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Unlocking Sustainable Shared Mobility: A Hybrid Choice Model of Docked Bike-Sharing Adoption with Latent Accessibility Perceptions

Abstract

Bike-sharing systems (BSS) offer a promising pathway toward sustainable urban mobility, yet their successful adoption depends on factors that existing demand models often treat in isolation. This study develops a Hybrid Choice Model (HCM) to jointly examine the influence of objective attributes (e.g., bike lane type, pricing, and bike characteristics) and a latent accessibility perception variable capturing commuters' attitudes toward the proximity of BSS stations to diverse urban functions (universities, offices, shopping malls, restaurants, and public transit stops). Data were collected through face-to-face stated preference interviews with 378 employed and university student commuters in Gorgan, a mid-sized city in northern Iran. Results show that dedicated bike lanes, especially median-protected lanes, increase BSS adoption intent, whereas mixed-traffic conditions and higher usage costs suppress it. The latent accessibility perception variable exerts a strong positive influence on willingness to use BSS, with proximity to transit stations producing the largest marginal effect, followed by proximity to educational centers and offices. Higher education level, absence of household car ownership, regular private bike use, and university student status are positively associated with favorable accessibility perceptions, while higher BMI and complex trip chains reduce them. Building on the HCM coefficients, a novel Station Suitability Index (SSI) is introduced to guide spatially optimized station placement across the city's 96 Traffic Analysis Zones (TAZs). Finally, BSS adoption is estimated to displace approximately 91.6 tons of vehicle emissions annually, valued at over $76,600 per year, concentrated in high-SSI zones, demonstrating a compelling economic rationale for system expansion in developing-country cities.

Keywords: *Bike-sharing system; Hybrid Choice Model; Latent variable; Accessibility perception; Station Suitability Index; Developing cities*

1. Introduction

Urban transportation has increasingly become a source of challenges, including air and noise pollution (Nikitas, 2018), traffic congestion (Julio et al., 2024), and significant time loss for commuters (Hickman and Banister, 2014). In response, officials have advocated for sustainable mobility options, including the expansion of bike-sharing systems (BSS). These projects aim to reduce pollution (Sivak and Schoettle, 2012) and greenhouse gas emissions (An et al., 2026), boost public health (Bullock et al., 2017), alleviate traffic congestion (Shaheen et al., 2010), reduce Body Mass Index (BMI) (Molina-García et al., 2015), minimize energy consumption (Mi et al., 2017), promote active transportation (Yin and Scott, 2026), and improve connectivity among various transportation modes (Jäppinen et al., 2013).

Cities serve a variety of purposes, including residential, administrative, commercial, educational, religious, and transportation services (Maurer et al., 2000; Newman and Kenworthy, 1996). To effectively implement a BSS, it is crucial to place the system's stations close to these urban services (Zhao et al., 2020). The proximity of bike-sharing stations to relevant urban activities can significantly influence individuals' willingness to adopt the system, thereby increasing demand (Guo et al., 2022). Moreover, previous studies have highlighted the importance of aligning bike-sharing station locations with public transportation systems to enhance compatibility and efficiency (Tamakloe et al., 2021; Xia et al., 2019). Accordingly, the first premise of this study is that proximity of BSS stations to PT hubs and other urban amenities affects commuters' likelihood of choosing this mode of transport.

Research has shown that the successful development of BSS depends on a range of policies. This encompasses the deliberate design of the built environment, including the creation of bike lanes (e.g., protected bike lanes) and the enhancement of safety through the segregation of bike traffic from motorized vehicles (de Freitas and Axhausen, 2025; El-Assi et al., 2017; Jafari et al., 2025; Wu et al., 2021b), along with the provision of BSS-related amenities, such as front baskets (Chang et al., 2020; Henriksson et al., 2022). However, the effectiveness of BSS hinges not only on infrastructure provision but also on strategic station placement that matches users' daily activity patterns (Wolniak and Turoń, 2025). While integration with PT is well-documented (Kim, 2023; Kong et al., 2025; Kong et al., 2020), the influence of proximity to diverse non-transit urban functions, such as offices, universities, malls, and restaurants, on perceived accessibility and adoption intent remains underexplored, particularly in the context of non-discretionary (work- and education-related) trips.

On the other hand, pricing schemes for BSS are essential for increasing demand in urban trips (Fukushige et al., 2022; Reckermann et al., 2024). Moreover, the effective implementation of BSS requires evaluating Socio-Demographic Characteristics (SDCs), such as age, gender, and income (Deng and Zhao, 2023; Teixeira and Cunha, 2023), alongside Trip Characteristics (TCs), including travel duration (Deng and Zhao, 2023; McKelvey and Zavoina, 1975; Ye et al., 2020). According to previous studies, existing BSS demand models typically treat SDCs (Kutela et al., 2024; Yu, 2024), TCs (Cortez-Ordoñez et al., 2024; Xue et al., 2024), built environment factors (Ethier et al., 2024; Yan and Chen, 2024), and pricing policies (Li et al., 2025; Manout et al., 2024) in isolation, often overlooking subjective perceptions of station accessibility that mediate behavioral responses. Additionally, nearly all prior studies focus on large metropolitan areas in developed countries, leaving a critical knowledge gap regarding BSS viability in small- to mid-sized cities in developing countries, where car ownership is rising, public transportation is informal, and cycling infrastructure is limited. This study addresses these gaps by developing a Hybrid Choice Model (HCM) that integrates a latent accessibility perception variable, constructed from agreement levels with proximity to different urban functional areas, thereby capturing attitude–behavior linkages.

