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Dilsel Özetleme ile Kentsel Hareketlilik Kalıpları: Bisiklet Paylaşım Sisteminden İçgörüler

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Anahtar Kelimeler
Bisiklet paylaşım sistemi,
Bulanık kümeler,
Dilsel özetleme,
Kentsel hareketlilik,
Seyahat örüntüsü,

Öz: Bu çalışma, tanımlayıcı veri analitiği araçlarından biri olan dilsel özetleme kullanılarak kentsel hareketlilik modellerinin nasıl analiz edilebileceğini incelemiştir. Makale, kentsel hareketlilik modellerini anlamak için zengin bir bilgi kaynağı olan kentsel bisiklet paylaşım sistemi verilerine odaklandı. Çalışmada gün, saat, istasyon ve kullanıcı türü gibi çeşitli değişkenlere sahip bir veri seti kullanıldı. Veriler, bulanık kümenin gücü aracılığıyla kentsel hareketliliğe ilişkin değerli bilgiler sunan dilsel açıklamalara dönüştürüldü. Seyahat modellerinin analizi, günün çeşitli zamanlarındaki yoğun istasyonların belirlenmesini, kullanıcı segmenti tercihlerini (öğrenciler ve öğrenci olmayanlar) ve genel hareketlilikteki değişiklikleri içeriyordu. Kentsel bisiklet verilerinin dilsel özetlemesinin sonuçları, kentsel seyahat kalıpları hakkında daha kapsamlı bir bilgiye olanak sağladı. Kent planlamacıları, karar vericiler ve ulaşım otoriteleri, kentsel hareketlilik dinamiklerine ışık tutan sonuçlar sayesinde kentin mevcut altyapısını optimize edebilir, erişilebilirliği artırabilir ve kent sakinlerinin geniş yelpazedeki ihtiyaçlarını karşılayabilirler. Çalışma, tanımlayıcı veri analitiğinin, özellikle şehir bisikletlerinden elde edilen bilgileri kullanarak seyahat modellerini incelemek için kullanıldığında, bilgiyi açığa çıkarmada ne kadar pratik olabileceğini gösterdi.

Urban Mobility Patterns with Linguistic Summarization: Insights from the Bicycle-Sharing System

Keywords
Bicycle-sharing system,
Fuzzy sets,
Linguistic summarization,
Urban mobility
Travel pattern

Abstract: This study examined how urban mobility patterns might be analyzed using linguistic summarization, one of the descriptive data analytics tools. The paper focused on urban bicycle-sharing system data, a rich source of knowledge for comprehending urban mobility patterns. The study used a dataset with several variables: day, hour, station, and user type. The data was turned into linguistic descriptions that offer valuable insights into urban mobility through the strength of the fuzzy set. The analysis of travel patterns included identifying busy stations at various times of the day, user segment preferences (students vs. non-students), and changes in general mobility. The results of the linguistic summarization of the urban cycling data allowed for a more thorough knowledge of urban travel patterns. Urban planners, decision-makers, and transportation authorities may optimize the city's current infrastructure, increase accessibility, and meet its residents' wide range of needs thanks to the results that shed light on the dynamics of urban mobility. The study showed how practical descriptive data analytics can be in revealing information, mainly when used to examine travel patterns utilizing information from urban bicycles.

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1. Introduction

The dynamic nature of urban surroundings and the sheer volume of commuters, residents, and tourists add to the complexity of urban mobility statistics [1]. Therefore, analyzing mobility in cities is difficult due to both this complexity and the size of the data. Additionally, metropolitan areas are distinguished by various mobility options, such as personal vehicles, public transportation, bicycle lanes, and pedestrian paths. The data generated by each form of transportation are unique, which increases the complexity of the entire dataset for urban mobility. Metropolitan mobility statistics are further complicated by metropolitan people's diversity and travel habits. Based on variables including demography, socio-economic level, and individual preferences, people have diverse travel patterns and travel preferences. Various data points must be considered when assessing urban mobility patterns due to the heterogeneity in travel behaviours.

It's vital to comprehend mobility trends and travel habits for several reasons [2]. First, it aids decision-makers and city planners in allocating resources wisely and developing appropriate infrastructure. By evaluating traffic patterns, decision-makers can enhance transportation networks and increase overall mobility by identifying peak travel times, congestion hotspots, and locations with insufficient transportation options. Understanding mobility trends also enables proactive planning and foreseeing future transportation requirements. Decision-makers can create policies that address the changing demands of the city's residents and ensure a sustainable and effective transportation system by examining data on changing travel patterns, developing mobility technology, and shifting demographics. Understanding mobility trends and travel habits is also crucial for solving environmental issues.

