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Between Smart Cities Infrastructure and Intention: Mapping the Relationship Between Urban Barriers and Bike-Sharing Usage

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Highlights

What are the main findings?

- Four distinct categories of urban barriers significantly affect bike-sharing usage: infrastructure deficits, environmental/personal constraints, spatial conflicts, and service accessibility issues.
- Two dominant user motivations for bike-sharing—recreational and functional—were identified and statistically linked to specific barrier types through multidimensional modeling

What is the implication of the main finding?

- Effective bike-sharing policy requires differentiated interventions tailored to diverse user needs and barrier profiles.
- Integrating user feedback and open innovation approaches can enhance system inclusivity, adaptability, and long-term urban mobility planning.

Abstract

Society's adaptation to shared mobility services is a growing topic that requires detailed understanding of the local circumstances of potential and current users. This paper focuses on analyzing barriers to the adoption of urban bike-sharing systems in post-industrial cities, using a case study of the Silesian agglomeration in Poland. Methodologically, the article integrates quantitative survey methods with multivariate statistical analysis to analyze the demographic, socioeconomic, and motivational factors that underline the adoption of shared micromobility. The study highlights a detailed segmentation of users by income, age, professional status, and gender, as well as the observation of profound disparities in access and perceived usefulness. Of note is the study's identification of a highly concentrated segment of young, low-income users (mostly students), which largely accounts for the general perception of economic and infrastructural barriers. These include the use of factor analysis and regression to plot the interaction patterns between individual user characteristics and certain system-level constraints, such as cost, infrastructure coverage, weather, and health. The study's findings prioritize problem-specific interventions in urban mobility planning: bridging equity gaps between user groups. This research contributes to the current literature by providing detailed insights into the heterogeneity of user mobility behavior, offering evidence-based recommendations for inclusive and adaptive options for shared transportation infrastructure in a changing urban context.

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Academic Editor: Pierluigi Siano

Received: 24 April 2025
Revised: 10 July 2025
Accepted: 23 July 2025
Published: 29 July 2025

Citation: Wolniak, R.; Turoń, K. Between Smart Cities Infrastructure and Intention: Mapping the Relationship Between Urban Barriers and Bike-Sharing Usage. *Smart Cities* **2025**, *8*, 124. https://doi.org/10.3390/smartcities8040124

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Keywords: bike-sharing systems; urban mobility; infrastructure management; bike-sharing problems; post-industrial regions; open innovation; open innovation applicability

1. Introduction

The ecological and customer-oriented reconstruction of the urban transport system is currently a priority in smart cities. One way to improve transport conditions is to use shared mobility services. Bike-sharing systems, as the most classic form of shared mobility, are considered to contribute significantly to mitigating traffic congestion, pollution, access inequalities, and public health problems in cities. The technical and environmental foundations of shared bike systems have been extensively studied in the scientific literature [1–3], but the human experience, particularly in post-industrial environments, has not been addressed. In other places, such as the Polish region of Silesia, where systemic tradition intersects with urban transformation, system quality, attitudes, and user behavior must be addressed more aggressively [4–6]. Most current research focuses on macro-efficiency, i.e., fleet management [7–10] and eco-scale [11–14], rather than user-centered issues on a micro-scale, primarily in disintegrated urban spaces [15]. Co-created mobility [16] is promoted by the theory of collaborative urbanism without empirical solutions. This paper fills this research gap to illustrate the influence of urban riders and barriers to the development of a bike-sharing system in Silesia, using quantitative questionnaires and advanced modeling. The study contributes to scholarly research on user-based positioning analysis within a socio-spatial framework by illustrating how infrastructure deficits and constraints influence perceived use [17–19]. The analysis also universalizes the bike-sharing system in the absence of mobility and lifestyle services as calculative and non-calculative uses of the otherwise analyzed mode of transport [20,21]. By tagging such uses with infrastructure and contextual tags, we obtain a more nuanced description of user actions [22–24]. This approach utilizes the Silesian Voivodeship, a previously industrially focused voivodeship with 4.3 million inhabitants and 74 cities [25], as a living laboratory in which to trace the infrastructural and socio-economic complexities of incorporating a bike-sharing system into urban renewal. This study is based on five interconnected research questions (RQs) aimed at exploring the complex relationship between urban infrastructure, user perceptions, and behavioral outcomes in bike-sharing systems. The RQs progress from the detailed identification of barriers and motivations (RQ1–RQ2) to their systemic interaction (RQ3–RQ5), culminating in a multidimensional explanatory model. The following diagram illustrates their interrelationships:

- RQ1 (Urban Barriers in Motion) What infrastructural, environmental, and personal barriers are perceived by bike-sharing systems users when moving around urban spaces?
- RQ2 (The Dual Pulse of Bike-Sharing) What is the primary motivation, both utilitarian and recreational, that drives people to use shared bikes in cities?
- RQ3 (Clash or Synergy?) How do identified barriers correlate with specific user motivations and what patterns emerge from these relationships?
- RQ4 (Predictive Cartography) Can a multidimensional statistical model be constructed to explain how particular problems affect different categories of bike-sharing usage?
- RQ5 (Hidden Architectures of Behavior) What latent factors can be identified through factor analysis that group user-perceived obstacles and motivations in a meaningful way?

The scientific contribution of the research is that it adopts an integrative and empirical approach to an understanding of the multifactored dynamics governing the use of urban bike-sharing, with special reference to post-industrial locations. Through the combination

of quantitative survey research and advanced statistical methods such as factor analysis and multiple regression modeling, the study provides a robust analytical model with the aim of revealing both user-perceived barriers and heterogeneous incentives influencing user behavior. The study, furthermore, breaks away from the purely descriptive accounts in deducing a multi-dimensional model to relate infrastructural and environmental constraints to actual patterns of use and thereby providing explanatory and predictive data with implications of relevance for application.

The article was divided into five parts. The Section 1 of the work presents an introduction to the topic. The Section 2 refers to the theoretical foundation of bike-sharing systems in the smart city paradigm. The Section 3 presents the methodology used. The Section 4 was dedicated to the presentation of the results that were discussed in the Section 5 and concluded in the Section 6, together with the limitations and future research directions.

2. Theoretical Foundations: Bike-Sharing Systems in the Smart City Paradigm

Smart cities are based on the seamless connection of physical infrastructure with digital technologies to improve the living conditions of society, ensure a high level of inclusion and environmental sustainability [25–28]. At the heart of the smart city idea is the idea of adaptive transport ecosystems that respond flexibly to user needs and urban problems [29]. Bike-sharing programs exemplify this concept, serving as a practical answer to traffic and environmental issues while also representing a sustainable urban identity, as they have transitioned from experimental mobility solutions to strategic instruments of urban sustainability, embedded in global agendas such as the Sustainable Development Goals of the UN (SDG 11) [30].

From a scientific perspective, bike-sharing services are examined in the literature through a broad and multifaceted lens. Depending on the chosen context, studies on bike-sharing in relation to smart cities can be identified that focus on the technical and technological [31,32], social [33,34], economic [35,36], or environmental aspects [37,38] of implementation [39,40], maintenance [41,42], and further adapting these systems within other transport and mobility services operating in urban centers [43,44]. In the following, we synthesize these themes, emphasizing their relevance to post-industrial contexts.

2.1. Bike-Sharing Generations

The evolution of bicycle sharing systems (BSS) dates to the 1960s, when early experiments such as Amsterdam's "White Bikes" failed due to theft but inspired later shared innovations. The 2000s saw the development of RFID-enabled dockless systems (e.g., Paris's Vélib), which reduced car dependency but struggled with equity issues [2]. The 2010s saw the introduction of station-less, app-based models, which grew rapidly but led to oversupply and environmental waste in cities such as Beijing [45,46]. Today's fifth-generation systems integrate artificial intelligence (AI) and the Internet of Things (IoT), enabling predictive balancing and adaptive routing [47]. These services are user-centric. A user-centric approach aligns bike-sharing services with what people value as ease of use, safety, and reliability, thus improving the overall user experience and encouraging repeat use [48,49].

2.2. Integration with Urban Infrastructure

A common topic in the literature is the incorporation of bike-sharing systems into current urban infrastructure and transportation networks. Bike-sharing is widely recognized as a complementary mode in smart city mobility, often serving as a first- and last-mile solution that extends the reach of public transport.

By strategically locating bike stations near major transit hubs (train and bus stations) and important destinations, cities can enable seamless intermodal travel [50]. Studies have found that the most favorable user feedback comes when public bicycles are well integrated with other transport options, for example, through stations at metro stops and extensive cycling lanes connecting to them [51]. Effective integration requires a robust cycling infrastructure (protected bike lanes, parking facilities) and real-time coordination with transit schedules. Indeed, there is a strong positive correlation between the density/quality of the bicycle infrastructure and the use of bike-share in a city [52]. In contrast, poor integration, such as stations too far from user's origins or destinations, is a common barrier that diminishes the utility of bike sharing systems [53]. Thus, smart city approaches emphasize the integration of bike-sharing in the larger urban transport ecosystem, treating it as an integral layer of infrastructure [54]. Integrated planning (e.g., unified payment systems, combined route information) can further strengthen the role of bike-sharing in urban mobility, amplifying its benefits for congestion reduction and transit access.

2.3. Behavioral and Motivational Factors

Understanding user behavior and motivation is another key pillar in bike-sharing research. Numerous studies have investigated what drives people to use or avoid bike-sharing in urban environments [55,56]. Convenience consistently emerges as the primary motivator due to the ease of finding a nearby bike, and the time savings compared to other modes are often cited as the top reasons for adoption.

Surveys in major cities indicate that many users join bike-sharing schemes because they find it faster or more convenient than their previous travel mode (e.g., it is quicker than walking or driving in congested areas) [53,57,58]. The enjoyment of cycling itself, understood as the intrinsic pleasure and freedom it provides, is also a significant motivational factor. It is also presented as a fun, healthy and environmentally friendly way of getting around, according to the desire of users for exercise and less environmental impact. However, research on barriers finds that if other modes of transport feel more convenient or if bike access is limited, people may shy away from bike-sharing [48]. Weather, safety concerns and the effort required can also influence usage patterns [59].

Beyond these general trends, demographic and situational factors play an important role. For example, a large study in China revealed that bike-sharing usage rates were statistically associated with gender, household bike ownership, trip purpose, and station proximity [60].

These behavioral insights have important implications. Research indicates that increasing perceived convenience, for example, through dense station networks and user-friendly apps and emphasizing the enjoyable and healthy elements of cycling can increase user interest in systems. User behavior research offers a nuanced perspective on how motivational factors and barriers influence the adoption of the bike-sharing system, guiding user-centered approaches to increasing ridership.

2.4. Socio-Spatial Dynamics in Post-Industrial Cities

Bike-sharing in post-industrial urban areas is associated with socio-spatial dynamics and equity issues. Many studies indicate that the benefits of bike-sharing systems are not evenly distributed in different communities within a city [50,55]. Station layout and usage patterns often reflect existing urban inequalities. Studies have shown that bike-sharing stations tend to be concentrated in affluent, densely populated or tourist-friendly neighborhoods, such as city centers and gentrified areas, with poor coverage in low-income or peripheral neighborhoods [61]. In practice, this translates into disparities in who uses the system. For example, an analysis of Chicago's Divvy bike-sharing system found signifi-

cantly lower take-up and more inconsistent use in disadvantaged communities, defined as lower-income and minority populations, compared to more affluent areas [62]. Such inequalities raise concerns that bike-sharing systems, if not carefully planned, may inadvertently exclude or underserve specific groups, often those most in need of affordable mobility. Indeed, case studies have linked low station availability in marginalized neighborhoods to broader patterns of urban exclusion. In the context of post-industrial cities, these socio-spatial issues are linked to the legacy of urban decline and renewal. Mobility initiatives must be understood within the racialized and classed spaces of cities [63]. Beyond practical mobility, cycling can convey cultural capital. Its presence often coincides with (and likely facilitates) the branding of regenerating neighborhoods as smart, green, and livable [45]. In contrast, areas lacking such investments may experience a sense of exclusion from the smart city vision. On the more positive side, some post-industrial cities have actively utilized cycling as a tool for urban renewal. For example, in the Silesian region in Poland, a historically heavy industrial region, new cycling programs have been introduced to revitalize neglected industrial spaces and promote active mobility in communities undergoing transformation.

In summary, previous studies on bike-sharing in smart cities emphasize the key role of the infrastructure-intention nexus–synergy between advanced technological solutions and local mobility practices. In post-industrial cities, where historical inequalities, dispersed development, and industrial heritage shape unique challenges, the literature indicates the following:

- Insufficient models considering the specificity of post-industrial–most works focus on global metropolises, ignoring the contexts of regions undergoing transformation (e.g., lack of analyses of logistics in depopulated areas);
- Superficial approach to the relationship of barriers and motivations–descriptive studies dominate, not offering multidimensional cause-and-effect models;
- Insufficient integration of behavioral data with spatial planning–discrepancy between "hard" infrastructure data and "soft" social factors.

The proposed study, focused on the Silesian agglomeration, addresses these gaps through an innovative combination of quantitative methods and contextual analyses, directly anchored in the post-industrial realities of Silesia, a region where the city bike can become a bridge between the industrial past and a sustainable future.

2.5. Open Innovation and Bike-Sharing Systems

Bike-sharing systems strive to incorporate customer feedback and feedback into their service innovations. Applications, for example, collect user tips, complaints, or route preferences, which they then optimize and evaluate for station locations, adjust pricing models, or introduce new features [63–65]. Co-participation transforms passive consumers into co-creative innovators and positions them in an open innovation model by incorporating external knowledge into the creation of organizational value, known as co-creation [66,67]. These operators form partnerships with external entities such as GPS technology companies, software companies, and IoT sensor companies. These partnerships enable the combined integration of advanced tracking and tracking features, data analytics, and AI-predicted maintenance capabilities into the system design. Instead of developing internally, operators leverage an innovative network system (a fundamental principle of open innovation) through which knowledge is shared between organizational boundaries [68–70]. Bike-sharing systems are increasingly publishing usage data on open data portals. External entities such as cities, researchers, and developers then use these data to improve infrastructure planning, create innovative mobile applications, and shape policy. Openness allows external entities beyond the system operator, such as universities and NGOs, to

openly innovate, demonstrating the external aspect of open innovation, where internal data becomes available for use outside the company to create external value [63–65,68,69,71].