To address the challenges of suboptimal station placement in BSS, which often lead to underutilization and inefficient resource allocation in urban environments, this study introduces a novel Station Suitability Index (SSI) as a comprehensive metric to guide optimal siting decisions. Unlike previous approaches, the SSI integrates objective land-use factors (proximity to universities, offices, shopping malls, restaurants, and public transit stations) to provide a data-driven framework for prioritizing locations that maximize accessibility and user adoption. This framework is practical for cities aiming to enhance

sustainable mobility, as it translates spatial data into actionable siting recommendations. Beyond the SSI, a second contribution of this paper is to jointly analyze commuters' preferences for proximity to different land-use types (e.g., offices, universities, restaurants, malls) alongside the provision of protected bike lanes, rather than treating them as separate factors. Most existing studies examine infrastructure or land use in isolation; this study explicitly integrates both to show how they interact to enhance BSS effectiveness and adoption. Together, the SSI and this integrated analysis help cities avoid underutilization and inefficient resource allocation. Furthermore, BSSs are a sustainable transport mode that remains largely neglected in many developing and mid-sized cities of developing countries. Nevertheless, BSS can generate significant public cost-saving benefits by reducing traffic emissions and encouraging commuters to shift from private motorized vehicles to more sustainable transport modes such as cycling.

This research examines four core questions:

(1) How does perceived proximity to urban functions influence the willingness to use BSS for urban trips in different traffic zones of a city?
(2) What role do dedicated bike lanes and pricing policies play in shaping the willingness to use the BSS in a city?
(3) How does perceived proximity vary across different observed factors?
(4) How can the adoption of BSS generate public cost savings?

The paper is organized in the following manner: Section 2 explores the existing literature; Section 3 delineates the HCM framework; Section 4 provides an overview of the case analysis in Iran; Section 5 illustrates the results; Section 6 examines policy applications and SSI; and Section 7 concludes with implications and recommendations.

2. Literature review

The studies show advancements in prioritizing BSSs in cities by improving commuters' access to stations for renting shared bikes and developing cycling lanes throughout the cities. With the advent of BSSs in the Netherlands during the 1960s and their progression through four generations, from rudimentary communal bikes to advanced dockless models leveraging GPS and apps (Shaheen et al., 2011), extensive research has explored the determinants of public adoption of this green transit option (Bergantino et al., 2021; Blazanin et al., 2022). Scholars, through interdisciplinary lenses, have examined SDCs, including gender (Fortes et al., 2024; Teixeira and Cunha, 2023), education level (Bergantino et al., 2021; Fishman, 2016a), car ownership (Barbour et al., 2019; Shaer et al., 2021), bike ownership (Böcker and Anderson, 2020; Curto et al., 2016; Fuller et al., 2013), BMI (de Haas et al., 2021), and employment status (Du and Cheng, 2018; Mohiuddin et al., 2024; Torrisi et al., 2021); TCs such as the frequency of trips (Politis et al., 2020), trip cost (Hajilari et al., 2025), and tour complexity (Bordagaray et al., 2016; Zhang et al., 2018; Zhao et al., 2015); infrastructural aspects like the bike's ROW (Amiri and Sadeghpour, 2015; Heinen et al., 2010) and station accessibility (Faghih-Imani et al., 2014; Wang and Akar, 2019). The following review examines bike-sharing station allocation based on land use and bike lane development.

2.1. Bike-sharing station allocation

Previous studies have shown that factors such as land use mixtures (Bachand-Marleau et al., 2012), population density (Buck and Buehler, 2012; Wang et al., 2016), and the proximity of bike-sharing stations to urban infrastructure, such as PT hubs (Wu et al., 2021b), can significantly influence individuals' willingness to use BSS. Among these, one of the key factors determining the success of any BSS is the location and distribution of its stations (Lin and Yang, 2011). Different strategies are used for station placement: in some cities, bike-sharing stations are concentrated in the city center, while in others, such as Paris, stations are spread across the entire urban area (García-Palomares et al., 2012). Notably, BSSs are primarily designed for individuals undertaking non-discretionary trips, which means stations should be strategically located near educational, administrative, and commercial areas (Midgley, 2011).

Many studies have focused on identifying the most effective locations for bike-sharing stations. For instance, Wang and Akar (2019) examined factors affecting BSS usage by gender in New York City. It revealed that the likelihood of using BSS decreases as the distance between stations and universities increases. Faghih-Imani and Eluru (2015) conducted a study in Chicago and showed a positive correlation between bike lanes and bike-sharing stations, suggesting that longer bike lanes near stations encourage users to choose those stations as their destination. This study also found that as the length of main streets surrounding bike-sharing stations increases, people are less likely to select those stations as a destination. A study in Suzhou, China, found that bike-sharing stations located near densely populated areas, such as large shopping malls, office buildings, universities, subway stations, commercial zones, and residential neighborhoods, resulted in higher BSS usage (Wu et al., 2021a).