By examining data on commuting patterns and transportation preferences, policymakers can achieve goals such as reducing carbon emissions, encouraging alternative modes of transportation and sustainable urban mobility options, optimizing transportation networks, and easing traffic congestion. Decision-makers can customize transportation policies, services, and infrastructure to meet the different demands of the city's residents by considering characteristics like user type (such as student or regular), user preferences, and more. Although the diversity of sources and factors used to create urban mobility statistics contributes to the complexity of these statistics, this diversity can contribute positively to the solution of the problems. For decision-makers to manage transportation networks, foresee future needs, address environmental problems, and ultimately improve the quality of urban life, it is essential to understand travel patterns and mobility trends.

The bicycle-sharing system has emerged as a popular mode of public transportation in recent years due to its ability to mitigate environmental effects and alleviate traffic congestion [3]. According to Galatoulas et al. [4], the global presence of shared bicycle networks has expanded to encompass over 2900 systems. Given the projected prominence of cycling as a fundamental mode of transportation in the future, it is imperative for policymakers to investigate the advancements and methodologies within this domain thoroughly [5]. Therefore, examining historical trip data has led to the investigation of bike-sharing systems in numerous cities as documented in existing literature. He et al. [6] employed Poisson regression analysis to examine the data related to Utah. Kaltenbrunner et al. [7] utilized data mining techniques to investigate Barcelona. Kou and Cai [8] focused on extracting statistical patterns of trips in eight US cities, including Boston, Washington DC, Chicago, and New York. Zhou [9] conducted a flow clustering analysis specifically for Chicago. Etienne and Latifa [10] employed a statistical approach based on Poisson mixtures to analyze data from Paris. García-Palomares et al. [11] developed a GIS-based method for studying Paris. Li et al. [12] proposed a hierarchical prediction model for New York and Washington. Kim [13] utilized machine learning techniques to analyze data from Seoul. Eren and Katanalp [14] presented a hybrid approach that incorporated a Fuzzy Logic (FL)-based Geographic Information System (GIS), Analytic Hierarchy Process (AHP), and VIse Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method for studying Izmir. Lathia et al. [15] conducted an empirical spatio-temporal analysis of London. Levy et al. [16] examined transportation and geostatistical models in Tel Aviv, namely regression and all-or-nothing traffic assignment. Similarly, Liu et al. [17] developed an optimization and artificial neural network-based model for analyzing transportation in New York. The significance of this topic and the necessity for novel approaches have been underscored by the utilization of travel chain matrices and transition matrices between activities in the study conducted by Zhang et al. [18] pertaining to Zhongshan. Hence, the primary objective of this study is to elucidate the travel patterns related to the bike-sharing system in Kayseri Province in Türkiye, an area that has not been previously investigated. The study also seeks to furnish decision-makers with crucial insights and information. It is envisaged that the use of the linguistic summarization method, a new approach to urban mobility, will provide significant progress both in the methodological advancement of this discipline and in increasing the efficiency and effectiveness of the bicycle sharing system.

The current study investigated how linguistic summarization might be used to analyze urban mobility trends using bicycle sharing system data. The research aims to transform the raw data into linguistically rich descriptions utilizing a descriptive data analytics technique, specifically linguistic summarization. This research seeks to identify travel patterns within a city depending on various factors, including day, hour, station, and user type. The ultimate objective is to give concise and simply understandable information about urban mobility, leading to a deeper understanding of travel behaviours and assisting urban planners and transportation authorities in making well-informed decisions.

2. Material and Method

The method steps followed are: (i) data collection: urban bicycle data were gathered during a particular period, including attributes like day, hour, station, and user type (student or regular); (ii) the fuzzy variables gathered, (iii) linguistic summarization method was applied to analyze the travel patterns, (iv) discussion of results. This section explained the problem definition following the basics of fuzzy sets and linguistic summarization.

2.1. Fuzzy sets

A mathematical framework called fuzzy set theory offers a flexible and accessible method for addressing uncertainty and imprecision in data. The fuzzy set theory allows for degrees of membership in the unit interval [0,1], in contrast to classical set theory, which assumes clear boundaries between elements as 0 or 1, allowing for the depiction of ambiguity and gradual changes across categories [19].

