_3 have the lowest Borda scores, making them the least favorable alternatives in the overall evaluation.

In all of the results of different MCDM methodologies, Alt_1, Alt_9, and Alt_10, although ranked differently, consistently appear at the top of the lists. Alt_9, with a young population of 14,150, and Alt_10, with 14,148 are the two districts with the highest young generation densities in the study area. Alt_2 and Alt_3 with the young population densities of 1,666 and 1,040 respectively consistently ranked last in all assessments. Each methodology's results for performance rankings of alternative BSS station are presented in Figure 3.

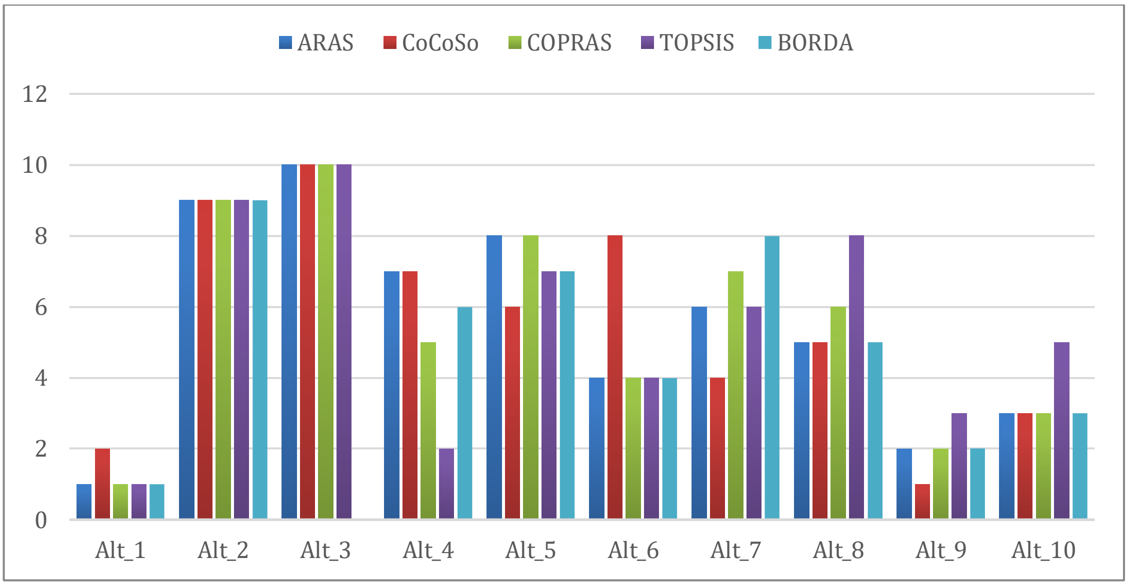

Figure 3. Performance Rankings of Alternatives

Alt_1 and Alt_9 have emerged as the two alternatives with the highest performance scores, indicating that these alternatives are the most suitable sites according to the considered criteria. Alt_1 has been identified as the closest alternative to the ideal solution according to the TOPSIS results, further supporting its overall suitability. However, Alt_9 ranked third in the TOPSIS method, with Alt_4 securing the second position. In both the ARAS and COPRAS methods, Alt_1 has demonstrated the strongest performance and Alt_9 has achieved the second-highest score, confirming their strong suitability as a station sites. Furthermore, Alt_1 and Alt_9 have ranked at the top in the Borda count, indicating consistent support for these two alternatives across all methods. Alt_2 and Alt_3 consistently have received the lowest scores across the CoCoSo, TOPSIS, ARAS, COPRAS, and Borda Count methods, clearly indicating that these sites are the least suitable according to the evaluated criteria.

3.4. MCLP for BSS Station Selection

In this section, the alternative BSS station, ranked based on the criteria considered within the MCDM framework, serve as the inputs to the mathematical model. Given that municipalities are obligated to ensure urban sustainability and provide services to the maximum number of city residents despite limited budgets, the strategic sites of BSS station of paramount importance. The integration of the MCDM approach with mathematical modeling is intended to determine the optimal sites. The primary objective is to allocate the available budget for station installations in a way that maximizes service coverage for urban residents. In our research problem, three centers are established from among the top six alternatives selected by the CoCoSo method. This decision aligns with the target established by officials at Kayseri Transportation Inc. to open three stations in 2025. The BSS station site selection problem is formulated as a Maximal Covering Location Problem (MCLP), and its formulation is presented below. In this model, the existing stations in service are explicitly taken into account to ensure that the allocation of new stations complements the current network. This approach not only maximizes service coverage under budget constraints but also optimizes the integration of new installations with the established infrastructure.