Furthermore, a study examined BSS usage in Montreal, Canada, and found that increased distance between bike-sharing stations and the city center negatively affected usage, while proximity to subway stations and restaurants within 250 meters had a positive influence (Faghih-Imani et al., 2014). These findings are aligned with research conducted in Washington, DC, by Tushar and Buehler (2024). Kim and Cho (2021) investigated BSS usage in Seoul, South Korea, and found that the proximity of bike-sharing stations to subway stations at both the origin and destination of trips, as well as their proximity to residential areas at trip destinations, had the greatest positive impact on individuals' willingness to use BSS. Prior research has highlighted the importance of integrating BSSs with PT networks in urban planning (Liu et al., 2022; Rogers III et al., 2023). For instance, a study conducted in New York City, which examined the destination choices of BSS users, found that the accessibility of bike-sharing stations to PT stations significantly influenced users' destination decisions (Faghih-Imani and Eluru, 2020). Similarly, a study in Shenzhen, China, revealed that the proximity of bike-sharing stations to commercial centers during workdays had a greater effect on increasing BSS usage among various user groups (Zhao et al., 2020).

Various studies have shown that the acceptable walking distance between PT stations and bike-sharing stations ranges from 100 to 200 meters. For example, interviews with operators, experts, and other stakeholders on the location and spacing of bike-sharing stations in a study conducted by Shaheen et al. (2014) in North America revealed that 16 operators considered an appropriate distance between bike-sharing and PT stations to be, on average, 120 meters or less. In addition, 15 operators indicated that the optimal distance between stations is 200 meters. Similarly, a study on the BSS in Warsaw, the capital of

Poland, found that the average distance between PT stations (bus and tram) is 112 meters (Betkier et al., 2025). Shu et al. (2019) in Beijing, China, reported that people tend to walk an average of 124 meters to reach a bike-sharing station. According to this study, 70% of respondents walk within 100 meters to access a bike-sharing station, and the optimal and tolerable distances between bike-sharing stations and bus stops are 30 and 130 meters, respectively.

2.2. Bike lane development

Studies have emphasized the importance of bike lanes as another critical factor in the success of BSSs (Amiri and Sadeghpour, 2015; Garrard et al., 2008; Heinen et al., 2010), as they reduce the risk of collisions with motor vehicles and alleviate the perceived threat from cars to cyclists (Broach et al., 2012; Fishman, 2016b). For instance, Fitch and Handy (2020) found that cyclists prefer routes with less mixed traffic. The study also revealed that a 30% increase in bike lanes leads to a 20% reduction in trip length. Similarly, another study that investigated factors influencing gender differences in cycling found that the presence of dedicated bike lanes positively impacts individuals' willingness to use BSS. (Wang and Akar, 2019). This study also revealed that women are more sensitive to BSS infrastructure than men, tend to use BSS for discretionary trips, and typically have longer trip chains. Likewise, a study conducted in Hamilton, Canada, found that the implementation of dedicated cycling lanes significantly increased BSS users' willingness to travel longer distances by shared bikes. This study also shows that following the intervention, bike-sharing trips increased by approximately 27% (Van Veghel and Scott, 2024). This finding indicates that dedicated bike lanes enhance the safety and accessibility of the cycling track for BSS users. AitBihiOuali and Klingen (2022) examined gender differences in BSS participation in relation to the safety of cycling infrastructure using data from New York City's BSS (Citibike). Their findings indicate that the implementation of segregated bike lanes increases BSS usage among both genders. Moreover, the results show that higher levels of protected bike-lane coverage along a route are associated with a greater willingness among women to use BSS.

On the other hand, studies have indicated that cyclists' willingness to use BSS decreases when they are required to travel on mixed-traffic lanes (Chataway et al., 2014; Fitch and Handy, 2020). Guo et al. (2023) investigated cyclists' physiological and behavioral variations across several intracity road configurations, including as-built, curbside bike lanes, and protected bike lanes. They found that both females and males perceive lower safety in mixed-traffic lanes compared to other roadway designs. Similarly, Chataway et al. (2014), in comparing the perceptions and behaviors of cyclists in Brisbane and Copenhagen, found that cyclists feel unsafe on shared roadways (e.g., mixed traffic), particularly when they are riding between parked automobiles and motorized traffic. This research also suggests that Danish cyclists feel safer riding compared to their Australian counterparts because of the implementation of segregated and wider cycling tracks. Another study conducted in Phoenix using BSS data (e.g., Grid Bikeshare) found that BSS users tend to favor routes with a higher proportion of cycling lanes. These lanes significantly influence cyclists' perceptions by reducing the perceived travel distance and enhancing both comfort and safety, making them more appealing to riders (Khatri et al., 2016).

Furthermore, many studies have identified mixed land use and commercial areas as positive factors influencing people's willingness to use BSSs (Lin et al., 2018; Zhou et al., 2024), as these areas can reduce travel distances and enhance the appeal of BSS (Sun et al., 2018). However, a study found that

many cyclists tend to avoid routes that pass through commercial areas, such as restaurants, offices, and shops (Fitch and Handy, 2020). This behavior is likely due to the fact that entering these areas increases the overall trip length.

Prior studies mostly attempt to investigate the relationship between bike-sharing stations' proximity to different urban configurations and have found that the presence of bike-sharing stations near high-density areas, PT stations, and commercial districts can increase BSS usage. However, there is a gap in research regarding individuals' attitudes toward the accessibility of bike-sharing stations to these functions. Given that psychological factors and attitudes toward accessibility can provide deeper insights into user preferences, incorporating these variables could lead to more accurate and effective strategies for bike-sharing station allocation in urban areas. Additionally, there are no mechanisms for bike-sharing station allocation based on the prevailing index related to attitudes toward accessibility. This gap in the literature suggests that existing allocation models may not fully capture the complexities of user preferences, which are influenced not only by physical proximity but also by how accessible users perceive these stations to be, based on their attitudes and experiences. Furthermore, to the best of the authors' knowledge, no study has investigated the elasticity of factors on shared bike usage based on attitudinal factors, which may be due to the complexity of statistical calculations.