A fuzzy set is described as a group of elements where each element has a degree of membership determined by a membership function. On universe X, a fuzzy set $\tilde{A}$ is defined as $\tilde{A} = \{x, \mu_{\tilde{A}}(x) | x \in X\}$ where $\mu_{\tilde{A}}(x): X \rightarrow [0,1]$ is the membership degree of x. Each element is assigned a value between 0 and 1, representing the degree to which it belongs to the set by the membership function. This level of participation accommodates the inherent ambiguity and uncertainty prevalent in real-world events by allowing for a continuum of options. For example, there is ambiguity when trying to express the time of the day with linguistic descriptions such as *morning* or *noon*. The degree of being noon of 11 a.m. may be 0.75, and the degree of being morning may be 0.25.

When converting fuzzy sets into crisp sets, α −cuts are used. If the membership degree of an element $\mu_A(x)$ is greater than or equal to α, the membership degree of this element to the crisp set defined by A_α is equal to 1. In the α^+ −cut, if the membership degree of an element $\mu_A(x)$ is greater than α, the membership degree of this element to the crisp set defined by A_{α^+} is equal to 1. The representations of α −cut and α^+ −cut are given in Eq. (1) and Eq. (2), respectively.

$$A_\alpha = \{x \in X | \mu_A(x) \geq \alpha\} \tag{1}$$

$$A_{\alpha^+} = \{x \in X | \mu_A(x) > \alpha\} \tag{2}$$

Fuzzy numbers are named according to the shape of their membership functions, such as triangular, trapezoidal, S-shape, etc. The most popular membership functions are given in Eq. (3), Eq. (4), and Eq. (5) and shown in Figure 1.

$$Triangular_{a,b,c}(x) = \begin{cases} (x-a)/(b-a) & a \leq x \leq b \\ (c-x)/(c-b) & b < x \leq c \\ 0 & otherwise \end{cases} \tag{3}$$

$$Trapezoidal_{a,b,c,d}(x) = \begin{cases} (x-a)/(b-a) & a \leq x \leq b \\ 1 & b < x \leq c \\ (d-x)/(d-c) & c < x \leq d \\ 0 & otherwise \end{cases} \tag{4}$$

$$S_{a,b}(x) = \begin{cases} 0 & x \leq a \\ 2\left(\frac{x-a}{b-a}\right)^2 & a < x \leq \frac{a+b}{2} \\ 1 - 2\left(\frac{x-b}{b-a}\right)^2 & \frac{a+b}{2} < x \leq b \\ 1 & x > b \end{cases} \tag{5}$$

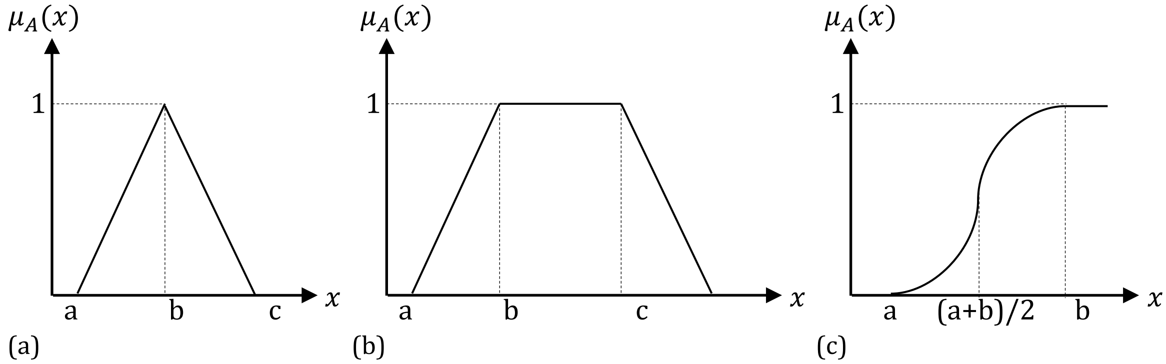

Figure 1. Fuzzy numbers (a) triangular, (b) trapezoidal, (c) S-Shape

Like in classical set theory, union and intersection procedures are supported by fuzzy sets. t-norm operator ($\otimes : [0,1] \times [0,1] \rightarrow [0,1]$) is used for intersection and t-conorm operator ($\oplus$: $[0,1] \times [0,1] \rightarrow [0,1]$) is used for union. Any of these operators should satisfy the following properties in Table 1.