3. Methodology

This study used a systematic survey approach to collect in-depth data on perceived bike transport issues between bike-sharing firms and evaluation of determinants of the utilization of bike-sharing schemes. The study aimed to conduct an in-depth analysis of the issues and determinants of the utilization of bike-sharing mechanisms in urban areas.

The study was split methodologically into two broad sections. The initial portion of the survey was utilized to determine perceived barriers to cycling travel in the city (P1–P14), such as inadequate levels of bike lanes, poor road conditions, safety concerns and the absence of supportive facilities. The second half asked the respondents about the various purposes for which people utilize public bikes (R1–R13), from utilitarian purposes like working or shopping to purposes such as recreation activities, enjoyment during vacation, etc. Both categories were operationalized using a Likert-type scale for quantitative comprehension of user's perception.

The study design of this research was based on a quantitative survey-based study to collect the attitudes of urban users towards bike-sharing systems. The survey instrument contained two main sections. The first section dealt with the identification of obstacles to urban cycling, which contained 14 variables (P1–P14) such as inadequate infrastructure, safety concerns and environmental or individual constraints. The second set of categories related to motivations for the use of bike-sharing systems, which were quantified using 13 variables (R1–R13), both utilitarian (e.g., shopping, commuting) and recreational in nature (e.g., recreation, entertainment). Both sets of variables were quantified on Likert-type scales—five-point scale for barriers and six-point scale for motivations—to allow extensive statistical analysis of degree and diversity of user attitudes.

Data were collected using an online survey instrument, placed in various electronic media outlets to maximize the number of respondents with knowledge or experience of urban bike-sharing schemes. The sample consisted of members of a variety of age, sex, and occupation groups, thus achieving some demographic representativeness. Before performing the core statistical calculations, the data were cleaned and checked for consistency and initial descriptive statistics were obtained to provide an impression of central tendencies, dispersion, and distribution characteristics. These included calculation of means, medians, standard deviations, skewness, and kurtosis for all variables. These descriptive results provided a basis for the identification of common patterns and outliers in user's perceptions.

Figure 1 illustrates the entire research lifecycle from data collection to analysis stage. Before starting the entire-scale survey, a pilot study was conducted in a bid to simulate the environment of the main research. This first stage was to determine any weaknesses of the questionnaire, that is, to test the pilot test and to determine if it was easy for subjects to access and understand the questions. The responses gathered at this stage were of importance in the construction of the survey instrument, leading to changes in the language of several items for clarity purposes and expanding the scope of the audience.

In addition to language adjustments, the pilot study allowed for careful structural integration and logical ordering of questionnaire verification. The researchers were careful about question placement to ensure natural ordering, as well as taking into account the overall length and the cognitive load of the respondents. This phase also revealed redundant items that may be omitted and conceptual gaps that needed new questions to be added to better address meaningful dimensions of the quality of e-learning. The

inferences derived here helped to provide a shorter and streamlined instrument for the ultimate survey.

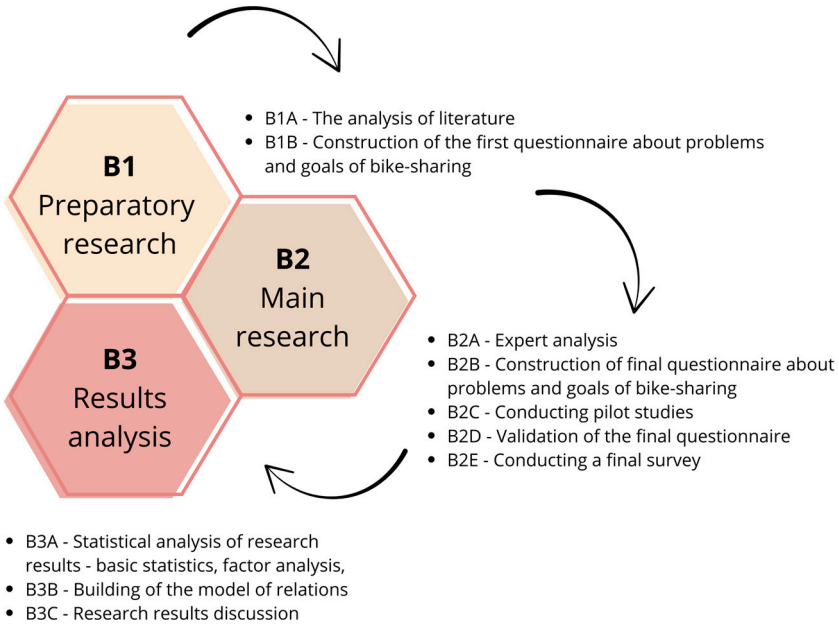


Figure 1. Stages of the research procedure.

To serve as a safeguard to ensure the internal consistency of the questionnaire, Cronbach's Alpha (α) was utilized as an indicator of reliability. The findings presented strong reliability coefficients—0.892 for part one and 0.902 for part two—attesting strong levels of inter-connectedness between the items. These indicate that the instrument well measures one latent construct, namely respondents' perception of e-learning quality. 0.8 to 0.9 are generally taken to be an ideal point: they reflect sufficient item homogeneity but sufficient heterogeneity to distinguish between different respondent perspectives.

To determine the sample size, the following formula was used [72,73]:

$$N_{min} = \frac{Np\left(\alpha^2 \times f(1-f)\right)}{Np \times e^2 \; + \; \alpha^2 \times f(1-f)} \tag{1}$$

where

N_{min}—the smallest acceptable sample size;
Np—total size of the population from which the sample is selected;
α—significance level, represented by Z-value derived from the normal distribution corresponding to the desired confidence;
f—fraction or proportion size;
e—permissible maximum error margin.
For this research, the parameters below were selected:
α—significance level set at 0.05;
Np—population size unknown;
f—0.5;
e—0.1.

The formula used considered the determination of the necessary sample size in relation to achieving results that would not just be generalizable but also statistically representative of the wider population even in the absence of reliable statistics related to bike-share use in the Silesian province. With a 95% confidence level, the researcher tried to obtain research results closest to the ground and representative. 196 questionnaires were obtained from

an online survey posted on social media based on a purposeful sampling plan to reach the local population and likely users most probable to utilize bike-sharing. The sample exceeded the minimum required by the formula, thereby validating the quality of the dataset. To determine the validity of the findings, strict response filtering criteria were used. Questionnaires of only those respondents who answered in the affirmative to using bike-sharing systems at any point were retained for analysis. Selective retention was exercised in a bid to have results extrapolated from the dataset represent real, firsthand data and not impressions or conjecture. So, the data collected is reflective of the actual status of cycling in the urban setup on shared bicycles and on a genuine basis on which conclusions about behavior patterns and perceived problems can be drawn.

By exceeding the minimum sample size threshold and following inclusion criteria strictly, the study achieved additional methodological rigor. This not only resulted in increased credibility of subsequent statistical findings but also ensured relevance of recommendations generated from the data to the subject user group under investigation. The combination of conservative sampling method and targeted outreach thus afforded a sound foundation for empirical analysis and subsequent interpretation of user behavior in the neighborhood bike-share environment.

The formula used was with consideration of the estimation of the sample size needed in accordance with the acquisition of results which not only would be generalizable but also statistically representative of the larger population despite the unavailability of credible statistics regarding bike-share usage in the Silesian province. On a 95% confidence level, the researcher tried to achieve research results closest to the ground and representative. 196 questionnaires were obtained from an online survey that was posted on social media with a deliberate sampling plan to reach the local community and likely users most likely to employ bike-sharing. The sample exceeded the minimum required by the formula, thereby justifying the quality of the dataset. To determine the validity of the findings, strict response filtering criteria were utilized. Those respondents who reported responding yes to whether or not they have used bike-sharing systems in any case had their questionnaires reserved for examination. Selective retention was practiced with a goal to make the outcomes from extrapolations on the dataset a representation of authentic firsthand data, as opposed to feelings or guessing. Thus, data collected is representative of the actual condition of cycling in the city life on shared bikes and on which assumptions about patterns of behavior and perceived problems are made.

By exceeding the minimum sample size requirement and maintaining strict inclusion criteria, the study achieved additional methodological accuracy. Not only did this result in increased credibility of subsequent statistical findings but also ensured relevance of recommendations based on the data to the target user population being investigated. The combination of conservative sampling method and targeted outreach thus laid a solid foundation for empirical study and subsequent interpretation of user behavior in the neighborhood bike-share environment [9,10].

Within the surveyed sample, there were 87 females and 109 males. The gender ratio is rather balanced, but men slightly dominate. Men represented about 56% of respondents, and women about 44%. Analysis of the age structure showed a definite dominance of one age group—people aged 18–24 made up as much as 66.8% of the entire sample (131 out of 196 interviewees). The other age groups were far less represented: 25–34 years, 15.3%; 35–55 years, 14.8%; under 18 and 55 and above. 1.5% of each of these groups in the sample. That there is such significant overrepresentation of young adults here confirms the inference that estimates of perceived barriers and motivations for use of bike-sharing systems here predominantly capture the experience of this specific age group. Therefore,

precautions must be taken to extrapolate the findings to the entire population, especially concerning older adults, whose presence in the sample was insignificant.

The structure of income among the respondents is evidently prevalent with low-income people—50% of the respondents contributed a monthly income of less than 2000 PLN, which could be due to a high number of students, youth, or people working part-time. The rest were quite low, since only 11.2% of the respondents earned more than 5000 PLN.

Employment status reflected a clear predominance of those in search of education. Pupils and students accounted for up to 71.4% of the surveyed population. Then there were working individuals, who accounted for 26.5% of the sample, and the unemployed, represented to a negligible extent by only 2%. The results lean towards the conclusion that the surveyed population comprised mostly people from the stage of life characterized by education, which applies to the age and income statistics as well.

Descriptive statistics are derived from a quantitative survey using 14 variables (P1–P14). Those variables measure perceived barriers to bike-sharing use. The following are the statistical formulas used to compute the values [73]:

Mean (Average)

The mean represents the central tendency of each variable:

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

where

Xi = individual response;
n = number of respondents.

Median

The median is the middle value in the ordered set of responses. If the number of observations is odd, it is the center value; if even, it is the average of the two central values:

$$Median = \begin{cases} X_{(\frac{n+1}{2})}, & if\ n\ is\ odd \\ \frac{X_{(\frac{n}{2})} + X_{(\frac{n}{2}+1)}}{2}, & if\ n\ is\ even \end{cases} \tag{3}$$

Standard Deviation

This measures the dispersion or variability of responses:

$$\delta D = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \overrightarrow{x}\right)^2} \tag{4}$$

Skewness

Skewness measures the asymmetry of the distribution. A positive skew indicates a tail on the right and a negative skew on the left.

$$Skewness = \frac{n}{(n-1)(n-2)}\sum_{i=1}^{n}\left(\frac{x_i - \overrightarrow{x}}{SD}\right)^3 \tag{5}$$

Kurtosis

Kurtosis measures the "peakedness" of the distribution. A negative kurtosis indicates a flatter distribution (platykurtic); a positive one indicates a peaked distribution (leptokurtic):

$$Kurtosis = \frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum_{i=1}^{n}\left(\frac{x_i - \overline{x}}{SD}\right)^4 - \left(\frac{3(n-1)^2}{(n-2)(n-3)}\right) \tag{6}$$

To examine the data, factor analysis with varimax rotation was applied. This statistical technique helps to uncover latent relationships among variables by identifying clusters of interrelated items. It simplifies complex data structures by reducing the number of variables through the formation of factors—unobserved constructs that account for shared variance among the original variables [73]. The primary objective is to capture the underlying structure of the dataset by representing it with a more concise set of factors.

Factor Model: The basic model for factor analysis can be expressed as

$$X = \Lambda F + \epsilon \tag{7}$$

where

X is the vector of observed variables.
Λ is the matrix of factor loadings.
F is the vector of latent factors.
ϵ is the vector of unique factors (error terms).

The covariance matrix of the observed variables can be expressed as

$$\Sigma = \Lambda \Phi \Lambda^T + \Psi \tag{8}$$

where

Σ is the covariance matrix of the observed variables.
Φ is the covariance matrix of the factors (often assumed to be the identity matrix if factors are orthogonal).
Ψ is a diagonal matrix of unique variances (the variances of the error terms).

Principal Component Analysis (PCA) is a technique under the umbrella of overall factor analysis, and it is a statistical method used to reduce dimensions of datasets with the least loss of variance. The principal aim of PCA is to translate a given set of potentially correlated variables into a new set of linearly uncorrelated variables called principal components. These are arranged so the first does the greatest possible variance in the data, the second next greatest proportion of variance, and so forth [72,73].

The procedure starts by standardizing the data to have all variables centered on a mean of zero and normalized to possess unit variance, that is convenient when the variables work on different measurement scales. Then, PCA builds a covariance matrix to summarize the correlation between the variables from which eigenvalues and eigenvectors are obtained. The eigenvalues represent the amount of variance in the overall set of the component, and the associated eigenvectors determine the direction of the components in the space of the original set of variables [72].

After determining the eigenvalues and eigenvectors, the principal components are ordered in decreasing order of their eigenvalues. The principal components explaining the most variance are typically retained only, thus dimensionality-reducing the data by retaining the most informative dimensions. It is helpful to improve data visualization, eliminate noise and maximize the efficiency of machine learning models by eliminating redundant variables [72–74].

The "variance explained" concept is one of decomposition of overall observed variance into variance due to common factors and variance due to individual variables and in the form $\mathrm{Var}(X) = \mathrm{Var}(\Lambda F) + \mathrm{Var}(\epsilon)$. For even more interpretability of the factor structure, varimax rotation is used. This orthogonal rotation process tries to maximize the variance of the squared loadings of every factor between variables and thus simplify the pattern of variables and extracted factors.