3. Methodology

As mentioned in the Section 1, this study seeks to examine the influence of both objective and subjective factors on BSS usage. To this end, an HCM was employed, since it effectively captures the role of subjective factors (Vij and Walker, 2016). It is worth noting that prior research on the behavioral aspects of BSS adoption has applied the HCM to evaluate the effects of attitudes on travel behavior (Ma et al., 2023; Zhang and Li, 2023). In this paper, we first explain the data collection process and then describe the HCM.

3.1. Data collection

Data collection was carried out by a trained team of undergraduate interviewers following a systematic respondent selection protocol. Five undergraduate students were recruited to form the interviewing team responsible for conducting the field data collection. To prepare them for the fieldwork ahead, a dedicated training session was held before operations began, during which interviewers were familiarized with the kinds of difficulties they might encounter and instructed on the appropriate procedures for random respondent selection. Under this protocol, each interviewer was asked to take up a position in a high-traffic area, designate a stationary landmark nearby, and invite every second passerby to participate in the survey. As soon as one interview concluded, the selection process would resume without delay. The typical duration of each interview was around 18 minutes.

Participation followed a structured screening procedure. Prospective respondents were initially asked whether they were willing to take part in the survey. Those who expressed willingness were then assessed against two eligibility criteria through the following questions: 1) "*Did all your travels within the past 24 hours originate and end in the city of Gorgan?*" and 2) "*Are you currently employed or enrolled in a university in Gorgan city?*" Individuals who could not confirm both conditions were not included in the study.

Within the interview itself, one question was posed to gauge each respondent's prior exposure to bike-sharing: "*Do you know what a bike-sharing system is?*" A simple yes or no response was expected. For those who were unfamiliar with the concept, interviewers stepped in to offer a comprehensive explanation of how such systems operate before proceeding.

To maximize the diversity and reliability of the sample, interviews were carried out face-to-face across multiple types of locations throughout Gorgan, encompassing public administration buildings, commercial zones, and university premises. Because the survey focused on travel patterns from the day before the interview, data collection was restricted to weekday hours between 9:00 and 17:00, deliberately avoiding Saturdays, which serve as the first day of the working week in Iran, as well as any designated public holidays. The overall data collection window extended from January 28 through April 9, 2023.

The determination of the minimum sample size was carried out by means of the simple random sampling technique, as introduced by Hensher et al. (2005), a method widely regarded as yielding the lowest statistically acceptable threshold for research of this nature. With respect to the parameters governing this calculation, both the confidence level and the maximum relative deviation having been fixed at 10%, and the true proportion being assumed at 40%, the resulting calculation necessitates a minimum of 101 fully completed questionnaires for the study to be considered methodologically sound.

3.2. Analytical method

The HCM includes three types of components: (i) the structural equations for the latent variables, (ii) the measurement equations, and (iii) the utility function of alternative (e.g., BSS mode choice). For this study, only one subjective factor (i.e., attitude toward BSS accessibility) is considered. Accordingly, the structural equation for the latent variable of attitude towards BSS accessibility can be formulated as Equation (1).

$$LV_{nt}=AX_{nt}+\gamma_{nt} \tag{1}$$

where LV_{nt} represents the latent variable for the n^{th} respondent in choice task t^{th}, A is the $(1\times L)$ vector of coefficients, X_{nt} is the $(L\times 1)$ vector of explanatory variables for the n^{th} respondent in choice task t^{th}, and γ_{nt} is the error term for the n^{th} respondent in choice task t^{th}, which is assumed to be Normally distributed with a mean of zero and variance σ_{γ}^2, (i.e., $\gamma_{nt} \sim N(0,\sigma_{\gamma}^2)$). Therefore, the Probability Density Function (PDF) for γ_{nt} can be written as Equation (2).

$$f_{LV_{nt}}\left(LV_{nt}\middle|X_{nt};A,\sigma_{\gamma}\right)=\left(\frac{1}{\sqrt{2\pi}\sigma_{\gamma}}\right)exp\left(-\frac{1}{2}\left(\frac{LV_{nt}-AX_{nt}}{\sigma_{\gamma}}\right)^2\right) \tag{2}$$

Equation (3) shows the measurement equation for the indicators of the latent variable (i.e., indicators of attitude towards BSS accessibility).

$$I_{snt}=\lambda_s LV_{nt}+\vartheta_{snt} \tag{3}$$

where I_{snt} is the predicted value of the s^{th} indicator for the latent variable LV_{nt} stated by the n^{th} respondent in choice task t^{th}, λ_s is the coefficient of the latent variable for the s^{th} indicator, and ϑ_{snt} is the random

error term in the equation of the s^{th} indicator, for the n^{th} respondent in choice task t^{th}. This error term is also assumed to be normally distributed with a zero mean and a variance of $\sigma^2_{s\vartheta}$, (i.e., $\vartheta_{snt} \sim N(0,\sigma^2_{s\vartheta})$).