Table 1. Properties of t-norm and t-conorm operators.

	t-norm	t-conorm
Identity / Neutral	$\otimes(x, 1) = x$	$\oplus(x, 0) = x$
Monotonicity	$y_1 \leq y_2$ için $\otimes(x, y_1) \leq \otimes(x, y_2)$	$y_1 \leq y_2$ için $\oplus(x, y_1) \leq \oplus(x, y_2)$
Commutativity	$\otimes(x, y) = \otimes(y, x)$	$\oplus(x, y) = \oplus(y, x)$
Associativity	$\otimes\left(x, \otimes(y, z)\right) = \otimes(\otimes(x, y), z)$	$\oplus\left(x, \oplus(y, z)\right) = \oplus(\oplus(x, y), z)$

The basic t-norm operator is the minimum operator. A new fuzzy set is created when two fuzzy sets are intersected, and its membership function represents the minimal degree of membership for each element in both sets. The basic t-conorm operator is the maximum operator. When two fuzzy sets are unionized, a new fuzzy set is created whose membership function represents the highest degree of membership that can be assigned to each element in either set. For the fuzzy subsets of the universal set A_1 and A_2, intersection and union of two fuzzy subsets are given in Eq. (6) and Eq. (7), respectively.

$$\mu_{A_1 \cap A_2}(x) = \otimes\left(\mu_{A_1}(x), \mu_{A_2}(x)\right) = min(\mu_{A_1}(x), \mu_{A_2}(x)) \tag{6}$$

$$\mu_{A_1 \cup A_2}(x) = \oplus\left(\mu_{A_1}(x), \mu_{A_2}(x)\right) = max(\mu_{A_1}(x), \mu_{A_2}(x)) \tag{7}$$

2.2. Linguistic summarization

Large databases are mined for insights via a process called data mining. Descriptive techniques are required to summarize and evaluate the data and find patterns and relationships [20]. A straightforward descriptive tool for data analysis is statistical summarization. Though they might be less precise than statistical summaries, consumers frequently prefer natural language summaries because of their superior understanding. Fuzzy quantifiers, first introduced by Zadeh [21,22], are commonly employed in linguistic summarization to handle the equivocal meanings of linguistic labels like *few* and *most.* Yager [23] continued to develop linguistic summarizing studies as a cutting-edge method for drawing out information from databases that is brief and simple to understand. Creating concise and understandable data summaries is the fundamental goal of linguistic summarization.

Two types of protoforms based on absolute and relative quantifiers, introduced by Zadeh are employed in most linguistic summary studies [24]. Absolute quantifiers are defined as a possibility distribution over non-negative integers, while relative quantifiers are defined as a possibility distribution in the unit interval [0,1]. Two types of protoforms are described as follows:

<u>Type-I protoform:</u> "Q Y A" [TD]. In this form, Q is a linguistic quantifier, Y is the object, A is a summarizer for any attributes about objects of Y, and TD is the truth degree related to the form. For example, "About 50 of the passengers are students." [0.54]. Here, *about 50* is an absolute linguistic quantifier, the *passenger* is the object, the *student* is a summarizer about the user type attribute of passengers, and *0.54* is the TD of the summary.

Type-II protoform: "Q B Y A" [TD]. In this form, in addition to the type-I form, B is a pre-summarizer for any attribute about objects of Y. For example, "Most student passengers rent a bike on weekdays." [0.92]. Here, *most* is a relative linguistic quantifier, *student* is a pre-summarizer about user type attribute of passengers, *passenger* is the object, *weekday* is a summarizer about the day attribute of passengers, and *0.92* is the TD of the summary.

The most essential step in linguistic summarization is evaluating the generated protoforms. Quantified protoforms are assessed by computing the related TDs. If the truth degree cannot be reliably obtained, then the generated summaries cannot reflect the dataset accurately. The most basic TD is proposed by Zadeh [22] according to absolute and relative quantifiers in Eq. (8) and Eq. (9), respectively.

$$TD = \mu_Q\left(\sum_{m=1}^{M} \mu_A(v_k^m)\right) \tag{8}$$

$$TD = \mu_Q\left(\frac{\sum_{m=1}^{M}(\mu_A(v_{k_1}^m) \otimes \mu_B(v_{k_2}^m))}{\sum_{m=1}^{M}\mu_B(v_{k_2}^m)}\right) \tag{9}$$

where v_k^m is the value for k^{th} attribute of m^{th} object, μ_A is the membership function of summarizer A for attribute k, μ_Q is the membership function of linguistic quantifier Q. Since there is a summarizer and a pre-summarizer (A and B) in type-II protoforms, there are two related attributes as k_1 and k_2. $v_{k_1}^m$ is the value for $k_1{}^{\text{th}}$ attribute of the m^{th} object, and $v_{k_2}^m$ is the value for $k_2{}^{\text{th}}$ attribute of m^{th} object. $\otimes$ is a t-norm operator used for the intersection of two fuzzy sets.