During initial extraction, factor loadings can be spread between several variables in a complex and uncertain way. Varimax rotation avoids this by redistributing the loadings so that a variable will load on one factor very highly and on the rest trivially. This simplifies to give a more interpretable factor pattern and allows for a more accurate determination of the way each variable loads on the underlying dimensions [72–77].

Mathematically, varimax rotation is an optimization of the sum of the variances of the squared loadings for each factor, which promotes the form of structure in which various variables are strongly associated with individual factors but weakly associated with others. The result is an orthogonal, and therefore uncorrelated, set of factors. This property is particularly valuable in psychology, marketing, and the social sciences, where understanding the distinct dimensions of multifaceted constructs is important [74–77].

The Varimax criterion can be mathematically expressed as

$$\text{Maximize} \sum_{j=1}^{k} \left(\sum_{i=1}^{p} a_{ij}^2 \right)^2 \tag{9}$$

subject to the constraint that the factors remain orthogonal, which means

$$\sum_{i=1}^{p} a_{ij} \times a_{ik} \text{ for j} \neq \text{k}$$

where

a_{ij} is the loading of variable i on factor j;
p is the number of variables;
k is the number of factors.

The Kaiser–Meyer–Olkin (KMO) test is a statistical measure used to assess the suitability of data for factor analysis. A higher KMO value indicates that the data is appropriate for factor analysis, while a lower value suggests that the data may not be suitable [78,79].

The KMO statistic is calculated using the following formula:

$$KMO = \frac{\Sigma_{\supset -1}^{p} \Sigma_{j-1, j \neq i}^{p} r_{ij}^2}{\Sigma_{\supset -1}^{p} \Sigma_{j=1, j \neq i}^{p} r_{ij}^2 + \Sigma_{\supset -1}^{p} \Sigma_{j=1, j \neq i}^{p} q_{ij}^2} \tag{10}$$

where

r_{ij} represents the correlation coefficients between variables i and j.
q_{ij} represents the partial correlation coefficients between variables i and j, which measure the correlation between two variables while controlling for the effects of other variables.

The Kaiser–Meyer–Olkin (KMO) measure ranges from 0 to 1 and is an indication of the suitability of the data for factor analysis. If the KMO value is close to 1—usually taken as acceptable at or above 0.6—it indicates that the variables have enough common variance to warrant the appropriateness for factor analysis. If below 0.5, it indicates that there is not enough common variance among the variables, making the data unsuitable for such utilization.

In practice, Bartlett's test of sphericity is applied routinely alongside KMO measure, to check whether a dataset's correlation matrix is significantly different from an identity matrix (i.e., a form in which all the variables are uncorrelated). A large Bartlett test p value alongside a high KMO value necessitates that factor analysis on the data is valid.

The KMO test yields a diagnostic assessment of whether inter-variable correlations and sample size are sufficient to warrant factor analysis. It is a screening instrument to ensure that the results of factor analysis are statistically significant and meaningfully interpretable.

Multiple regression analysis is another statistical measure used in the study. This statistical measure is utilized for the analysis of the association between one dependent variable and two or more predictor variables. The measure allows the researcher to determine the impact of more than one predictor on a single outcome variable, and as such, it is a useful measure for predicting and analyzing causes in various fields, such as social sciences, economics and health sciences [71–79].

In multiple regression, the objective is to represent the dependent variable YY as a linear combination of independent variables $X_1, X_2, \ldots, X_k$. The general multiple regression model can be symbolically written as given below:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \epsilon \quad (11)$$

where

Y is the dependent variable (the outcome we are trying to predict).
β_0 is the intercept of the regression line, representing the expected value of Y when all independent variables are equal to zero.
$\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients of the independent variables, indicating the change in the dependent variable Y for a change in one-unit in the respective independent variable, with all other variables constant.
$X_1, X_2, \ldots, X_k$ are the independent variables (predictors).
ϵ is the error term that represents the variation in Y that cannot be explained by the independent variables.

For multiple regression analysis to yield valid and useful results, some basic assumptions must be met.

- Linearity—There must be linear relationship between the dependent variable and each independent variable.
- Independence—The error terms or residuals must be independent of each other.
- Homoscedasticity—The variance of the residuals should be constant across all levels of the independent variables.
- Normality—The residuals should have an approximately normal distribution.

The least squares estimation method is used to find the regression coefficients $\beta_0, \beta_1, \ldots, \beta_k$. It minimizes the overall sum of the squared differences between the predicted and actual values from the regression model to the least value. The mathematical formula of the least squares criterion is as below:

$$\text{Minimize} = \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \quad (12)$$

where

Y_i is the observed value of the dependent variable.
$\hat{Y}_i$ is the predicted value of the dependent variable based on the regression model.
n is the number of observations.

Multiple regression analysis is an advanced statistical approach that facilitates the examination of the relationship between one dependent variable and several independent variables. It offers a structured means of assessing the extent to which different predictors influence a given outcome, making it highly effective for analytical, predictive, and decision-support purposes across numerous scientific fields. In the context of this study, the method was employed to investigate the association between barriers to scooter sharing and users' physical health conditions [80,81].

A survey about bike-sharing obstacles was divided into two parts.

The first part concerned the main problems to moving around by bike. In this case, the following variables were considered:

- P1—Too few bicycle paths;
- P2—Poor condition of bicycle path surfaces;
- P3—Poorly designed or routed bicycle paths;
- P4—Parked cars on bicycle paths or sidewalks;
- P5—Pollution or debris on bicycle paths;
- P6—Pedestrians on bicycle paths;
- P7—Inadequate infrastructure (e.g., parking spots, bicycle repair stations);
- P8—Too much distance between bicycle rental stations;
- P9—Poor signage of bicycle paths;
- P10—Safety concerns;
- P11—Health condition prevents the use of a bicycle;
- P12—Weather conditions prevent the use of a bicycle;
- P13—Too steep inclines making uphill riding difficult;
- P14—Car traffic.

The second part concentrate on the reasons to using bikes from bike-sharing systems. We have differentiated the following variables:

- R1—Commuting to work/university/school;
- R2—Traveling for shopping;
- R3—For recreational purposes;
- R4—For practicing sports;
- R5—Meeting with friends;
- R6—Returning home at night;
- R7—Occasionally covering short distances (e.g., getting to a bus stop), so-called first and last mile transport;
- R8—As a complement to public transport (avoiding traffic jams);
- R9—Traveling to recreational areas;
- R10—Traveling to restaurants/cafés;
- R11—Traveling to places offering services;
- R12—For entertainment;
- R13—Traveling during pleasant weather conditions;

In the numerical analysis, Statistica 13 was used.

4. Results

4.1. The Problems Connected with Moving in City Using Bike-Sharing Systems

Table 1 summarizes descriptive statistics for 14 perceived barriers (P1–P14) that may be problems in using bikes in the city. Each barrier is measured on a 5-point Likert scale (presumably from 1 = "strongly disagree" to 5 = "strongly agree"). The following statistical indicators are provided: mean, median, minimum, maximum, standard deviation, skewness, and kurtosis.

From an open innovation perspective, the top-rated challenge—P6: Pedestrians on bike paths (Mean = 3.71)—is a system conflict over claiming city space, evidence of breakdown of inclusive, multi-constituent design. Infrastructure planning in an open innovation platform must never be a top-down decree but a co-evolved exercise by cyclists, pedestrians, city planners, and citizens. The high mean rating here suggests that end-users likely were not heavily involved in early design phases of infrastructure planning. Open innovation supports crowd-sourced problem-solving and participatory urbanism—values

that might have anticipated and prevented such dysfunctional interaction between cycle and pedestrian space.

Table 1. Basic statistics for the benefits of bike travel from the bike-sharing system.

Variable	Mean	Median	Min	Max	Standard Deviation	Skewness	Kurtosis
P1—Too few bicycle paths	3.21	3.00	1.00	5.00	1.22	−0.15	−0.84
P2—Poor condition of bicycle path surfaces	2.69	3.00	1.00	5.00	1.14	0.43	−0.22
P3—Poorly designed or routed bicycle paths	2.88	3.00	1.00	5.00	1.16	0.26	−0.60
P4—Parked cars on bicycle paths or sidewalks	2.73	3.00	1.00	5.00	1.33	0.20	−1.08
P5—Pollution or debris on bicycle paths	2.21	2.00	1.00	5.00	1.17	0.72	−0.33
P6—Pedestrians on bicycle paths	3.71	4.00	1.00	5.00	1.12	−0.41	−0.64
P7—Inadequate infrastructure (e.g., parking spots, bicycle repair stations)	2.92	3.00	1.00	5.00	1.16	0.17	−0.72
P8—Too much distance between bicycle rental stations	2.74	3.00	1.00	5.00	1.16	0.33	−0.51
P9—Poor signage of bicycle paths	2.37	2.00	1.00	5.00	1.19	0.60	−0.41
P10—Safety concerns	2.62	3.00	1.00	5.00	1.17	0.37	−0.54
P11—Health condition prevents the use of a bicycle	2.10	2.00	1.00	5.00	1.34	0.97	−0.26
P12—Weather conditions prevent the use of a bicycle	3.06	3.00	1.00	5.00	1.22	0.01	−0.88
P13—Too steep inclines making uphill riding difficult	2.41	2.00	1.00	5.00	1.23	0.40	−0.97
P14—Car traffic	3.06	3.00	1.00	5.00	1.30	−0.12	−0.99

The high means for P1: Inadequate bicycle routes (Mean = 3.21) and P14: Motor traffic (Mean = 3.06) indicate more widespread structural limits—i.e., the inappropriate low scale of cycle provision and its inappropriateness for car-oriented city planning. From an open innovation point of view, this requires a sectoral coordination appeal: urban mobility arrangements must be developed not just within the transport ministry but also alongside environmental ministries, civil society organizations, local entrepreneurs, and technological firms. These types of collaborations would have the possibility to trigger innovations like adaptive routing algorithms, real-time dynamic urban design, or even micro-level interventions by residents to test and pilot new bike routes.

Limitations like P12: Meteorological conditions (Mean = 3.06) and P3: Insufficiently routed or designed ways (Mean = 2.88) also point to open innovation being able to address not only infrastructural deficits, but adaptive service design as well. For example, shared data platforms that merge weather data, usage patterns, and local feedback may supply real-time routing guidance and long-term planning. These are simple open innovation questions—seeding coordination between public data owners, service companies,

and participating user communities. Rather than considering weather as an immovable impediment, it is an optimized parameter for collective re-shaping of the system.

On the lower end of the scale, innovations like P11: Health condition (Mean = 2.10) and P5: Pollution or debris (Mean = 2.21) might also seem inconsequential, but they have embedded innovation potential. Open innovation is not only better than solving proximate problems but also in finding latent user requirements. For instance, partnerships with medical experts can introduce flexible cycling equipment or personalized programs for the mobility-disadvantaged communities. Similarly, data-sharing collaborations with local sanitation departments or with community science organizations can initiate community-based initiatives toward maintaining trail surfaces unblemished. These less-than-obvious barriers, while lower in mean severity, are fertile soil for socially inclusive, accountable innovation.

The mid-range barriers—P2: Poor surface quality on bicycle paths (Mean = 2.69), P4: Cars parked on the bicycle path or sidewalk (Mean = 2.73), P7: Lack of infrastructure (Mean = 2.92), P8: Too great a distance between rental stations (Mean = 2.74), and P10: Safety concerns (Mean = 2.62)—form a broad spectrum of operation problems that cumulatively point to design fragmentation and service inconsistency. On an open innovation basis, these challenges highlight the need to create modular, responsive infrastructure systems that dynamically change in response to citizen input. Ineffective infrastructure and illicit parking, for instance, would be alleviated by open data platforms and civic apps enabling real-time user reporting, triggering instant city action. Similarly, extended station-to-station distances and scattered end-point facilities such as parking racks or repair kiosks reflect the absence of combined service design. An open innovation approach would emphasize iterative development—processing genuine user feedback and allowing third-party input (such as micromobility firms or urban labs) to add system capabilities without central command.

The last two variables—P9: Inadequate signing of bike routes (Mean = 2.37) and P13: Hills (Mean = 2.41)—though graded reasonably as minor, do express frictions that can potentially be addressed through open technological innovation and spatial know-how. Inadequate signing is not just a matter of physical signage but also a failure to utilize digital overlays, such as augmented reality cycling software or user-contributed dynamically updated cycling maps. In the same way, inclined slopes can be addressed not only by city planning but also by the implementation of electric-assist shared bicycles—coordination required between private mobility companies and local transport authorities. These instances capture the way open innovation recasts even such seemingly rigid environmental boundaries as surmountable challenges in terms of openness of platform, co-creation, and the need to integrate decentralized inputs into the mainstream operating system of public bike-sharing schemes.

A look at median values is revealing in nearly all variables, the median is 2.00 or 3.00, which means people's opinions congregate around mid-levels of agreement or disagreement, with very few people expressing extreme views. This pattern, while perhaps quiet, has tremendous implications from the point of view of open innovation. This means a population neither fully satisfied nor fully dissatisfied, but with latent potential for participatory engagement. Factors such as P2: Bad condition of cycling routes, P4: Cars parked on cycling routes, P7: Inadequate infrastructure, and P10: Safety concerns, all suggest a median of 3.00. These reflect ambivalence or middle-of-the-road worry—places where public sentiment could be changed greatly by carefully targeted effort, user-co-designed. Open innovation performs well in such middle grounds where a deficiency of polarized opinions leaves room for deliberation, co-creation, and feedback loops among users, service providers, and policymakers.

On the other hand, variables with a median of 2.00, such as P5: Pollution or litter, P9: Inadequate signage, P11: Health status, and P13: Sloping terrain, represent obstacles that most respondents perceive as less frequent or less severe. From the perspective of the open innovation ecosystem, these cannot be overlooked but rather should be viewed as low-hanging fruits for incremental growth or niche innovation. Solving these challenges may not mean system-wide reforms but can instead encourage small-scale interventions on the part of startups, civic tech groups, or local advocacy organizations. Moreover, the low medians point towards a hidden heterogeneity in user experience—there could be some barriers that are highly localized or demographic in nature, which would need open data methods and hyperlocal experimentation. This median observation supports the need for open, user-centered systems continually responding to highly nuanced feedback, rather than relying on high-level assumptions.