The indicators are measured based on a Likert scale with K levels. In this regard, the approach introduced by McKelvey and Zavoina (1975) has been used to formulate the indicators as discrete levels. In this approach, it is assumed that each measured indicator follows a function as given in Equation (4).

$$i_{snt}=\begin{cases} 1, & if\ \tau_0 \leqslant I_{snt} < \tau_1 \\ \vdots & \vdots \\ K, & if\ \tau_{K-1} \leqslant I_{snt} < \tau_K \end{cases} \qquad \forall(\tau_0 = -\infty \leqslant \tau_1 \leqslant \cdots \leqslant \tau_{K-1} \leqslant \tau_K = +\infty) \tag{4}$$

where i_{snt} is the measured s^{th} indicator for the n^{th} respondent in choice task t^{th}, τ_k and τ_{k-1} are the upper and lower thresholds for the k^{th} and $(k\text{-}1)^{th}$ level of predicted indicators, respectively. The measured s^{th} indicator can be reformulated as a matrix, as shown in Equation (5).

$$Z_{st} = \begin{bmatrix} Z_{s,1,1} & \cdots & Z_{s,1,K} \\ \vdots & \ddots & \vdots \\ Z_{s,N,1} & \cdots & Z_{s,N,K} \end{bmatrix} \tag{5}$$

where Z_{st} shows the measured indicator matrix for the s^{th} representative across all respondents in the sample, N is the total number of respondents, and K is the number of indicator levels. Each element of the Z_{st} matrix, $Z_{s,nt,k}$ can be formulated as a dummy variable, as follows:

$$Z_{s,nt,k}=\begin{cases} 1 & If\ decision\text{-}maker\ n^{th}\ chooses\ the\ indicator\ at\ level\ k \\ 0 & Otherwise \end{cases} \qquad \forall(k \in \{1, \ldots, K\}) \tag{6}$$

Based on the normality assumption, the probability of the k^{th} level for the s^{th} indicator, which can be chosen by the n^{th} respondent in choice task t^{th}, will be written as Equation (7).

$$Pr_{s,nt,k}\left(Z_{s,nt,k}=1|X_{nt},LV_{nt},\lambda_s,\tau_k,\sigma_\vartheta\right)=\varphi\left(\frac{\tau_k-\lambda_s LV_{nt}}{\sigma_\vartheta}\right)-\varphi\left(\frac{\tau_{k-1}-\lambda_s LV_{nt}}{\sigma_\vartheta}\right) \qquad \forall(k\in\{1,\ldots,K\}) \tag{7}$$

The joint probability of the n^{th} respondent in choice task t^{th} choosing the levels of indicators is given in Equation (8).

$$g_{nt}(Z_{nt}|X_{nt},LV_{nt},\lambda,\tau_k,\sigma_\vartheta)=\prod_{s=1}^{S}\prod_{k=1}^{K}\left(\left(\varphi\left(\frac{\tau_k-\lambda_s LV_{nt}}{\sigma_{s\vartheta}}\right)-\varphi\left(\frac{\tau_{k-1}-\lambda_s LV_{nt}}{\sigma_{s\vartheta}}\right)\right)^{Z_{s,nt,k}}\right) \tag{8}$$

It should be noted that identifying the structural equation model for latent variables requires certain assumptions regarding the fixation of specific parameters in the HCM to ensure an appropriate scaling of the latent variables. Typically, the variance of the error term and the coefficient of the latent variable in one of the measurement equations are fixed to unity to address the identification problem associated with the latent variable (Abou-Zeid and Ben-Akiva, 2024; Hess et al., 2018).

Furthermore, assuming that the discrete measured indicators follow a normal PDF, the thresholds can be treated as symmetrical, consistent with approaches adopted in prior studies (Forero et al., 2009; Rhemtulla et al., 2012). Therefore, the approach suggested by Bierlaire (2016) was adopted to

reformulate the thresholds for indicators measured on a five-point scale. Following this approach, the thresholds are expressed as a function of two parameters, δ_1 and δ_2, as shown in Equations (9) to (12).

$$\tau_1 = -\delta_1 - \delta_2 \tag{9}$$

$$\tau_2 = -\delta_1 \tag{10}$$

$$\tau_3 = \delta_1 \tag{11}$$

$$\tau_4 = \delta_1 + \delta_2 \tag{12}$$

The utility of using BSS can be formulated as Equation (13), while the utility function for other modes can be written as Equation (14).

$$U_{Shared\ bike,\ nt} = \beta X_{nt} + \alpha LV_{nt} + \eta_n + \varepsilon_{Shared\ bike,\ nt} \tag{13}$$

$$U_{Others,\ nt} = \varepsilon_{Others,\ nt} \tag{14}$$

where $U_{Shared\ bike,\ nt}$ is the utility of using the BSS for the n^{th} respondent in choice task t^{th}, $U_{Others,\ nt}$ is the utility of other modes of transportation for the n^{th} respondent in choice task t^{th}, β is the $(1 \times L)$ vector of coefficients (i.e., non-random parameters) for the observed variables, α is the coefficient of the latent variable of attitude towards BSS accessibility, $\varepsilon_{Shared\ bike,\ nt}$ and $\varepsilon_{Others,\ nt}$ are the error terms associated with the utility functions of BSS and the other modes of transportation, respectively. In addition, $\eta_n \sim N(0, \sigma_\eta^2)$ is a random effect capturing serial correlation across tasks for the respondent n,

Given that the observation of the commuters' behavior is binary, choosing BSS ($j=1$) or not ($j=0$), the choice indicator can be assumed to be a dummy variable representing the commuters' choice. Therefore, Equation (15) can be written in terms of this dummy.