Evaluation methods are grouped under two categories: scalar cardinality-based and fuzzy cardinality-based [25]. Although scalar cardinality-based methods such as Zadeh's are simple, fast, and popular for finding TDs, they have a deficiency, causing inconsistencies in exceptional cases. They rely on counting the occurrences of elements; therefore, they cannot distinguish the difference between the small amount of high and large amount of low membership degrees. To overcome this inconsistency, fuzzy cardinality-based methods, such as the GD and ZS methods, are proposed [26]. Fuzzy cardinality-based techniques such as restriction level-based method [27], gradual number-based method [28], and semi-fuzzy quantifier-based method are also proposed to evaluate linguistic summaries [29,30].

By suggesting a semi-fuzzy quantifier based method, which is a generalized version of a fuzzy linguistic quantifier, Glöckner [31] has contributed to the fusion of linguistics and logic. The characteristics of both the classical and fuzzy quantifiers are present in a semi-fuzzy quantifier, which accepts crisp arguments like a classical quantifier and generates a TD in the range [0,1] like a fuzzy quantifier [29]. Semi-fuzzy quantifiers handle crisp features like a classical quantifier and generate a TD truth degree in unit interval like a fuzzy quantifier. Compared with fuzzy quantifiers, it is easy to define semi-fuzzy quantifiers but hard to evaluate. For example, "About 70% of the passengers are students" can be evaluated by a semi-fuzzy quantifier-based method, "About 70% of passengers rent a bike in the mornings" cannot be evaluated by semi-fuzzy quantifiers without a Quantifier Fuzzification Mechanism (QFM). Being a *student* is a crisp fact in the first phrase, whereas *morning* is a fuzzy phenom in the second phrase.

A probabilistic QFM, F^I, is proposed as in Eq. (3) by Diaz-Hermida et al. [29].

$$F^I(Q)(X_1, \dots, X_s) = \int_0^1 \dots \int_0^1 Q\big((X_1)_{\geq\alpha_1}, \dots, (X_s)_{\geq\alpha_s}\big)\, d\alpha_1 \dots d\alpha_s \tag{10}$$

where X_s is a fuzzy property for $s = 1, \dots, S$, $(X_s)_{\geq\alpha_s}$ is α-cut of X_s, and Q is a semi-fuzzy quantifier of arity S. If different α-cuts on $X_1, \dots, X_s$ are finite, F^I is defined as in Eq. (4),

$$F^I(Q)(X_1, \dots, X_s) = \sum_{i_1=0}^{m_1} \dots \sum_{i_s=0}^{m_s} Q\left((X_1)_{\geq\alpha_{1,i_1}}, \dots, (X_s)_{\geq\alpha_{s,i_s}}\right) \mathfrak{m}(\alpha_{1,i_1}) \dots \mathfrak{m}(\alpha_{s,i_s}) \tag{11}$$

where $0 = \alpha_{s,m_s+1} < \alpha_{s,m_s} < \cdots < \alpha_{s,1},\ \alpha_{s,0} = 1,\ 1 \leq s \leq S$, and the mass assignment corresponding to $\alpha_{s,j}$ is defined as $\mathfrak{m}(\alpha_{s,j}) = \alpha_{s,j} - \alpha_{s,j+1},\ j = 0,1, \dots, m_s$. The distribution of probabilities could be interpreted from mass assignments. Although Martin and Yun [32] initially defined it as a confidence measure, it is now employed for evaluating linguistic summaries.

2.3. Problem definition

Kayseri Ulaşım A.Ş. operates the Urban Bicycle System (KAYBIS), a shared bicycle system implemented in Kayseri Province, Türkiye. KAYBIS provides services in Kayseri Province with 90 kilometres of bicycle paths, 51 bicycle stations, 1,000 specially designed bicycles, a structure suitable for expansion, and qualified personnel with a level of knowledge and skills. KAYBIS has been awarded the 'Sustainable Development Award' by the International Association of Public Transport (UITP). This study was conducted for KAYBIS in Kayseri, and the data belongs to 2023.