Standard deviation measures in the table range from 1.12 to 1.34, indicating there is a moderate but substantial amount of variation across respondents' opinions for all barriers. Greater values of standard deviation—such as those for P11: Health condition (1.34), P4: Parked cars on paths or sidewalks (1.33), and P14: Car traffic (1.30)—show where views are more dispersed, meaning high heterogeneity in the experience of the system by different users. From an open innovation perspective, such heterogeneity suggests a need for adaptive personalized solutions. Rather than imposing homogenous interventions, mobility systems must be designed to meet a variety of user needs—something only open, multi-actor ecosystems allow. For instance, including multiple user personas within the design phase or facilitating modular add-ons (e.g., physical support systems for users with health restrictions) is an embodiment of the very concept of open innovation: solution diversity through stakeholder plurality.

Variables with smaller standard deviations—P6: Pedestrians on bike paths (1.12) and P2: Path surfaces in poor condition (1.14)—suggest relatively consistent identification of these problems across respondents, across locations or demographics. In both cases, standardization of response suggests systemic, universally felt problems, which are ideal candidates for coordinated, mass interventions. Open innovation here plays a different role: not in experience tailoring but in facilitating collective action, typically in the form of collaborative planning websites, participatory budgeting, or community-initiated pilot schemes. The alignment of user perception provides a robust mandate to public authorities and platform operators to act swiftly and invite crowdsourced ideation or prototyping of alternative solutions. Consequently, both high and low standard deviations hold complementary opportunities—either to personalize or to rally—each in accordance with the philosophy of open, user-integrated innovation systems.

The skewness measures in the table range from -0.41 to $+0.97$, indicating that the response distribution is skewed for several variables. Skewness in a positive direction, identified for metrics like P11: Health condition (0.97), P5: Pollution or debris (0.72), and P9: Poor signage (0.60), indicates that even though most of the users evaluated these barriers as quite insignificant, a smaller number of users had them as critical hindrances. In the open innovation context, this is an exemplary case of inclusive design strategy: even if a barrier is not common among a population, the outlier group is still a valid user group whose needs can be overlooked by mainstream, majority-oriented planning paradigms. Open innovation thinking is making an argument for the utility of edge users—individuals who push systems to be more robust, inclusive, and fair. These positively skewed measures can thus be understood as invitations to engage underrepresented or diverse groups of stakeholders within the co-design process, possibly by means of participatory mapping, ethnographic methods, or user hackathons.

Negative skewness—e.g., in P6: Pedestrians on bike paths (−0.41), P1: Not enough bicycle paths (−0.15), and P14: Car traffic (−0.12)—means a reversal in perception: many users find these issues quite serious, while comparatively few overestimate their seriousness. These signals reveal strong consensus regarding structural problems in the cycling setting, so they are ideal targets for system-level, concerted interventions. Open innovation-wise, this type of user clarity facilitates the formation of public–private innovation alliances, where government, urban planning, and technology actors can collaborate around easily identified issues. That is, negative skewness can serve as an agent of collective action, enabling cities to direct innovative resources toward interventions that are salient to the widest possible section of the user base. Such values not only offer diagnostic specificity but also directional direction for multi-actor, inclusive response channels.

All kurtosis measures presented in the table are negative, between −0.22 and −1.08, which indicates that the distribution of responses is platykurtic—less curved than a standard distribution, with fewer extreme observations and more equal dispersion around the mean. Such a statistical pattern suggests that the users are inclined to have a broad array of intermediate opinions rather than congregate their perceptions towards the extremes (e.g., "strongly agree" or "strongly disagree"). In open innovation parlance, this refers to a rich, multi-faceted user experience, in which attitudes are not influenced by overwhelming, highly polarizing forces but by situational or contextual variables. These conclusions reinforce the imperative to employ design thinking, scenario testing, and iterative feedback loops in innovation. Urban mobility planners and service operators should oppose solutions that fit all and instead embed modular system architectures that can be updated continually in response to ongoing, moderately distributed user feedback.

The lack of peakedness (leptokurtosis) in these distributions means that users do not strongly congregate around some small number of strong, leading barriers; rather, their perceptions are shaped by individual conditions, spatial variation, and time-dependent experience. From a point of open innovation, this is a great call to action for decentralized experimentation and user-driven micro-innovations. Cities could, for example, launch localized pilots or "living labs" in areas where specific barriers—such as signage (P9), slopes (P13), or infrastructural imbalances (P7)—are experienced differently. Flatter response distributions are indicative of a rich landscape for open-ended dialog, citizen co-research, and platform-enabled tailoring. Negative kurtosis, here, is not a lack of clarity or obscurity, but diversity of user interactions—precisely the type of environment where open innovation is most effective by welcoming nuance, encouraging pluralism, and iteratively co-creating value in tandem with communities.

Application of factor analysis for the exploration of issues in terms of using bicycles in bike-sharing systems is a sophisticated statistical method for unearthing hidden structures behind the users' experience. By virtue of employing rotation methods—i.e., normalized Varimax rotation—the method raises the interpretability of the dimensions found without the cost of jeopardizing their uniqueness so that every factor can uncover an independent source of influence.

The primary objective of the factor analysis was to achieve a reduction in many observed variables into fewer meaningful and interpretable factors. This was achieved by normalized Varimax rotation to enhance the interpretability of the factor loadings. The Kaiser–Meyer–Olkin (KMO) statistic, which was 0.83, ensures high sampling adequacy, i.e., the correlation matrix is prepared for such an analysis. Based on Kaiser's rule of eigenvalue of more than one, four factors were statistically significant. This is also attested to by Cattell's scree plot which further supports the retention of four distinct factors.

The results of factor analysis reveal that perceived benefits of bike-sharing utilization are organized into three distinct factors that account for a total of 61% of the total variance

in the data. Each of these dimensions captures a distinct aspect of the rewards that have been discovered to be linked with bike-sharing, as evidenced by the corresponding factor loadings presented in Table 2. Utilizing Varimax rotation in performing this exercise served to enhance the interpretability of the factors by maximizing the variance explained by each in and of itself, while simultaneously preserving their orthogonality—that is, their status as statistically independent of one another.

Table 2. The loadings of factors—problems of moving around by bike from bike-sharing system.

Variables	Factor 1	Factor 2	Factor 3	Factor 4
P1—Too few bicycle paths	0.780	−0.020	−0.009	0.153
P2—Poor condition of bicycle path surfaces	0.600	0.139	0.103	0.222
P3—Poorly designed or routed bicycle paths	0.743	0.141	0.145	0.106
P4—Parked cars on bicycle paths or sidewalks	0.182	0.240	0.749	−0.081
P5—Pollution or debris on bicycle paths	0.041	0.295	0.730	0.194
P6—Pedestrians on bicycle paths	0.177	−0.110	0.602	0.270
P7—Inadequate infrastructure (e.g., parking spots, bicycle repair stations)	0.385	−0.062	0.234	0.726
P8—Too much distance between bicycle rental stations	0.195	0.164	0.089	0.826
P9—Poor signage of bicycle paths	0.631	0.229	0.261	0.121
P10—Safety concerns	0.417	0.495	0.300	0.012
P11—Health condition prevents the use of a bicycle	0.159	0.704	0.102	−0.118
P12—Weather conditions prevent the use of a bicycle	−0.055	0.795	−0.144	0.283
P13—Too steep inclines making uphill riding difficult	0.086	0.747	0.253	0.147
P14—Car traffic	0.324	0.567	0.287	−0.117
Explained value	2.487	2.532	1.885	1.554

Factor 1 is named “Infrastructure and Network Deficiencies” because the factors such as P1: Too few bicycle paths (0.780), P3: Poorly designed paths (0.743), and P9: Poor signage (0.631) possess heavy loadings. They reflect structural limitations within the cycling network. In particular, P2: Bike path quality is low (0.600), also suggesting the interpretation that this measure is indicative of systemic weaknesses in cycling infrastructure’s integrity and quality. Overtly from an innovation point of view, this dimension suggests an imperative for co-designed planning of the infrastructure since city planners, cyclists, and local stakeholders collaborate to envision and prototype space arrangements.

Factor 2, with substantial loadings on P12: Weather (0.795), P13: Slopes (0.747), and P11: Health (0.704), can most accurately be labeled as a “Individual and Environmental Constraints” dimension. These are largely non-systemic barriers because of the physical condition of users or external, uncontrollable conditions. P14: Traffic (0.567) and P10: Safety (0.495) also load moderately here, possibly suggesting the interaction of environmental challenge with self-rated personal weakness. Open innovation initiatives can reverse this dimension by technological convergence, i.e., the emergence of e-bikes, or by engaging public health and climate authorities in mobility planning.

Factor 3 loads “Path Obstruction and User Conflicts.” Loadings are high on P4: Cars parked on paths (0.749), P5: Pollution or litter (0.730), and P6: Pedestrians on cycle paths (0.602). These suggest conflict in city space where a lot of users (car drivers, pedestrians,

cyclists) compete for scarce space with obstructions and safety concerns being created. This factor suggests the necessity for more integrated, multi-user design practice, ideally supplemented by participatory observation, direct user input, and intermodal coordination made possible by open platforms.

Factor 4 emphasizes P7: Inadequate infrastructure such as repair stations (0.726) and P8: Distances between rental stations (0.826). It can be interpreted as "Service Accessibility and Support Facilities." Factor 4 highlights the design weaknesses in the operation, where customers feel that the bike-sharing system does not have support or convenience facilities. As opposed to the core infrastructure, this is all about service-level enhancements-things that can be rapidly prototyped and tested in an open innovation ecosystem through collaboration with startups, civic tech communities, and local stakeholders. Examples include pop-up stops, mobile repair garages, or decentralized maintenance programs being co-designed and tested to meet user-specified requirements.

All four factors are presented in Figure 2.

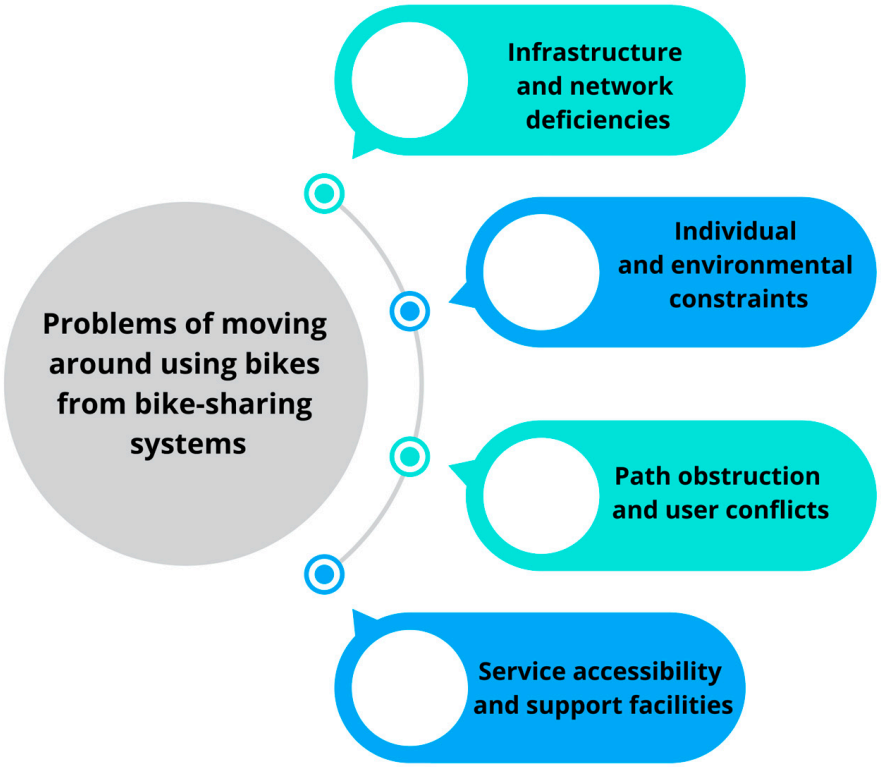


Figure 2. Identified factors of problems of moving around using bike from bike-sharing system.

4.2. Classification of the Reasons for Using Bike-Sharing System

Table 3 presents descriptive statistics for various reasons why individuals use bike-sharing systems, based on responses measured on a 5-point scale (0–5). The data includes measures of central tendency (mean, median), dispersion (standard deviation), and distribution shape (skewness and kurtosis) for each reason. The most common motives, indicated by higher means, include recreation, entertainment, and travel in good weather, while more utilitarian purposes such as commuting or shopping appear less frequently among respondents.

Table 3. Basic statistics for reasons to use bike-sharing systems.

Variable	Mean	Median	Minimum	Maximum	Standard Deviation	Skewness	Kurtosis
R1—Commuting to work/university/school	0.88	0.00	0.00	5.00	1.42	1.43	0.85
R2—Traveling for shopping	0.83	0.00	0.00	5.00	1.34	1.49	1.16
R3—For recreational purposes	1.62	1.00	0.00	5.00	1.83	0.64	−1.05
R4—For practicing sports	1.49	0.00	0.00	5.00	1.79	0.77	−0.86
R5—Meeting with friends	1.29	0.00	0.00	5.00	1.66	0.95	−0.48
R6—Returning home at night	1.06	0.00	0.00	5.00	1.62	1.23	0.02
R7—Occasionally covering short distances (e.g., getting to a bus stop), so-called first and last mile transport	1.21	0.00	0.00	5.00	1.69	1.09	−0.25
R8—As a complement to public transport (avoiding traffic jams)	1.12	0.00	0.00	5.00	1.65	1.23	0.09
R9—Traveling to recreational areas	1.32	0.00	0.00	5.00	1.78	0.93	−0.67
R10—Traveling to restaurants/cafés	0.80	0.00	0.00	5.00	1.43	1.67	1.52
R11—Traveling to places offering services	0.82	0.00	0.00	5.00	1.36	1.46	0.88
R12—For entertainment	1.71	1.00	0.00	5.00	1.87	0.57	−1.17
R13—Traveling during pleasant weather conditions	1.61	0.50	0.00	5.00	1.91	0.71	−1.08

The most highly ranked reasons for the operation of bike-sharing schemes, as represented by the mean scores in Table 3, are recreation (R3—1.62), leisure (R12—1.71), and good weather travel (R13—1.61). This indicates that current riders use shared bikes only as an accessory of amusement consumption and to some extent as an integral part of the daily mobility routine. From an open innovation perspective, this means that value propositions becoming more mainstream and co-developed with users are experience-based and affective and not functional. These usage patterns provide strategic possibilities for multi-stakeholder cooperation to enhance the recreational aspects of bike-sharing services—by coupling platforms with local event culture, tourist infrastructure, and outdoor fitness apps through API-based openness or modularity of the service layer.