$$y_{jnt} = \begin{cases} 1;\ If\ the\ respondent\ n\ at\ choice\ task\ t\ chooses\ alternative\ j^{th} \\ 0;\ Otherwise \end{cases} \tag{15}$$

where y_{jnt} is equal to 1 when the n^{th} respondent in choice task t^{th} chooses the alternative j^{th}, and otherwise is zero. Accordingly, the probability of the n^{th} respondent in choice task t^{th} choosing the j^{th} alternative can be written as shown in Equation (16).

$$P_{ntj}\left(y_{ntj}=1 | X_{nt}, LV_{nt};\ \beta, \alpha\right) = \frac{e^{U_{j,\ nt}}}{\sum_{h=1}^{2}(e^{U_{h,\ nt}})} \tag{16}$$

The likelihood of choosing between J modes ($j=1$ for the BSS and $j=2$ for the other modes) by n^{th} respondent in choice task t^{th} can be formulated as Equation (17).

$$P_{nt}(y_{nt} | X_{nt}, LV_{nt},\ \beta, \alpha) = \prod_{j=1}^{J} \left(P_{ntj}\left(y_{ntj} | X_{nt}, LV_{nt};\ \beta, \alpha\right)\right)^{y_{ntj}} \tag{17}$$

The likelihood function for the observation nt represents the joint probability of choosing mode (i.e, BSS or other modes) and the probability associated with choosing the levels of indicators as presented in Equation (18).

$$f_{nt,i}(y_{nt},\ i_{nt}|X_{nt},\ \beta,\alpha,\ \lambda,\tau_k,\ A)=$$

$$\int_{LV} P_{nt}(y_{nt}|X_{nt},LV_{nt},\ \beta,\alpha)g_{nt}(Z_{nt}|X_{nt},LV_{nt},\lambda,\tau_k,\sigma_9)f_{LV_{nt}}\left(LV_{nt}\middle|X_{nt}\ ;A,\sigma_\gamma\right)dLV \tag{18}$$

As the integral in the above equation has no closed-form solution, a numerical simulation approach should be used for its estimation (Vij and Walker, 2016).

4. Case study

The city of Gorgan, situated to the southeast of the Caspian Sea, has been selected as the focal point of this research study. Characterized by an average annual relative humidity of 69.73% and an average annual temperature of 17.80°C, Gorgan spans an area of 36.73 km², with a population totaling 676,350 (Statistical Center of Golestan Province, 2016). Administratively, the city is partitioned into three overarching districts, subdivided further into eight distinct zones, each encompassing a total of 109 neighborhoods. In terms of land allocation, 31% of the entire area is designated for residential purposes, while 14% is reserved for activity and facility-based uses, and 20% is dedicated to the development of access networks. Moreover, it is noteworthy that over 35% of the urban land either remains fallow or is earmarked for non-urban endeavors (Dadashpoor and Rostami, 2017). The overall population density stands at a modest 1,000 individuals per square kilometer, whereas the average neighborhood density is considerably higher, reaching 12,300 individuals per square kilometer. This notable discrepancy can largely be attributed to the significantly low population density observed in certain underdeveloped areas of the city, where infrastructure and urbanization are still in the nascent stages (Statistical Center of Golestan Province, 2016). Figure 1 presents the location and land-use map of Gorgan City.

Gorgan was selected for this study for two principal reasons: first, the absence of prior research on the allocation of bike-sharing stations based on commuters' preferences in northern Iranian cities, and second, Grogan’s status as the political hub of Golestan Province, which results in it experiencing the highest frequency of non-discretionary trips among the province’s cities, thereby leading to significant traffic congestion on its primary arterial roads during peak hours.