The objective was to effectively assess and analyze the circulation patterns within a community utilizing bicycle data collected over seven days, which covers 17,596 rows of information, including day, hour, station, and card details. This dataset contained essential data, such as the precise time of day, the station where the bicycles were rented, and the type of card used (student or regular). Investigating this dataset makes it possible to learn significant details about usage trends, popular stations during the day, and the preferences of different user segments, such as students and non-students. A sample from the dataset is shown in Table 2.

Table 2. The sample data set of bike rental.

ID	User Type	Day	Hour	Station
ID00001	Regular	Monday	05:00	Public Hospital
ID04568	Student	Thursday	21:00	Faculty of Architecture
ID07654	Regular	Sunday	13:00	State Hydraulic Works
ID12980	Student	Friday	16:00	Dormitories

User type is categorized under two values: *regular* and *student*. If the passenger is a student, then the value of the student variable takes the value of 1; otherwise, it is 0. Similarly, if the passenger is a regular passenger, it takes the value of 1; otherwise, it is 0. The day is categorized under two values: *weekdays* and *weekend*. If the boarding is on Monday, Tuesday, Wednesday, Thursday, or Friday, the value of weekdays is 1; otherwise, it is 0. If the boarding is on Saturday or Sunday, the weekend's value is 1; otherwise, it is 0. The station is categorized under 51 variables as *station names* (Public Hospital, Faculty of Architecture, etc.). If the passenger rented a bicycle from any station, the station's value is 1; otherwise, it is 0. The hour is categorized under four values: *morning*, *noon*, *evening,* and *night,* according to the fuzzy membership functions in Figure 2.

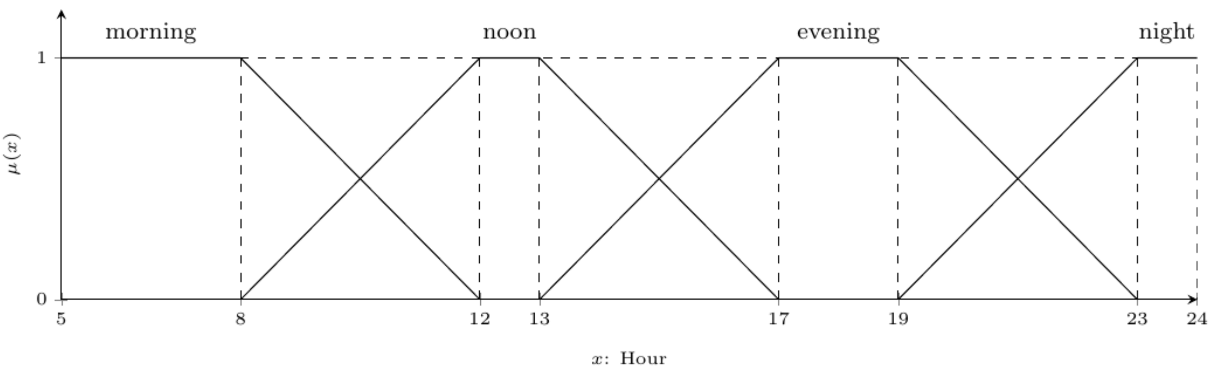

Figure 2. Fuzzy membership functions according to hours

The pre-summarizer and summarizer of a linguistic summary were selected from the categorized variables above italicized. "*Most*" was used as a linguistic quantifier, defined by a trapezoidal membership function (0.5;0.75;1;1). A total of 3136 linguistic summaries were generated through MATLAB code using a semi-fuzzy quantifier-based method in Eq. (11) [33]. The 173 linguistic summaries had a TD greater than 0, and 38 had a TD greater than 0.80. The final 38 linguistic summaries are given in Table 3.

3. Results

This paper utilized a linguistic summarization method to examine the information on the KAYBIS system. The findings of this investigation are shown in Table 3. Out of the total of 38 linguistic summaries acquired, it was determined that three of them pertain to the bicycle utilization period. Weekdays witnessed the highest bicycle utilization levels among students and regular commuters. During weekdays, the morning hours exhibited the highest levels of bicycle activity, as indicated by a TD value of 1. Out of the collected summaries, 18 were associated explicitly with KAYBIS stations. Patterns were successfully acquired for a total of 18 out of the 51 stations that were included in the analysis.