Conversely, utilitarian activities such as commuting to work or school (R1—0.88), going shopping (R2—0.83), or going to services (R11—0.82) register significantly lower mean values. These relatively low scores point towards a latent capability of the bike-sharing system, particularly in the case of first-order functional mobility activities. Translated across the open innovation model, however, this gap could be thought of as an innovation latent space—a space potentially occupied by co-design with consumers, collaboration with public transport firms, or even city planners. Shared testing, for instance, pilot-testing for-purpose bicycle-sharing roads or intermodal mobility hubs, may increase perceived

system value and stimulate a move towards frequent usage from occasional usage, in accordance with user-led and demand-led innovation principles.

The heterogeneity of motives—between 1.34 and 1.91 in standard deviations—implies a diverse group of users with varying tastes, which is further justification for open innovation for inclusiveness and modularity of platforms. As an alternative to being approach-of-the-jaw type planning, bike-sharing operators and city governments could leverage open data approaches and crowdsourced sources to their advantage in tracking, monitoring, and automatically responding to rider sentiments and commute patterns. Through this, there can be an environment of agile innovation where solutions are conceived through relentless dialog with sets of customers, independent software developers, and civic planners. In general, the low mean values for all variables imply a partially open innovation system—i.e., one that offers high potential for growth via cooperative, boundary-spanning processes.

Standard deviations are between 1.34 and 1.91, reflecting a high heterogeneity of the usage motivations of bike-sharing systems, and therefore that consumers' desires are anything but homogeneous. This scatter indicates that although there are some of the users who quite regularly employ bike sharing for certain purposes, others barely make use of the system for comparable intentions. From the management of innovation perspective, such diversity highlights the necessity to embrace versatile, user-oriented service concepts that can learn in various patterns of behavior. It also underscores the strategic value of open innovation mechanisms, such as web-based feedback loops or participatory design workshops, that allow operators and municipal stakeholders to improve services iteratively based on real, localized usage patterns. In this way, bike-sharing can be reimagined from supply-oriented, one-size-fits-all platforms to demand-responsive mobility ecosystems reflecting the multifaceted, dynamic mobility needs of urban residents.

The skewness values are primarily positive, ranging from 0.57 to 1.67 for most of the variables whereas some variables have negligible negative skewness. This reflects positive skew and suggests that the majority of the users will have low frequencies of bike-share usage for reasons stated with some system users making more frequent uses of it. In the open innovation context, this difference is particularly telling it is the presence of lead users or early adopters whose actions will not be norm but can be a fertile source of knowledge on which to draw when making progress towards the future. These heavy users will test the system to its limits and are able to assist with key feedback or collaborate on fixes that mitigate present barriers. Through ongoing sensing and interacting with such outlier users—through digital engagement platforms, open calls for ideas, or living labs—bike-sharing operators can tap into user-driven innovation potential and turn it into new functions, integration points, or incentive models that have the potential to drive more adoption among the larger user base.

The kurtosis values range broadly from highly negative (e.g., R12—Eating out for leisure at −1.17) to positive (e.g., R10—Eating out at restaurants/cafés at 1.52), and exhibit variation in the "peakedness" or the degree of concentration of user responses compared to the mean. Negative kurtosis values point to flatness, with the answers less dense around the mean and more spread out over the scale, indicating higher diversity of usage intensity between respondents. Positive kurtosis, in contrast, detects a distribution where all the users are concentrated at the lower part of the scale, and with hardly any large frequency outliers. As an open innovation, this can be used in guiding the course of targeted segmentation strategy: vastly scattered motivations (low kurtosis) enable modular service innovations towards specialized usage contexts, while peaked distributions (high kurtosis) signal possibilities for standardized interventions to realign mainstream behavior. In either case, discovery of these statistical patterns enables stakeholders to architect more informed, user-centered systems that accommodate mass participation as well as the

complex requirements of a given subgroup of users, thereby creating adaptive capacity in urban mobility infrastructure.

Factor analysis was used to collapse variables into fundamental constructs, using normalized Varimax rotation for interpretation ease without loss of independence of the extracted factors. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.86—the criterion that the correlation matrix was adequate for factor analysis in the present case. Two factors were selected based on Kaiser's rule, which states that factors with eigenvalues above 1 are to be retained. This rationale was also seen from Cattell's scree plot, which also suggested a two-factor solution. The users' subjective perception of the bike-sharing system was examined. Two factors that differentiated were discerned and were found to together explain 73% of variance. All these factors are distinct thematic areas that concern infrastructure assessment as is evident from factor loadings in Table 4. Normalized Varimax rotation facilitated the factors that do not only account for large proportions of variance individually but also remain uncorrelated with one another, hence being independent to analyze.

Table 4. The loadings of factors—reasons for using bike-sharing system.

Variables	Factor 1	Factor 2
R1—Commuting to work/university/school	0.303	0.709
R2—Traveling for shopping	0.533	0.473
R3—For recreational purposes	0.866	0.281
R4—For practicing sports	0.903	0.240
R5—Meeting with friends	0.583	0.521
R6—Returning home at night	0.155	0.816
R7—Occasionally covering short distances (e.g., getting to a bus stop), so-called first and last mile transport	0.186	0.861
R8—As a complement to public transport (avoiding traffic jams)	0.267	0.825
R9—Traveling to recreational areas	0.751	0.501
R10—Traveling to restaurants/cafés	0.535	0.557
R11—Traveling to places offering services	0.588	0.638
R12—For entertainment	0.882	0.146
R13—Traveling during pleasant weather conditions	0.826	0.235
Explained value	5.067	4.269

Factor 1 (Recreational Usage) is most associated with recreational. The variables with high loadings on this factor are R3—For recreational purposes (0.866), R4—For practicing sports (0.903), R12—For entertainment (0.882), and R13—Traveling during pleasant weather (0.826). These strong correlations suggest that this factor encompasses the hedonic or discretionary aspects of bike-sharing activity—targeting recreation, health, season delight, and inessential mobility. This would equate to having a large portion of users taking shared bikes as modes for quality-of-life improvement, spontaneous action, and sociability.

Factor 2 (Functional and Mobility-Integrated Use) is dominated by function and utilitarian travel purposes. R6—Returning home evenings (0.816), R7—First and last mile transport (0.861), and R8—Used as an addition to public transport (0.825) strongly load on this factor. In addition, R1—Working/university/school commute (0.709) and

R11—Trips to sites offering services (0.638) also suggest strong associations. This factor may be interpreted as the pragmatic or transport-integration factor, referring to organized, goal-directed usage where bike sharing is embedded within broader mobility practices, especially in multimodal mobility behavior. It is used to describe the application of bike-sharing systems to resolve logistical challenges and improve accessibility within cities.

Identified factors are illustrated in Figure 3.

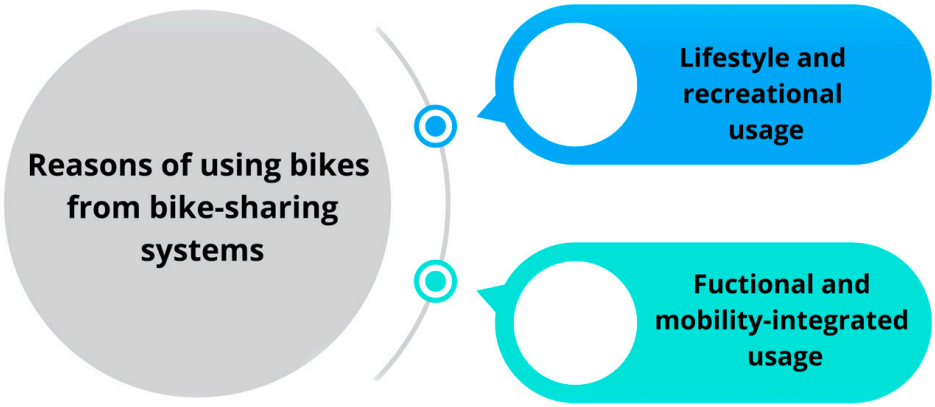


Figure 3. Identified factors of reasons for using bikes from bike-sharing system.

4.3. The Multidimensional Model of Relationships Between Problems of Moving Around by Bike from Bike-Sharing and Reason of Using Bike-Sharing System

In the next stage of the analysis, a multiple regression procedure was employed using the available dataset. For regression models to be methodologically sound, it is essential that the included independent variables display strong associations with the dependent variable, while exhibiting minimal multicollinearity, that is, low intercorrelation among themselves. To construct the most effective regression models, the backward stepwise selection method was implemented. This technique allows for a systematic reduction in variables, retaining only those that contribute meaningfully to explaining the dependent variable. The approach enables a comprehensive assessment of how a single outcome variable is influenced by several predictors simultaneously, thus allowing for the estimation of the dependent variable based on patterns observed in the explanatory variables.

The multidimensional model (Table 5) offers a detailed view of how different infrastructural and environmental challenges influence the various motivations for using bike-sharing systems. The regression coefficients represent the strength and direction of relationships between each usage motive (R1–R13) and the corresponding barriers (P1–P14), while statistical indicators such as the intercept, R, R^2, adjusted R^2, and standard error of estimation provide information on model fit and explanatory power.

The quite low mean scores on barriers like “health condition” and “weather conditions” in the study should not be taken to indicate that they are insignificant factors. Rather, the effect is highly differentiated between various user groups. Statistical measures of standard deviation and skewness capture extreme variability in response, particularly for barriers to health, and suggest the presence of subpopulations (e.g., older adults, those with mobility impairments) for whom these barriers are strongly salient. Factor analysis substantiates this by grouping these factors under a separate dimension titled “Individual and Environmental Constraints,” pointing to their systematic exclusion from infrastructural problems and underlining the imperative of context-specific, targeted interventions as opposed to generic fixes.

Table 5. The multidimensional model of relationships.

Reasons	Problems													
	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**
R1														
R2		0.161		0.172							0.217			
R3		0.255			−0.163	0.255					−0.18		−0.189	
R4					0.191	−0.208				−0.269	0.213			
R5						−0.217								−0.222
R6					−0.179			−0.254			−0.313	−0.158		
R7	−0.138			−0.286									0.15	
R8				0.389	0.329						0.284		−0.167	
R9		−0.203	−0.269		−0.244				−0.221	−0.311				−0.191
R10									0.152					
R11						0.277						0.325	0.434	0.34
R12				−0.149					0.189					
R13			0.117	0.246	0.165		0.189	0.138	0.249	0.161			0.155	0.289
Intercept	3.27	2.44	2.31	2.52	1.99	3.64	2.87	2.66	2.28	2.41	2.17	3.24	3.34	2.88
R	0.28	0.26	0.28	0.41	0.4	0.38	0.22	0.24	0.3	0.35	0.37	0.26	0.35	0.39
R^2	0.079	0.069	0.079	0.17	0.16	0.148	0.05	0.073	0.093	0.125	0.13	0.069	0.12	0.15
Adjusted R^2	0.72	0.62	0.72	0.077	0.06	0.046	0.44	0.66	0.87	0.02	0.035	0.61	0.023	0.055
Standard error of estimation	1.19	1.17	1.14	1.24	1.1	1.06	1.21	1.2	1.19	1.15	1.29	1.23	1.24	1.27

Regression models show that even these comparatively weaker barriers have strong impacts on the behavior of specific user segments. For example, consumers who depend on bike-sharing to tap urban services are positively correlated with weather adversity, indicating a need-for-others-to-overcome-convenience. Conversely, consumers who use bike-sharing for leisurely or evening activities will be deterred by health constraints or adverse weather conditions, indicating that such constraints selectively reduce utilization in some situations. Short, although they are not prevalent in the whole population, "weather" and "health" play important drivers for specific behavior and must be tackled by inclusive, responsive measures in smart mobility planning.

4.3.1. Key Positive Relationships

One of the most robust positive associations is associated with recreational-oriented use of bike-sharing systems. This is since, in the fore, R3 (for leisure purposes) is positively associated with P1 (lack of adequate bicycle paths, 0.255) and P5 (pollution or litter on bicycle paths, 0.255). Similarly, R4 (to train in sport) is also positively associated with P3 (poor design of bicycle paths, 0.191). These findings initially read counterintuitively—why should the incidence of infrastructural problems be positively correlated with higher usage? But understood from a behavioral and open innovation framework, these findings show that under less-than-ideal circumstances, users driven by individual recreation, health, or enjoyment continue to utilize bike-sharing systems. This works to emphasize an enduring need for recreational cycling that picks out an undeniable potential for urban creatives to collaborate on working toward the improvement of green infrastructure, scenic cycling corridors, and intelligent routing technologies as solutions to repeat quality issues in recreational corridors.

A second group of positive correlations is found within problem-solving behavior and mobility integration. R8 (bike-sharing as a supplement to public transport) has extremely high positive correlations with P3 (poorly routed routes, 0.389), P4 (parked cars obstructing routes, 0.329), and P9 (poor signposting, 0.284). These scores indicate that riders who utilize bike-sharing as part of an intermodal daily trip routine are more likely to encounter—and tolerate—more infrastructural malfunction. This means that their incentive is less because of the existence of ideal cycling infrastructure and more because of the functional imperative of bridging gaps in the urban mobility network. From the point of view of innovation strategy, this set of users is full of insights for co-creating intermodal design solutions, including intermodal transport apps, dynamic route systems, or reward schemes that enhance the reliability and connectivity of bike-sharing and public transport hubs.