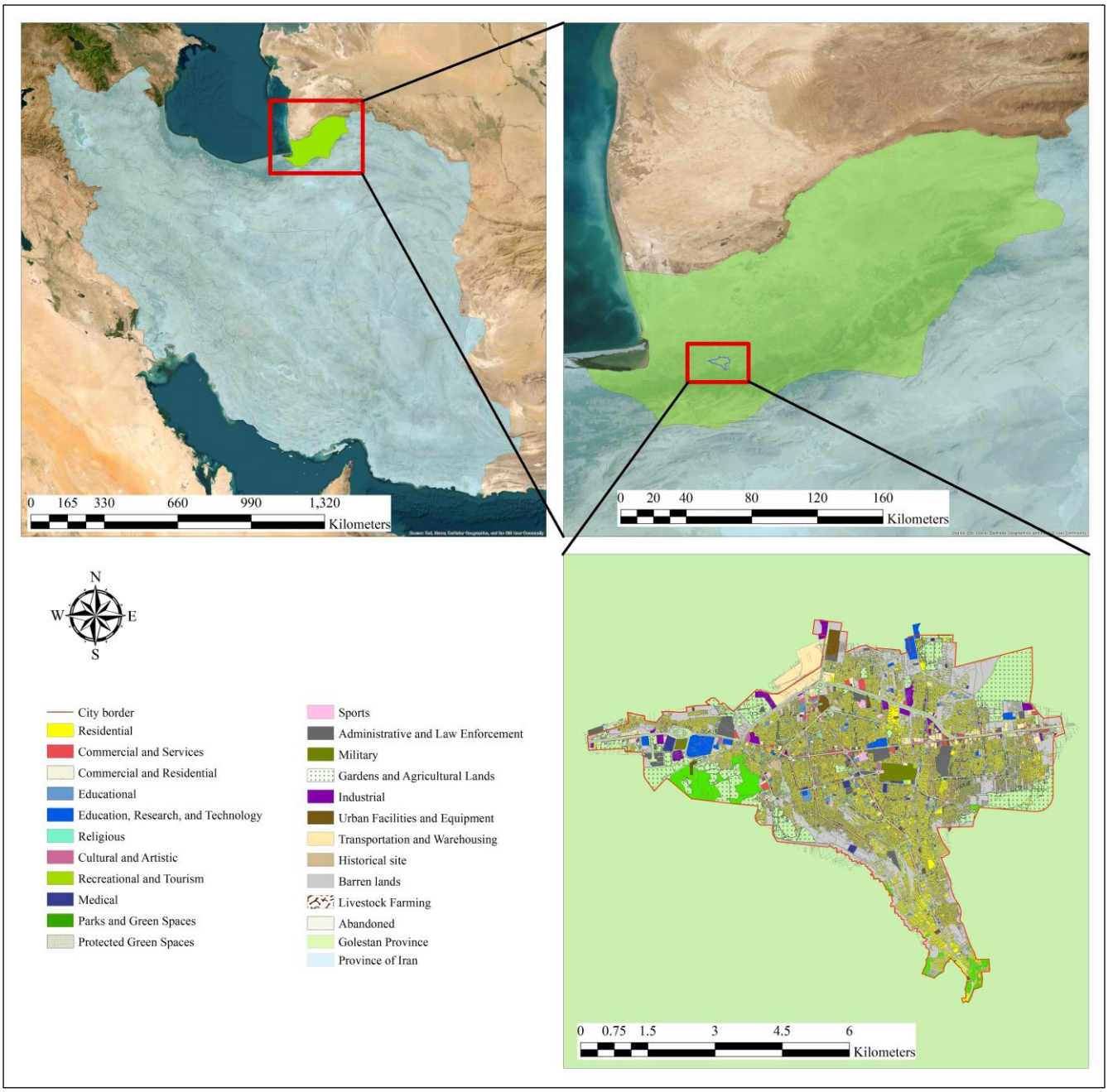


Figure 1. Case study area, Gorgan city, Iran (Created by ArcMap 10.8)

According to the literature review section, this study, by using a Stated Preferences (SP) questionnaire, examined seven factors that influence an individual's willingness to use BSS. The following factors were considered: (1) the BSS pricing; (2) bike lane type; (3) shared bike type; (4) the presence of rear and front lights; (5) the presence of a front basket; (6) the presence of a horn; and (7) the presence of an airbag. Given the extensive array of parameters considered, a Design of Experiment (DOE) methodology was employed, utilizing an optimized design strategy to curtail the number of choice experiments. As depicted in Table 1, the DOE framework comprised 16 distinct scenarios, yielding a D-Efficiency value of 96.16%. To alleviate respondent fatigue and enhance the quality of the interviews, these scenarios were systematically randomized and allocated across four distinct questionnaire codes.

Table 1. DOEs for the survey

Attributes	*Levels*
BSS cost (Cent/15 minutes)	*3, 4, 5*
Bike lane type	*Median bike lane, Curb bike lane, Buffered bike lane, Mixed traffic*
Bike-sharing type	*Regular, Geared, Electric*
Basket	*Available / Not available*
Horn	*Available / Not available*
Headlight and taillight	*Available / Not available*
Cycling airbag	*Available / Not available*

The questionnaire utilized in this study consisted of four primary sections: (1) trip diaries, (2) scenarios for assessing their willingness to utilize BSS, (3) aspects concerning the accessibility of bike-sharing stations to critical locations, and (4) SDCs. The initial segment collected comprehensive data regarding participants' intracity trip diaries from the preceding day. It included information on the purpose of the trip, the mode of transportation, the approximate origins and destinations, and the stated departure and arrival times. Furthermore, it evaluated the participants' willingness to employ a free BSS option.

Four SP scenarios were introduced in the second section, which was developed using the DOE framework to evaluate the probability of participants adopting BSS. Each questionnaire was accompanied by a supplementary card and focused on distinct categories of bike lanes (see Figure 2a). The introduction to this section began with a comprehensive overview of the diverse categories of bike lanes, which were presented to the interviewees as follows:

I. Median bike lanes are fully protected lanes located centrally, within the median of vehicular traffic, and are exclusively reserved for cyclists, ensuring complete separation from other modes of transportation.
II. Curb bike lanes are lanes that are delineated from vehicular traffic by barriers placed along the curbside, thereby safeguarding cyclists while still maintaining proximity to motorized vehicles.
III. Buffered bike lanes are designated bicycle lanes that, although intended for cyclist use, are situated in such a manner that they may potentially interact with or be influenced by adjacent motorized traffic, thus necessitating a careful balance of spatial allocation.
IV. Mixed traffic lanes are shared lanes where cyclists and motorized vehicles coexist, navigating the same space and requiring mutual awareness and respect for safety and efficiency.

Then, the interviewees were asked the question: "*If there had been a bike-sharing system with the following features, would you consider using this shared-bike service for your trips yesterday?*" As presented in Figure 2b, afterward, the respondents were instructed to select a choice for each scenario.