Table 3. Linguistic summaries of -bicycle sharing system

Linguistic Summary	TD
Most students rent a bike on weekdays.	0.92
Most morning passengers rent a bike on weekdays.	1.00
Most noon passengers rent a bike on weekdays.	0.86
Most passengers renting from Aydınlıkevler station rent a bike on weekdays.	0.85
Most passengers renting from Ayşe Baldöktü station rent a bike on weekdays.	0.95
Most passengers renting from Bahçelievler station are students.	1.00
Most passengers renting from Beşyol station rent a bike on weekdays.	0.80
Most passengers renting from the public Hospital station rent a bike on weekdays.	0.95
Most passengers renting from the Dental Hospital station rent a bike on weekdays.	0.90
Most passengers renting from East Campus station are students.	1.00
Most passengers renting from East Campus station rent a bike on weekdays.	1.00
Most passengers renting from East Terminal station rent a bike on weekdays.	0.83
Most passengers renting from the State Hydraulic Works station are regular passengers.	0.81
Most passengers renting from the Faculty of Education station are students.	1.00
Most passengers renting from the Faculty of Education station rent a bike on weekdays.	1.00
Most passengers renting from Emirgan station are regular passengers.	1.00
Most passengers renting from Old Industrial Zone station are regular passengers.	1.00
Most passengers renting from Old Industrial Zone station rent a bike on weekdays.	1.00
Most passengers renting from the Faculty station are students.	1.00
Most passengers renting from the Faculty station rent a bike on weekdays.	1.00
Most passengers renting from the Faculty of Science and Literature station are students.	1.00
Most passengers renting from the Faculty of Science and Literature station rent a bike on weekdays.	1.00
Most passengers renting from Fuzuli station are regular passengers.	1.00
Most passengers renting from Kaskı station are regular passengers.	0.97
Most passengers renting from Koçak station are regular passengers.	1.00
Most passengers renting from Küçükçalık station are regular passengers.	1.00
Most passengers renting from the Faculty of Architecture station are students.	1.00
Most passengers renting from the Faculty of Architecture station rent a bike on weekdays.	1.00
Most passengers renting from Mustafa Şimşek station are regular passengers.	1.00
Most passengers renting from Mustafa Şimşek station rent a bike on weekdays.	1.00
Most passengers renting from the 30 August station rent a bike on weekdays.	0.86
Most passengers renting from Şeker station rent a bike on weekdays.	0.92
Most passengers renting from Technopark station are students.	0.87
Most passengers renting from Technopark station rent a bike on weekdays.	1.00
Most passengers renting from TOKİ station are students.	0.95
Most passengers renting from Yıldız Park station rent a bike on weekdays.	1.00
Most passengers renting from the19 May station rent a bike on weekdays.	0.93
Most passengers renting from Dormitories station are students.	1.00

The KAYBIS system may be found around the city and contains stations in various districts. Linguistic summaries of stations and usage times were obtained as a result of the linguistic summarization. The information collected as a consequence of linguistic summarization revealed that the number of stations has fallen to 18, and the conclusion that can be drawn from this information is that these stations are used more frequently. It is essential to consider these outcomes when making decisions, such as those involving planning additional stations or an increase in capacity. Information regarding the different kinds of KAYBIS users and stations can be found in the remaining 17 summaries. Table 4 and Figure 3 show the stations acquired by linguistic summarizing and their station name.

Table 4. Station Name and Number

Code	Station Name	Code	Station Name
A	Old Industrial Zone	J	Faculty of Architecture
B	Ayşe Baldöktü	K	Faculty of Education
C	Beşyol	L	Mustafa Şimşek
D	Dental Hospital	M	19-May
E	Aydınlıkevler	N	30 August
F	Public Hospital	O	Technopark
G	Şeker	P	Yıldız Park
H	East Terminal	Q	Faculty
I	East Campus	R	Faculty of Science and Literature