Positive correlations are also present in R11 (trips to destinations offering services), which correlates with P6 (pedestrians on the bike path, 0.277), P9 (insufficient signage, 0.325), P10 (problems with safety, 0.434), and P12 (weather, 0.34). These positive correlations describe a world in which users making pragmatic errands or going to urban services meet significant contextual challenges. Strengths in these relations are that the residents actively use bike-sharing while continually experiencing repeated hassle or uncertainty about the cycling environment. This customer segment, as such, presents a particularly inviting niche for concentrated intervention, such as weather-adjustable facilities (e.g., covered paths), readily readable indications, and people–cycle collision management. From an open innovation point of view, involving this segment in the design and testing of adaptive urban mobility systems could yield rich, experiential feedback on how infrastructure shortfalls affect daily transport behavior.

4.3.2. Key Negative Relationships

Of the strongest negative correlations, recreational and entertainment-related utilizations of bike-sharing systems emerge as highly responsive to some infrastructural and environmental barriers. For example, R3 (recreation) is inversely correlated with P4 (parked cars on bike paths, −0.163), P9 (sufficient signage, −0.18), and P10 (perceived safety, −0.189). Similarly, R12 (entertainment) is inversely correlated with P3 (poorly designed paths, −0.149). These are negative coefficients and reflect that customers of enjoyable or recreational activities are highly discouraged by physical obstacles, navigational confusion, and security-related inconvenience. Compared to utilitarian customers who may tolerate or compromise with these issues out of necessity, recreational customers appear to be more inclined to be discouraged from using bike-sharing systems if these conditions are present. This implies a need for public–private partnerships to co-design clean, safe, and legible cycling environments that align with the aspirations of hedonic motivation-led users—a strategy aligned with human-centered design principles in open innovation frameworks.

A second cluster of aversive relationships is identified with R6 (evening return home), which is negatively correlated with P5 (trash or pollution, −0.179), P7 (incomplete infrastructure, −0.254), P9 (lack of signage, −0.313), and P10 (risk or insecurity, −0.158). These coefficients suggest that off-peak evening users—who are already likely to be exposed to diminished visibility and increased personal exposure—are especially burdened by infrastructural incompleteness and environmental deterioration. Insufficient illumination, lack of adequate route marking, and untidy routes severely lower the possibilities for the use of shared bicycles as a mode of late-evening transportation. It reflects a glaring necessity for specific innovation on assistance in late-night cycling in terms of intelligent light technologies, live safety monitoring, and better guidance along routes, ideally co-created with the eventual users and supplied via open data collaboration among cities and mobility operators.

In the field of first and last mile mobility, R7 (moving short distances such as to a bus stop) has a strong negative correlation with P3 (poorly designed or routed bicycle paths, −0.286) and a weaker but still significant correlation with P1 (insufficient bicycle paths, −0.138). These results pinpoint a specific barrier in the micro-mobility category: the absence of continuous, uninterrupted cycling routes through high-density urban centers. Residents who rely on public bikes for short functional journeys obviously are discouraged if route planning is unclear, circuitous, or at odds with their travel patterns. In open innovation terminology, the point is to emphasize the need for user-sensitive urban planning that integrates bike-sharing routes into the overall transport systems. Engaging users in the repeated testing of micro-corridors, behavioral studies, and participatory mapping could lead to smoother, more intuitive transitions between transport modes, thereby increasing the actual and perceived value of bike-sharing in first- and last-mile scenarios.

4.3.3. Model Fit and Reliability

The goodness-of-fit and validity of the multidimensional model for relationships between reasons for bike-sharing are examined through a range of statistical measures given in Table 5. Significant factors such as R (correlation coefficient), R^2 (coefficient of determination), adjusted R^2, and standard error of estimation provide a good platform for model fit for the regression equations. Typically, these actions suggest a high to moderate model fit in the selected cases, particularly for some use purposes like recreation, exercising sports, and traveling to recreational places. For instance, the adjusted R^2 values for R3 (recreational usage) and R4 (exercising sports) are particularly high at 0.72, indicating that over 70% of variance in these use patterns can be explained by the selected set of barriers in the model.

Among the motive for use, R9 (recreational travel to destinations) possesses the highest adjusted R^2 value of 0.87 and is therefore the best-explained behavioral dimension in the dataset. Such high model fit implies a strong and consistent relationship between recreational travel behavior and tangible infrastructural issues such as route design deficiency, litter, and signage. Similarly, R7 (first and last mile travel) and R2 (travel for shopping) also have high adjusted R^2 values of 0.66 and 0.62, respectively, which confirm the model's capability to explain functional and everyday motivations through problem variables. The high values indicate a well-structured model capable of explaining subtle user behavior that is suitable for both diagnostic and strategic applications in mobility innovation.

On the other end of the spectrum, some behavioral variables such as R1 (work/university daily travel), R10 (restaurant/cafés trip), and R13 (trips with good weather) have very low adjusted R^2 values (between 0.02 and 0.06), which reflect poor explanatory power. They point towards the fact that the selected infrastructural issues are, in some travel purpose, not the underlying drivers of use frequency. Instead, they are probably affected by other context variables not modeled yet today—such as cultural norms, price patterns, convenience, social convention, or unmeasured personal preference. This needs more model specification, quite possibly through the introduction of psychosocial or economic indicators, or respondent segmentation along demographic or recreational bases.

The standard error estimates, 1.06 to 1.29, reflect the distance that predicted values deviate from actual responses. These are reasonably close across models and reflect no serious anomalies or heteroscedasticity in estimation quality. While not highly low, these measures are in reasonable ranges for behavioral data involving subjective opinions and Likert-scale measures. The homogeneity of standard errors among many regression models serve to further boost the validity of the model, supporting the perception that the observed relationships are free from the influences of outliers and non-uniform variance across varying usage categories.

In general, the model performs consistently well in some application settings, e.g., those involving recreational behavior, and performs poorly in recognizing more functional, everyday travel purposes. Methodologically, the use of multiple regression on disaggregated use types is a strength, as it allows for the high-grained analysis of motivation to behavior. However, future uses of the model should also seek to expand the number of predictors and possibly incorporate latent variable modeling (e.g., structural equation modeling) to account for unobserved effects. From an open innovation perspective, the current model provides a robust empirical foundation to detect user pain points, guide participatory design, and tailor interventions in infrastructure planning and shared mobility system design.

5. Discussion

The findings of this study illuminate the complex interplay between infrastructural barriers, user motivations, and behavioral outcomes in bike-sharing systems, particularly within post-industrial urban contexts such as Silesia, Poland. By integrating quantitative analyses (descriptive statistics, factor analysis, and regression modeling) we reveal critical insights into how smart city principles and open innovation frameworks can address systemic gaps between infrastructure design and user intention. Below, we contextualize these results within broader theoretical and practical debates.

5.1. Infrastructural Barriers: A Call for Collaborative Urbanism

Descriptive statistics of perceived barriers presented in Table 1 indicate conflicts between pedestrian and bicycle paths (P6, mean = 3.71) as the most significant challenge in the Silesian region. This result reflects a systemic failure of multi-stakeholder urban design,

where cyclists and pedestrians compete for limited space. Such conflicts are consistent with critiques of "top-down" urban planning, where technocratic solutions neglect bottom-up user experiences. From an open innovation perspective, this barrier highlights the need for participatory spatial management, integrating cyclists, pedestrians, and urban planners in the co-design of shared spaces through platforms such as digital crowdsourcing or citizen hackathons. It is worth noting that structural shortcomings, such as insufficient bicycle paths (P1, mean = 3.21) and car traffic (P14, mean = 3.06), were widely reported in the study. These problems are rooted in legacy urban systems designed for industrial logistics rather than sustainable mobility, suggesting the region's post-industrial nature. Factor analysis further categorized these barriers into four latent dimensions:

1. Infrastructure and network deficiencies (Factor 1: P1, P3, P9).
2. Individual and environmental constraints (Factor 2: P12, P13, P11).
3. Traffic obstructions and user conflicts (Factor 3: P4, P5, P6).
4. Availability of services and support facilities (Factor 4: P7, P8).

These factors demonstrate that barriers are not isolated but interconnected, requiring holistic interventions. For example, Factor 3 (parked cars, pedestrian conflicts) highlights the need for real-time reporting tools and community-led maintenance initiatives, creating an opportunity for open innovation platforms to leverage solutions from the community. Similarly, factor 4 (distance from station, access to repairs) requires modular, adaptive infrastructure designed in cooperation with local entrepreneurs.

5.2. Motivational Duality: Reconciling Hedonic and Utilitarian Use

The analysis of motivations for using bike-sharing systems, presented in Table 3, reveals a clear divide. Recreational purposes dominate (R3, R12, R13), while utility trips (R1, R2, R11) lag. These results indicate that bike-sharing services are perceived as recreational systems rather than functional mobility tools [80–82]. Factor analysis highlighted this duality along two dimensions:

- Factor 1 (recreational use), which is related to leisure, sports, and weather-dependent travel.
- Factor 2 (functional and integrated mobility use), which is related to commuting, first/last mile trips, and public transport integration.

The dominance of recreational use (factor 1) suggests that the success of bike-sharing systems in post-industrial cities depends on affective city design, such as scenic routes, event-related cycling promotions, and gaming applications that enhance hedonic rewards. On the other hand, lower utilitarian use (factor 2) signals untapped potential. Regression models show that functional users tolerate infrastructure barriers such as poor signage or parked cars but consider these to be significant weaknesses. To fill this gap, cities must prioritize intermodal connectivity, such as mobility hubs.

5.3. Multivariate Relationships: Barriers as Behavioral Moderators

Regression analysis (shown in Table 5) revealed nuances in the interactions between barriers and motivations. From the perspective of recreational resilience, counterintuitively, recreational use (R3, R4) correlated positively with barriers such as poor bike paths (P1) and pollution (P5). This suggests that recreational cyclists prioritize experiential benefits over infrastructure quality—a finding with design implications. For example, cities could implement augmented reality applications to enhance scenic routes while incrementally improving physical infrastructure. From the perspective of frustration with functional bike-sharing systems, utilitarian users (R7, R8) showed negative correlations with barriers such as poor route design (P3) and inadequate signage (P9), underscoring the need for user-centered route optimization and real-time navigation aids. From the perspective

of safety and equity gaps, returning home at night (R6) users were disproportionately deterred by safety concerns (P10) and poor lighting (P9). This is consistent with research linking gendered mobility patterns to infrastructure safety [83]. This points to the need to implement participatory safety audits in collaboration with marginalized communities and to implement AI-controlled lighting systems.

The variable explanatory power of the model (adjusted R^2: 0.02–0.87) highlights that infrastructure barriers alone cannot fully predict bike-sharing use. Psychosocial factors in the form of cultural stigma, or economic factors in the form of prices and social norms play a key role, especially in post-industrial regions, where cycling retains historical links with socio-economic insecurity.

5.4. Policy and Innovation Pathways

From the perspective of the innovation approach and policy issues, the study showed the need for the following issues:

- Different types of civic technology activities should be properly used for participatory mapping of bike paths, parking nodes and conflict zones to create infrastructure that is truly tailored to the needs of bike-sharing users.
- Start-ups and NGOs should be partnered to pilot different types of innovative modular solutions—e.g., electric bikes for hilly areas (P13), weather-responsive pricing models (P12) and community-led path maintenance (P5). Such behavior will allow for the creation of adaptive ecosystems of shared services.
- Equity-based governance should be built on, which will allow for solving the problem of, for example, clustering of bike docking stations in affluent neighborhoods.

In the case of post-industrial cities, this framework will help to reconcile industrial heritage with the future of smart mobility.

5.5. Potential Applicability of Findings Beyond the Silesian Region

The Silesian experience, being place-specific—due to the complexity of the local post-industrial transformation process—involves general implications for other post-industrial cities in a period of socio-economic transformation and restructuring mobility. The generated typology of barriers—i.e., the distinction between infrastructural deficiencies, individual/environment barriers, and services restrictions—is a challenge for cities with legacy industries, segmented development, and vintage transportation infrastructure.

Central and Eastern European, North English, American Heartland, or East Asia's post-industrializing regional urban centers may also be vulnerable to the same infrastructural dislocation and unregulated mobility service accessibility. The multi-dimensional explanatory model thus developed in the research is thus an exportable diagnostic tool for the study of user-based barriers to bike-sharing adoption where top-down city planning has traditionally excluded perceptual and behavioral factors.

Methodological synthesis of factor analysis and regression modeling of quantitative survey data provides a scalable analytical model for urban mobility planning. Micromobility-friendly cities can employ this model to reveal underlying user needs and segment users based on motivation and constraints.

In particular, the study cites the successful application of open innovation, collaborative governance, and infra tours in modular format—concepts emerging in international smart city agendas. By consideration of both hedonic and utilitarian motivation and geographically specific obstacles (meteorology or disease), this paper enables the governments of the municipalities and mobility providers in other geographies to transfer the solutions to other population groups and urban patterns and thereby to make the bike-sharing systems much more socially inclusive and equitable than in the Silesia region.

5.6. Limitations

The main limitation of this article is that the study focuses only on the Silesia region in Poland, which may limit the generalizability of the results. The data are based on self-reports, which carries a risk of perceptual bias. The design is cross-sectional, so changes over time are not considered. Furthermore, the quantitative approach may not fully capture the experiences of minority or vulnerable groups.

5.7. Future Research Directions

Future studies about bike-sharing systems should consider conducting comparative research in other post-industrial or transitioning urban regions to assess the generalizability of the findings presented in that article. Longitudinal designs are also recommended to capture how user motivations and perceived barriers evolve over time in response to infrastructural improvements or policy changes. What is more, researchers should explore how bike-sharing systems interact with other smart mobility services to create more integrated and propose additional research as analysis of fleets to use in bike-sharing systems as was done in the case of car-sharing systems [84] to gain user-friendly urban mobility ecosystems.