The formalization of MCLP is given below [85];

Indexes;

i = Demand nodes, $i \in I$

j = Potential sites for bike-sharing system stations, $j \in J$

k = Existing bike-sharing system stations, $k \in K$

p = Number of bike-sharing system stations to be established

Parameters;

w_i **=** Population of the i. neighborhood

N_i = The set of potential sites that can cover neighborhood i within the acceptable service distance

S = Maximum acceptable service distance to cover any neighborhood

T = Maximum critical distance to the existing bike-sharing system stations

d_{kj}= Distance between the existing bike-sharing system station and the potential station

Decision Variables;

$$z_i = \begin{cases} 1, \text{if demand node i is covered by at least one station} \\ 0, otherwise \end{cases}$$

$$x_j = \begin{cases} 1, \text{if a station is established at candidate sites j} \\ 0, otherwise \end{cases}$$

$$Y_{kj} = \begin{cases} 1, \text{if } d_{kj} \text{ is greater than the critical distance between the existing station k and potential sites } j \\ 0, otherwise \end{cases}$$

Mathematical Model;

$$Max\ Z = \sum_i w_i * z_i \tag{19}$$

$$\sum_{j \in J} x_j = p \tag{20}$$

$$z_i \leq \sum_{j \in N_i} x_j \qquad \forall_i \in I \tag{21}$$

$$x_j \leq Y_{kj}, \forall_j \in J, \forall_k \in K \tag{22}$$

$$x_j \in \{0,1\}, \forall_j \in J \tag{23}$$

$$z_i \in \{0,1\}, \forall_i \in I \tag{24}$$

$$Y_{kj} \in \{0,1\}, \forall_j \in J, \forall_k \in K \tag{25}$$

Eq. (19) is the objective function that maximizes the population served. Eq. (20) restricts the maximum number of stations that can be opened. Eq. (21) provides service to a neighborhood, at least one station must be opened within acceptable distance limits. Eq. (22) ensures that the new stations to be opened are at a certain distance from the existing stations. Eq. (23-25) determine the type of decision variables.

The problem has been solved for neighborhoods whose information is given in the Appendix. Due to budget constraints, the municipality intends to open only three out of the 10 alternative stations. Based on expert consultations, the model incorporates the condition that newly established stations must be at least 500 meters away from existing stations (T = 500). Additionally, the maximum distance that residents are willing to walk to use the BSS (accepted service distance) has been determined as 1000 meters (S = 1000). The model has been solved using GAMS-CPLEX on a PC with 12th Gen Intel(R) Core (TM) i7 in less than one CPU second. In the optimal solution, 146,813 residents are covered by the opened Alt_7, Alt_8, and Alt_10 BSS stations.

3.5. Scenario Analysis

In this section, scenario analyses have been conducted to examine the model's behavior under different values of S. To assess the model's sensitivity to parameter changes, the T value has been considered at 500 meters, while S has been varied between 500 and 2000 meters, generating 9 different scenarios. The covered population for each scenario has then been compared. This comprehensive scenario analysis enabled us to examine the robustness of the solution and to determine the impact of key parameter variations on the optimal site selection outcomes. The results are presented in Table 13.

Table 13. Results of the Scenarios

Scenario	S	Covered Population	Decided to be opened stations
1	500	16,033	Alt_1, Alt_6, Alt_8
2	700	38,854	Alt_1, Alt_6, Alt_8
3	900	132,403	Alt_6, Alt_8, Alt_10
4	1000	146,813	Alt_7, Alt_8, Alt_10
5	1200	174,310	Alt_7, Alt_8, Alt_10
6	1300	195,800	Alt_6, Alt_8, Alt_10
7	1500	202,324	Alt_6, Alt_8, Alt_10
8	1700	205,724	Alt_6, Alt_7, Alt_10
9	2000	264,033	Alt_6, Alt_7, Alt_10

As the acceptable service distance (S) increases, the value of the optimum solution generally increases. This indicates that allowing a greater coverage distance enables more residents to be included within the coverage area of selected stations. It should be noted that the higher the S value, the lower the level of service, even though the number of residents covered increases.

4. Discussion and Conclusion

The transportation sector plays a pivotal role in ensuring urban sustainability, underscoring the importance of implementing environmentally friendly mobility solutions. Among these, Bike-Sharing Systems (BSS) have emerged as viable alternatives to conventional modes of transportation, particularly due to their potential to reduce greenhouse gas emissions and promote healthier lifestyles. However, a critical factor influencing the success and long-term sustainability of BSS lies in the strategic selection of station locations, which directly affects system accessibility, usage frequency, and public acceptance.