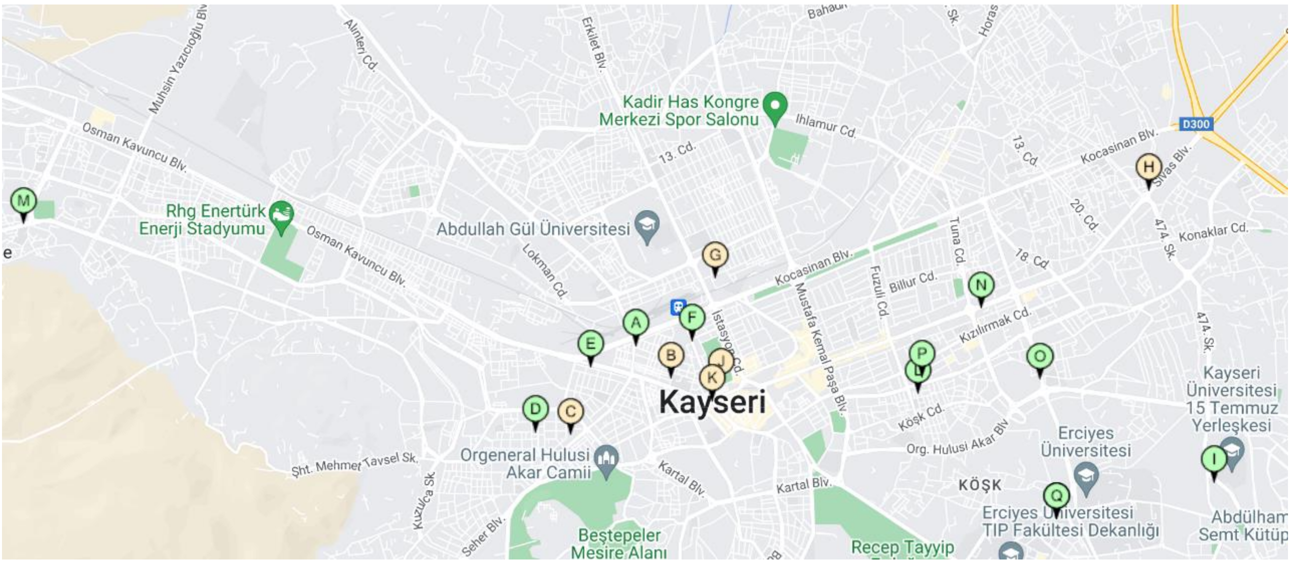

Figure 3. Locations of the stations

In contemporary urban environments characterized by fast development, there is a growing imperative to enhance sustainability, mitigate carbon emissions, and maximize urban mobility. Within this particular environment, urban areas encounter many obstacles [34]. These issues encompass a range of elements, including shifts in travel patterns, advancements in technology, alterations in population demographics, and the emergence of pandemic-related risks. Consequently, cities are compelled to reassess and reconsider their conventional transportation plans. This paper seeks to utilize linguistic summarization techniques in the context of bicycle-sharing systems to enhance urban mobility. The primary goal was to equip decision-makers with valuable insights derived from data on evolving travel patterns, advancements in mobility technology, and shifting demographics. These insights can then inform the development of policies that effectively address the evolving needs of city residents. By adopting this approach, urban areas can implement crucial measures to cultivate a sustainable and efficient transportation infrastructure. To optimize the operation of bike share systems, it is imperative to discern recurring usage patterns and ascertain the factors contributing to them, elucidating the underlying demand dynamics [13].

4. Discussion and Conclusion

The study's objective was to evaluate urban cycling data using linguistic summarization techniques so that urban planners and politicians can quickly detect trip patterns, improve infrastructure, and better understand urban mobility dynamics. The study's conclusions are highly significant and provide numerous contributions to the study of urban mobility. First, enhanced insight into travel patterns was provided. Based on bicycle-sharing system data, the study's conclusions provided a better understanding of how people move around the city. The study also announced valuable insights into how people move around in urban environments by identifying popular stations at various times of the day and examining user preferences. Urban planners, decision-makers, and transportation authorities can use this improved understanding to help them make informed decisions on improving infrastructure and transportation systems. Second, the study's results are highly beneficial for data-driven decision-making because they are based on examining real-world cycling data. The study simplifies complex information using linguistic summarization, enabling clear communication and well-informed decision-making. Third, the study's results contribute to the optimization of urban mobility by pointing out trends and patterns that can be utilized to raise the effectiveness and efficiency of transportation networks. Both city residents and visitors would benefit from improved traffic management, less congestion, and more environmentally friendly mobility options that could arise from this. Finally, the work contributes to the application field by examining urban mobility patterns using linguistic summarization. To sum up, the study's results improved our knowledge of urban mobility patterns and provided practical guidance to decision-makers. The study's conclusions could positively influence urban mobility, leading to the development of cities that are more effective, sustainable, and centred on people. To develop a more thorough understanding of the dynamics of urban mobility, future studies may expand on this approach to include other forms of transportation and explore more variables.

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