6. Conclusions

The research outlines a wide range of barriers experienced by users when accessing city spaces through bike-sharing systems (RQ1). They are divided into infrastructural (e.g., insufficient bicycle paths, bad-quality surface, insufficient signs, and distance between rental points), environmental (e.g., weather, pollution or litter on paths, slopes), and personal constraints (e.g., health, safety). Two of the most highly rated issues were cycleway pedestrians (mean = 3.71), absence of specialist cycle provision facilities (mean = 3.21), and disturbance caused by car traffic (mean = 3.06). These were lower but still noteworthy restrictions in health (mean = 2.10) and ambiguous signage (mean = 2.37). These findings indicate the multifaceted nature of such issues deterring wider implementation of bike-sharing facilities in cities with problems ranging from physical infrastructure availability to environmental as well as personal constraints.

Bike-sharing systems use motivations are more surprisingly diverse and encompass both utilitarian and hedonic motivations (RQ2). Based on the survey, recreational usage motivations have the most impact. Specifically, the most positively rated motivations consisted of joyriding (mean = 1.71), leisure (mean = 1.62), and on a nice day (mean = 1.61). On the contrary, utilitarian purposes such as riding a bicycle to work, school, or university (mean = 0.88), store (mean = 0.83), or out to services (mean = 0.82) were less common. This confirms that, under this urban sprawl covered within the present research, bike-sharing is not as primarily a form of daily use transportation but first and foremost a form of amusement. Nonetheless, some percentage of users evidently sees the system as an extension of the public transportation system and as a first-mile/last-mile solution.

Analysis reveals several fascinating inter-correlations of personal barriers and reasons for using (RQ3). The positive correlations in that there exist some users sustaining the usage of bike-sharing systems despite infrastructural shortages, notably for recreational use. For instance, the reason “recreational purposes” (R3) is correlated positively with self-experienced problems such as insufficient bike path (P1) and pollution (P5), and so the ongoing demand despite the lack of a supportive environment. Conversely, there were substantial negative correlations for more sensitive uses: entertainment users (R12) and evening cyclists (R6) are strongly discouraged by poor path design (P3), signs (P9), and safety (P10). These patterns imply user segmentation: some tolerate inconvenience because

of necessity or habit, but others, particularly leisure users, require better, safer, and more agreeable conditions in order to be interested.

The study can effectively establish a multivariable regression model (RQ4) between 14 issues (P1–P14) and 13 reasons (R1–R13) of the users. Following a backward stepwise selection method, scholars construct separate regression models for each strong statistical requirement such as correlation coefficients (R), explained variance (R^2), and adjusted R^2 for each motive group. For instance, travel motives to recreation sites (R9) reported an extremely high adjusted R^2 value of 0.87 with a satisfactory explanation power. Similarly, sports (R4) and shopping (R2) motives also reported strong models (adjusted R^2 = 0.72 and 0.62, respectively). All these results provide evidence for the practicability of a more advanced, statistically grounded system in explaining how specific barriers affect user behavior across different motivational domains. The summary of the main findings is presented in Table 6.

Table 6. Summary of main findings.

Dimension	Main Findings	Open Innovation Implications
Perceived barriers (P1–P14)	• Top-rated problems: Pedestrians on bike paths (P6, Mean = 3.71), too few bike paths (P1, Mean = 3.21), car traffic (P14, Mean = 3.06). • Lower-rated issues: Health limitations (P11), debris on paths (P5), poor signage (P9). • Mid-range standard deviations and skewness suggest a diversity of experiences.	• Co-creation in urban infrastructure planning is crucial. • Use of civic apps and participatory platforms can facilitate real-time reporting and feedback. • Even minor-rated barriers hold potential for user-driven micro-innovations and targeted interventions.
Motivations to use (R1–R13)	• Strongest motives: Entertainment (R12), recreation (R3), pleasant weather (R13). • Weakest motives: Commuting (R1), shopping (R2), visiting services (R11). • Standard deviations indicate a heterogeneous user base.	• Collaborative innovation with tourism, fitness, and cultural sectors. • Integrate with public transport through interoperable digital solutions. • Use crowdsourced data to tailor services to diverse user segments.
Factor analysis—barriers	Four latent dimensions identified: 1. Infrastructure and network deficiencies (e.g., poorly designed paths, insufficient lanes) 2. Environmental and personal constraints (e.g., weather, hills, health) 3. Obstructions and user conflicts (e.g., parked cars, pedestrian interference) 4. Service accessibility issues (e.g., long distance between stations, no repair points)	• Enables structured co-creation workshops addressing specific barrier groups. • Supports collaborative policy design between municipalities, service providers, and citizens. • Encourages testing of local solutions in ‘urban living labs’.
Factor analysis—motivations	Two factors uncovered: 1. Recreational usage (entertainment, sport, weather) 2. Functional and mobility-integrated usage (commuting, first/last mile, errands)	• Design flexible, modular service offerings aligned to user typologies. • Leverage open APIs with transport ecosystems. • Promote co-development of services that target hedonic and utilitarian needs.

Table 6. *Cont.*

Dimension	Main Findings	Open Innovation Implications
Regression Model	• Positive correlations: R3 (recreation) ~ P1, P5; R8 (public transport complement) ~ P3, P4, P9. • Negative correlations: R6 (night use) ~ P5, P7, P9, P10; R12 (entertainment) ~ P3. • Strongest explanatory models: R9 (Adjusted R^2 = 0.87), R4 (0.72), R2 (0.62).	• Recreation users sustain usage despite barriers—ideal co-design partners for aesthetic and scenic enhancements. • Night and intermodal users require safety, clarity, and infrastructure—potential for innovation in lighting, signage, and safety apps. • Segment-specific innovations can be developed via participatory research and behavioral modeling.
Model validity and fit	• High model fit for recreational and sports motivations. • Low fit for utilitarian travel (e.g., R1—commuting), suggesting missing variables. • Standard errors consistent, indicating robust methodology.	• Indicates need for inclusion of social, cultural, and psychological factors in future models. • Supports adaptive, multi-layered planning frameworks. • Reinforces the utility of open innovation in identifying hidden user segments and leveraging their insights.

Using normalized Varimax-rotated factor analysis, the present research identifies latent structures of perceived motivations and barriers (RQ5). For obstacles, four dissimilar factors emerge: (1) Network and Infrastructure Shortfalls, with poorly designed paths and inadequate indications; (2) Personal and Environmental Obstacles, with health, weather, and gradients; (3) Obstruction to Route and Conflict between Users, with halting autos and foot path hindrance; and (4) Access to the Service and Service Establishments, with repair stores and station interruptions. Similarly, factor analysis of motivational uses yields two broad factors: (1) Recreational Use, for example, entertainment, weather-sensitive use, and sport; and (2) Functional and Mobility-Integrated Use, for example, commuting, shopping, and public transport integration. These underlying dimensions not only yield interpretive parsimony but also facilitate purposeful policy and design interventions into user needs in a systematic and segmented manner.

To sum up, this study reveals that bike-sharing systems in post-industrial smart cities exist at the intersection of legacy infrastructure and evolving user intentions. While recreational riders navigate barriers through sheer enthusiasm, utilitarian adoption remains stifled by systemic gaps. By adopting open innovation strategies—participatory design, modular pilots, and equity-focused governance—cities can transform BSS into inclusive mobility ecosystems. For regions like Silesia, this means honoring industrial pasts while co-creating sustainable futures, one bike lane at a time.

Author Contributions: Conceptualization, K.T. and R.W.; literature review: K.T. and R.W.; methodology, K.T. and R.W.; validation, K.T. and R.W.; formal analysis, K.T. and R.W.; investigation, K.T. and R.W.; writing—original draft preparation, K.T. and R.W. writing—review and editing, R.W.; funding acquisition, R.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author(s).

Acknowledgments: During the preparation of this manuscript, the author(s) used DeepL and Writefull tools for the purposes of [text editing (translation, grammar, structure, spelling, punctuation and formatting)]. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Ma, X.; Ji, Y.; Yuan, Y.; Van Oort, N.; Jin, Y.; Hoogendoorn, S. A Comparison in Travel Patterns and Determinants of User Demand between Docked and Dockless Bike-Sharing Systems Using Multi-Sourced Data. *Transp. Res. Part A Policy Pract.* **2020**, *139*, 148–173. [CrossRef]
2. DeMaio, P. Bike-Sharing: History, Impacts, Models of Provision, and Future. *JPT* **2009**, *12*, 41–56. [CrossRef]
3. Zhang, L.; Zhang, J.; Duan, Z.; Bryde, D. Sustainable Bike-Sharing Systems: Characteristics and Commonalities across Cases in Urban China. *J. Clean. Prod.* **2015**, *97*, 124–133. [CrossRef]
4. Sikorski, D.; Smętkiewicz, K. The Contemporary Transformation of Post-Industrial Areas in Post-Socialist Polish Cities: Case Studies from Wrocław (Kleczków) and Kraków (Zabłocie). *Stud. Reg. I Lokal.* **2025**, *26*, 22–38. [CrossRef]
5. Jingxiao, S. Research on the Impact of Transportation Infrastructure on Industrial Structure. *E3S Web Conf.* **2021**, *253*, 02055. [CrossRef]
6. Starczewski, T.; Rogatka, K.; Kukulska-Kozieł, A.; Noszczyk, T.; Cegielska, K. Urban Green Resilience: Experience from Post-Industrial Cities in Poland. *Geosci. Front.* **2023**, *14*, 101560. [CrossRef]
7. Jiménez-Meroño, E.; Soriguera, F. Optimization of Bike-Sharing Repositioning Operations: A Reactive Real-Time Approach. *EURO J. Transp. Logist.* **2024**, *13*, 100138. [CrossRef]
8. Tang, J.; Ren, M.; Yuan, Z.; Cai, J.; Liang, Y. System-Wide Optimization of Free-Floating Bike-Sharing for Urban Rail Stations: A Demand Prediction and Scheduling Approach. *Comput. Ind. Eng.* **2025**, *204*, 111121. [CrossRef]
9. Chen, Q.; Ma, S.; Li, H.; Zhu, N.; He, Q.-C. Optimizing Bike Rebalancing Strategies in Free-Floating Bike-Sharing Systems: An Enhanced Distributionally Robust Approach. *Transp. Res. Part E Logist. Transp. Rev.* **2024**, *184*, 103477. [CrossRef]
10. Bencekri, M.; Van Fan, Y.; Lee, D.; Choi, M.; Lee, S. Optimizing Shared Bike Systems for Economic Gain: Integrating Land Use and Retail. *J. Transp. Geogr.* **2024**, *118*, 103920. [CrossRef]
11. Saltykova, K.; Ma, X.; Yao, L.; Kong, H. Environmental Impact Assessment of Bike-Sharing Considering the Modal Shift from Public Transit. *Transp. Res. Part D Transp. Environ.* **2022**, *105*, 103238. [CrossRef]
12. Shen, H.; Weng, J.; Lin, P. Exploring the Nuanced Correlation between Built Environment and the Integrated Travel of Dockless Bike-Sharing and Metro at Origin-Route-Destination Level. *Sustain. Cities Soc.* **2025**, *119*, 106090. [CrossRef]
13. Yang, H.; Shi, J.; Tao, T. Where Do Built Environment Attributes Most Effectively Influence Bike Sharing Usage? *Transp. Res. Part D Transp. Environ.* **2025**, *143*, 104717. [CrossRef]
14. Zhou, J.; Lai, Y.; Tu, W.; Wu, Y. Exploring the Relationship between Built Environment and Spatiotemporal Heterogeneity of Dockless Bike-Sharing Usage: A Case Study of Shenzhen, China. *Cities* **2024**, *155*, 105504. [CrossRef]
15. Rauws, W.; Van Dijk, T. A Design Approach to Forge Visions That Amplify Paths of Peri-Urban Development. *Environ. Plann. B Plann. Des.* **2013**, *40*, 254–270. [CrossRef]
16. Anthony, B. The Role of Community Engagement in Urban Innovation Towards the Co-Creation of Smart Sustainable Cities. *J. Knowl. Econ.* **2024**, *15*, 1592–1624. [CrossRef]
17. Jonek-Kowalska, I.; Wolniak, R. *Smart Cities in Poland: Towards Sustainability and a Better Quality of Life?* Taylor & Francis: Oxford, UK, 2024; ISBN 1000935396.
18. Jonek-Kowalska, I.; Wolniak, R. Sharing Economies' Initiatives in Municipal Authorities' Perspective: Research Evidence from Poland in the Context of Smart Cities' Development. *Sustainability* **2022**, *14*, 2064. [CrossRef]
19. Wolniak, R. European Union Smart Mobility–Aspects Connected with Bike Road System's Extension and Dissemination. *Smart Cities* **2023**, *6*, 1009–1042. [CrossRef]
20. Wolniak, R. Analysis of the Bicycle Roads System as an Element of a Smart Mobility on the Example of Poland Provinces. *Smart Cities* **2023**, *6*, 368–391. [CrossRef]
21. Stecuła, K.; Wolniak, R.; Grebski, W.W. AI-Driven Urban Energy Solutions—From Individuals to Society: A Review. *Energies* **2023**, *16*, 7988. [CrossRef]
22. Skubis, I.; Wolniak, R.; Grebski, W.W. AI and Human-Centric Approach in Smart Cities Management: Case Studies from Silesian and Lesser Poland Voivodships. *Sustainability* **2024**, *16*, 8279. [CrossRef]