This study proposed a hybrid, data-driven framework that integrates Multi-Criteria Decision-Making (MCDM) and spatial optimization techniques to determine optimal station locations for BSS deployment. By systematically identifying 17 evaluation criteria and 10 candidate sites based on expert input and literature review, the study applied the IDOCRIW method for weighting the criteria. The results revealed that proximity to bicycle lanes, proximity to tram stops, and the percentage of young population were the most influential factors, while proximity to cinemas, theaters, and libraries played a comparatively minor role. Subsequently, the CoCoSo method was used to rank the alternatives, highlighting Alt_9 and Alt_1 as the most suitable sites. These findings were further validated through TOPSIS, ARAS, and COPRAS methods and the Borda Count method was employed to aggregate rankings under the framework of group decision-making theory. The consistency of the results across multiple methods confirmed the robustness of the proposed evaluation process. In the second stage, the study incorporated the Maximal Covering Location Problem to enhance spatial coverage efficiency under real-world constraints. Among the top six alternatives identified through MCDM, only three could be selected due to budgetary limitations. An additional spatial constraint (minimum 500-meter distance from existing stations) was imposed. Scenario-based analyses were conducted to assess how different service distance thresholds would affect the total covered population. The analysis revealed that with a service distance of 2000 meters, the total covered population increased to 264,033, and the optimal locations shifted to Alt_6, Alt_7, and Alt_10. These findings provide practical insights for local governments to design flexible and responsive BSS expansion strategies under varying policy scenarios. This research presents several strengths. First, it offers a methodologically rigorous and replicable approach that combines objective weighting and robust evaluation techniques. Second, it addresses spatial realism by integrating urban context-specific constraints, and third, it proposes a novel application of MCLP with service distance flexibility, which enhances practical relevance. However, the study also has limitations. It does not account for temporal dynamics such as seasonal effects, weather conditions, and peak commuting hours, which can significantly influence user behavior. Additionally, although demographic and infrastructure-related indicators were used, individual user preferences and real-time data were not incorporated into the model.

Future research could address these limitations by incorporating time-series data, user mobility patterns, and weather-dependent usage statistics. Moreover, integrating agent-based simulations, machine learning algorithms, or AI-driven predictive models could enable dynamic decision-making that reflects real-time system needs and behavioral tendencies. Finally, applying the proposed framework to larger datasets across different cities could further validate its generalizability and support the development of context-specific sustainable mobility solutions. In conclusion, this study not only contributes to literature through its methodological innovation but also provides valuable policy guidance for municipalities seeking to implement data-informed, sustainable, and user-centric BSS planning frameworks.

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Appendices

Appendix A. Latitude-Longitude and Population for Neighborhoods

Neighbourhood	Latitude- Longitude	Population
Köşk	38.71950555, 35.51655239	24305
Yıldırım Beyazıt	38.72965915, 35.53900303	26221
Fevzi Çakmak	38.73089905, 35.50069996	18282
Esentepe	38.72730214, 35.42303087	18079
Hürriyet	38.71649354, 35.46353909	14841
Erciyesevler	38.73558712, 35.52086609	15301
Alpaslan	38.72801421, 35.51918750	23731
Mevlana	38.70802382, 35.56138269	89989
Bahçelievler	38.68857823, 35.54719064	22821
Kılıçarslan	38.72355930, 35.50386112	9133
Gültepe	38.71623017, 35.50509099	10713
Esenyurt	38.69332760, 35.48971069	21980
Kiçiköy	38.68951314, 35.55703780	5320
Hunat	38.71994542, 35.49533488	3560
Sahabiye	38.72780123, 35.49057548	16296
Gülük	38.71857801, 35.47837230	8353
Selçuklu	38.69455384, 35.47090074	20838
Kazımkarabekir	38.71492238, 35.43478894	12291
Cumhuriyet	38.71955321, 35.48767597	434
Tacattinveli	38.71374702, 35.48643880	6090
Gevhernesibe	38.72427997, 35.48271453	3452
Aydınlıkevler	38.71998800, 35.46965804	10613
Battalgazi	38.70762796, 35.48130103	22141
Erenköy	38.67933492, 35.51804378	12794
Yenidoğan	38.69831447, 35.54856019	27497
Tablakaya	38.69387831, 35.56918577	2462
Germir	38.73387191, 35.55756651	10947
Alsancak	38.74066265, 35.50599397	4079
Osman Kavuncu	38.72915606, 35.44339276	9634
Sanayi	38.72806123, 35.4629570	1145

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