23. Wolniak, R.; Stecuła, K. Artificial Intelligence in Smart Cities—Applications, Barriers, and Future Directions: A Review. *Smart Cities* **2024**, *7*, 1346–1389. [CrossRef]
24. Wolniak, R.; Turoń, K. The Model of Relationships Between Benefits of Bike-Sharing and Infrastructure Assessment on Example of the Silesian Region in Poland. *Appl. Syst. Innov.* **2025**, *8*, 54. [CrossRef]
25. Silesian Voivoidship. Available online: https://www.slaskie.pl/content/gospodarka (accessed on 21 April 2025).
26. Zyoud, S.; Zyoud, A.H. Advancing Sustainable Cities and Communities with Internet of Things: Global Insights, Trends, and Research Priorities for SDG 11. *Results Eng.* **2025**, *26*, 104917. [CrossRef]
27. Siano, P.; Shahrour, I.; Vergura, S. Introducing Smart Cities: A Transdisciplinary Journal on the Science and Technology of Smart Cities. *Smart Cities* **2018**, *1*, 1–3. [CrossRef]
28. Anwar, A.H.M.M.; Oakil, A.T. Smart Transportation Systems in Smart Cities: Practices, Challenges, and Opportunities for Saudi Cities. In *Smart Cities*; Belaïd, F., Arora, A., Eds.; Studies in Energy, Resource and Environmental Economics; Springer International Publishing: Cham, Germany, 2024; pp. 315–337. [CrossRef]
29. Jacques, E.; Neuenfeldt Júnior, A.; De Paris, S.; Francescatto, M.; Siluk, J. Smart Cities and Innovative Urban Management: Perspectives of Integrated Technological Solutions in Urban Environments. *Heliyon* **2024**, *10*, e27850. [CrossRef]
30. Bike-Sharing Systems. Available online: https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://sustainabledevelopment.un.org/content/documents/4803Bike%2520Sharing%2520UN%2520DESA.pdf&ved=2ahUKEwiNmoG87OuMAxU5cfEDHeEZA4UQFnoECBkQAQ&usg=AOvVaw2IQBa6BKdFHSCQ09KevyMs (accessed on 21 April 2025).
31. Cheng, P.; OuYang, Z.; Liu, Y. Understanding Bike Sharing Use over Time by Employing Extended Technology Continuance Theory. *Transp. Res. Part A Policy Pract.* **2019**, *124*, 433–443. [CrossRef]
32. Bonilla-Alicea, R.J.; Watson, B.C.; Shen, Z.; Tamayo, L.; Telenko, C. Life Cycle Assessment to Quantify the Impact of Technology Improvements in Bike-sharing Systems. *J. Ind. Ecol.* **2020**, *24*, 138–148. [CrossRef]
33. Zahertar, A.; Lavrenz, S. Transit and Bikeshare Connectivity in Detroit: New Insights on Socioeconomic and Infrastructure Factors Impacting Perceived Quality of Service. *J. Urban Mobil.* **2025**, *7*, 100120. [CrossRef]
34. Fraser, T.; Van Woert, K.; Olivieri, S.; Baron, J.; Buckley, K.; Lalli, P. Cycling Cities: Measuring Urban Mobility Mixing in Bikeshare Networks. *J. Transp. Geogr.* **2025**, *126*, 104223. [CrossRef]
35. Li, J.; Wang, W. From Renting Economy to Sharing Economy: How Do Bike-Sharing Platforms Grow in the Digital Era? *J. Knowl. Econ.* **2023**, *15*, 8097–8117. [CrossRef]
36. Qiu, L.-Y.; He, L.-Y. Bike Sharing and the Economy, the Environment, and Health-Related Externalities. *Sustainability* **2018**, *10*, 1145. [CrossRef]
37. Zhu, L.; Ali, M.; Macioszek, E.; Aghaabbasi, M.; Jan, A. Approaching Sustainable Bike-Sharing Development: A Systematic Review of the Influence of Built Environment Features on Bike-Sharing Ridership. *Sustainability* **2022**, *14*, 5795. [CrossRef]
38. Guo, Y.; Yang, L.; Chen, Y. Bike Share Usage and the Built Environment: A Review. *Front. Public Health* **2022**, *10*, 848169. [CrossRef]
39. Dell'Olio, L.; Ibeas, A.; Moura, J.L. Implementing Bike-Sharing Systems. *Proc. Inst. Civ. Eng.—Munic. Eng.* **2011**, *164*, 89–101. [CrossRef]
40. Schuhmacher, L.; Kübler, J.; Wilkes, G.; Kagerbauer, M.; Vortisch, P. Comparing Implementation Strategies of Station-Based Bike Sharing in Agent-Based Travel Demand Models. *Procedia Comput. Sci.* **2024**, *238*, 396–403. [CrossRef]
41. Bruzzone, F.; Scorrano, M.; Nocera, S. The Combination of E-Bike-Sharing and Demand-Responsive Transport Systems in Rural Areas: A Case Study of Velenje. *Res. Transp. Bus. Manag.* **2021**, *40*, 100570. [CrossRef] [PubMed]
42. Guido, C.; Rafal, K.; Constantinos, A. A Low Dimensional Model for Bike Sharing Demand Forecasting. In Proceedings of the 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), Cracow, Poland, 5–7 June 2019; pp. 1–7. [CrossRef]
43. D'Andreagiovanni, F.; Nardin, A.; Carrese, S. An Analysis of the Service Coverage and Regulation of E-Scooter Sharing in Rome (Italy). *Transp. Res. Procedia* **2022**, *60*, 440–447. [CrossRef]
44. Fu, C.; Huang, Z.; Scheuer, B.; Lin, J.; Zhang, Y. Integration of Dockless Bike-Sharing and Metro: Prediction and Explanation at Origin-Destination Level. *Sustain. Cities Soc.* **2023**, *99*, 104906. [CrossRef]
45. Migdley, P. The Role of Smart Bike-Sharing Systems in Urban Mobility. Available online: https://www.academia.edu/download/79547632/The-Role-of-Smart-Bike-sharing-Systems.pdf (accessed on 21 April 2025).
46. Ferrari, G.; Tan, Y.; Diana, P.; Palazzo, M. The Platformisation of Cycling—The Development of Bicycle-Sharing Systems in China: Innovation, Urban and Social Regeneration and Sustainability. *Sustainability* **2024**, *16*, 5011. [CrossRef]
47. Haj Salah, I.; Mukku, V.D.; Kania, M.; Assmann, T.; Zadek, H. Could the next Generation of Bike-Sharing with Autonomous Bikes Be Financially Sustainable? *J. Urban Mobil.* **2024**, *6*, 100084. [CrossRef]
48. Julio, R.; Monzon, A.; Susilo, Y.O. Identifying Key Elements for User Satisfaction of Bike-Sharing Systems: A Combination of Direct and Indirect Evaluations. *Transportation* **2024**, *51*, 407–438. [CrossRef]
49. Bejarano, M.; Ceballos, L.M.; Maya, J. A User-Centred Assessment of a New Bicycle Sharing System in Medellin. *Transp. Res. Part F Traffic Psychol. Behav.* **2017**, *44*, 145–158. [CrossRef]

50. Fan, Z.; Harper, C.D. Taking a Multimodal Approach to Equitable Bike Share Station Siting. *J. Transp. Geogr.* **2024**, *115*, 103814. [CrossRef]
51. Heinen, E.; Bohte, W. Multimodal Commuting to Work by Public Transport and Bicycle: Attitudes Toward Mode Choice. *Transp. Res. Rec. J. Transp. Res. Board* **2014**, *2468*, 111–122. [CrossRef]
52. Griffin, G.P.; Sener, I.N. Planning for Bike Share Connectivity to Rail Transit. *J. Public Transp.* **2016**, *19*, 1–22. [CrossRef]
53. Filipe Teixeira, J.; Diogo, V.; Bernát, A.; Lukasiewicz, A.; Vaiciukynaite, E.; Stefania Sanna, V. Barriers to Bike and E-Scooter Sharing Usage: An Analysis of Non-Users from Five European Capital Cities. *Case Stud. Transp. Policy* **2023**, *13*, 101045. [CrossRef]
54. Liu, J.; Wang, M.; Chen, P.; Wen, C.; Yu, Y.; Chau, K. Riding towards a Sustainable Future: An Evaluation of Bike Sharing's Environmental Benefits in Xiamen Island, China. *Geogr. Sustain.* **2024**, *5*, 276–288. [CrossRef]
55. Antón-González, L.; Pans, M.; Devís-Devís, J.; González, L.-M. Cycling in Urban Environments: Quantitative Text Analysis. *J. Transp. Health* **2023**, *32*, 101651. [CrossRef]
56. Buehler, R.; Goel, R. A Global Overview of Cycling Trends. In *Advances in Transport Policy and Planning*; Elsevier: Amsterdam, The Netherlands, 2022; Volume 10, pp. 137–158. [CrossRef]
57. Hess, A.-K.; Schubert, I. Functional Perceptions, Barriers, and Demographics Concerning e-Cargo Bike Sharing in Switzerland. *Transp. Res. Part D Transp. Environ.* **2019**, *71*, 153–168. [CrossRef]
58. Chen, S.-Y. Green Helpfulness or Fun? Influences of Green Perceived Value on the Green Loyalty of Users and Non-Users of Public Bikes. *Transp. Policy* **2016**, *47*, 149–159. [CrossRef]
59. Caulfield, B.; O'Mahony, M.; Brazil, W.; Weldon, P. Examining Usage Patterns of a Bike-Sharing Scheme in a Medium Sized City. *Transp. Res. Part A Policy Pract.* **2017**, *100*, 152–161. [CrossRef]
60. Guo, Y.; Zhou, J.; Wu, Y.; Li, Z. Identifying the Factors Affecting Bike-Sharing Usage and Degree of Satisfaction in Ningbo, China. *PLoS ONE* **2017**, *12*, e0185100. [CrossRef] [PubMed]
61. Qian, X.; Niemeier, D. High Impact Prioritization of Bikeshare Program Investment to Improve Disadvantaged Communities' Access to Jobs and Essential Services. *J. Transp. Geogr.* **2019**, *76*, 52–70. [CrossRef]
62. Wang, B.; Guo, Y.; Chen, F.; Tang, F. The Impact of the Social-Built Environment on the Inequity of Bike-Sharing Use: A Case Study of Divvy System in Chicago. *Travel Behav. Soc.* **2024**, *37*, 100873. [CrossRef]
63. Waitt, G.; Buchanan, I.; Lea, T.; Fuller, G. Embodied Spatial Mobility (in) Justice: Cycling Refrains and Pedalling Geographies of Men, Masculinities, and Love. *Trans. Inst. Br. Geogr.* **2021**, *46*, 917–928. [CrossRef]
64. Behrendt, F.; Heinen, E.; Brand, C.; Cairns, S.; Anable, J.; Azzouz, L.; Glachant, C. Conceptualising Micromobility: The Multi-Dimensional and Socio-Technical Perspective. *Transp. Sci. Technol.* **2023**, preprint. [CrossRef]
65. Turoń, K.; Kubik, A. Open Innovation—Opportunities or Nightmares for the Shared Transport Services Sector? *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 101. [CrossRef]
66. Turoń, K. Open Innovation Business Model as an Opportunity to Enhance the Development of Sustainable Shared Mobility Industry. *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 37. [CrossRef]
67. Turoń, K.; Kubik, A. Business Innovations in the New Mobility Market during the COVID-19 with the Possibility of Open Business Model Innovation. *J. Open Innov. Technol. Mark. Complex.* **2021**, *7*, 195. [CrossRef]
68. Ruhrort, L. Reassessing the Role of Shared Mobility Services in a Transport Transition: Can They Contribute to the Rise of an Alternative Socio-Technical Regime of Mobility? *Sustainability* **2020**, *12*, 8253. [CrossRef]
69. Goudis, P.; Victoriano-Habit, R.; Carvalho, T.; El-Geneidy, A. Barriers, Adoption, and Use of a Bike-Sharing System: A Market-Segment Approach to Current and Potential Users in Montréal, Canada. *Transp. Res. Rec.* **2025**, 03611981251340377. [CrossRef]
70. Wang, J.; He, T. To Share Is Fair: The Changing Face of China's Fair Use Doctrine in the Sharing Economy and Beyond. *Comput. Law Secur. Rev.* **2019**, *35*, 15–28. [CrossRef]
71. Turoń, K. Car-Sharing Systems in Smart Cities: A Review of the Most Important Issues Related to the Functioning of the Systems in Light of the Scientific Research. *Smart Cities* **2023**, *6*, 796–808. [CrossRef]
72. Spiegelhalter, D. *How to Learn from Data*; Penguin Book: London, UK, 2019.
73. Freedman, D. *Statistics*; Viva Book; Norton Company: London, UK, 2011.
74. Timothy, B. *Confirmatory Factor Analysis for Applied Research*, 2nd ed.; Guilford Publications: New York, NY, USA, 2015.
75. Mulak, S.A. *Foundations of Factor Analysis*; Taylor and Francis: New York, NY, USA, 2009.
76. Pett, M.A.; Lackey, N.R.; Sullivan, J.J. *Making Sense of Factor Analysis: The Use of Factor Analysis for Instrument Development in Health Care Research*; Sage: Thousand Oaks, CA, USA, 2003.
77. Kim, J.O. *Introduction to Factor Analysis: What It Is and How to Do It*; Sage Publication: Thousand Oaks, CA, USA, 1978; p. 13.
78. Gaurav, K. *Multiple Regression Analysis: Key to Social Science Research*; GRIN Verlag: Munich, Germany, 2011.
79. Lütkepohl, H. *New Introduction to Multiple Time Series Analysis*; Springer: Berlin/Heidelberg, Germany, 2006.
80. Halvadia, N.B.; Bhatt, K.; Sharma, M.; Sharma, A.; Dash, S. Consumers' Intention to Use Bicycle-Sharing Services: The Role of Consumer Consciousness. *Clean. Responsible Consum.* **2022**, *7*, 100076. [CrossRef]
81. Bradley, K. Bike Kitchens—Spaces for Convivial Tools. *J. Clean. Prod.* **2018**, *197*, 1676–1683. [CrossRef]

82. Jinping, Y.; Yuxuan, W.; Xianna, Y. Beidou+ Industry Convergence Development and Intellectual Property Protection. *Lect. Notes Electr. Eng.* **2018**, *498*, 741–754.
83. Ferreras, L.E. iTRANS: Proactive ITS Based on Drone Technology to Solve Urban Transportation Challenge. In *Disrupting Mobility: Impacts of Sharing Economy and Innovative Transportation on Cities*; Springer Nature: Berlin/Heidelberg, Germany, 2017; pp. 323–333.
84. Turoń, K. Multi-Criteria Decision Analysis during Selection of Vehicles for Car-Sharing Services—Regular Users' Expectations. *Energies* **2022**, *15*, 7277. [CrossRef]

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