2a) Types of bike lanes (Unity 3D software output)

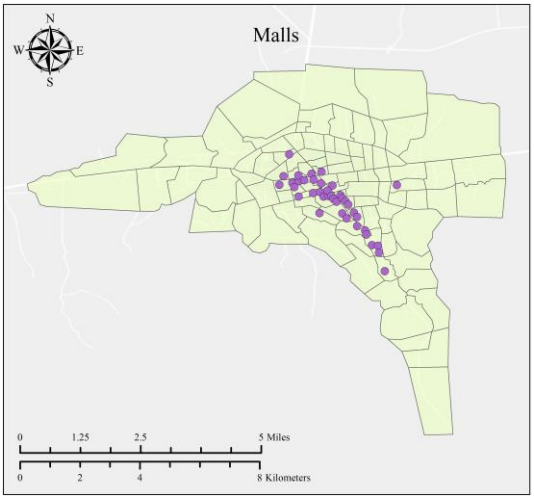
If there had been a bike-sharing system with the following features, would you consider this shared bike service for your yesterday's trips?

Cost (Cent/15 minutes)	Share-bike type	Lane type	Cycling airbag	Light	Horn	Basket	Choice
3	E-bike	Buffered lane	Avail.	N/A	Avail.	Avail.	☐ BSS ☐ No change

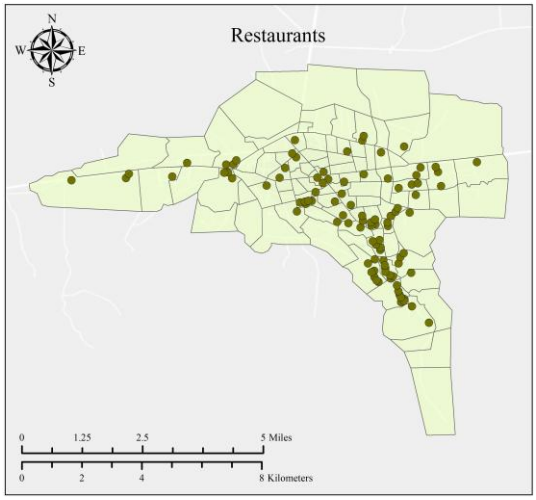
2b) A stated preferences scenario from block 2

Figure 2. Case study area, Gorgan city, Iran (Created by ArcMap 10.8)

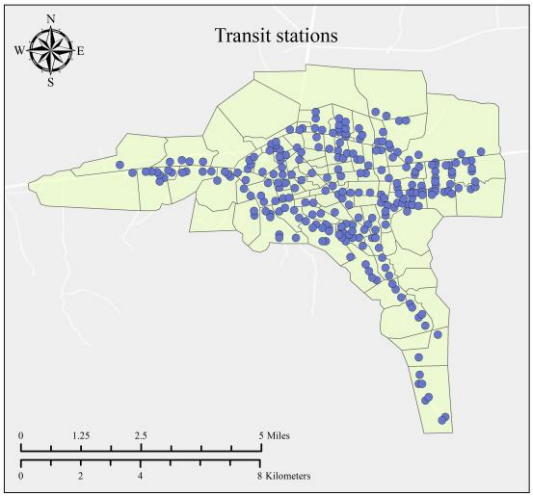
The third section assessed the extent of respondents' agreement regarding the placement of bike-sharing stations at specific locations, including but not limited to restaurants, malls, PT stations (e.g., public bus stations), workplaces, universities, and religious sites (e.g., mosques). Responses were systematically recorded using a five-point Likert scale, with the range spanning from "*Strongly agree*" to "*Strongly disagree*." Figure 3 illustrates the distribution of these locations in the city of Gorgan. The coordinates of these locations were obtained from Neshan, an Iranian navigation platform (Neshan, 2025). Moreover, Figure 4 summarizes the average values for these indicators. Finally, the fourth section includes questions about the respondents' SDCs, such as age, gender, employment status, number of household members, and household car ownership.



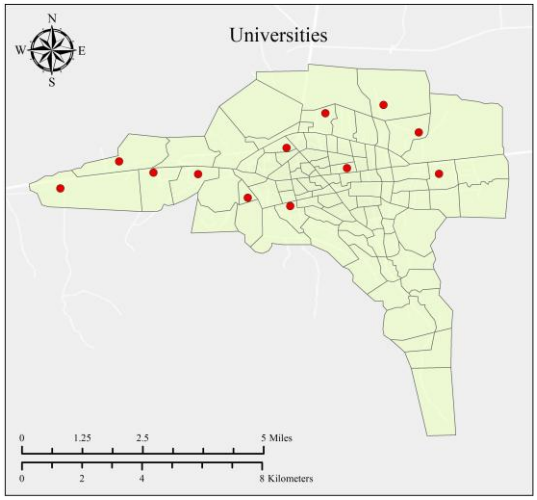
a. Malls



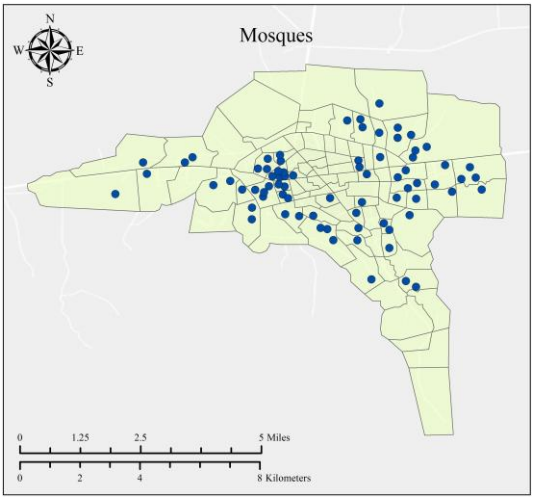
b. Restaurants



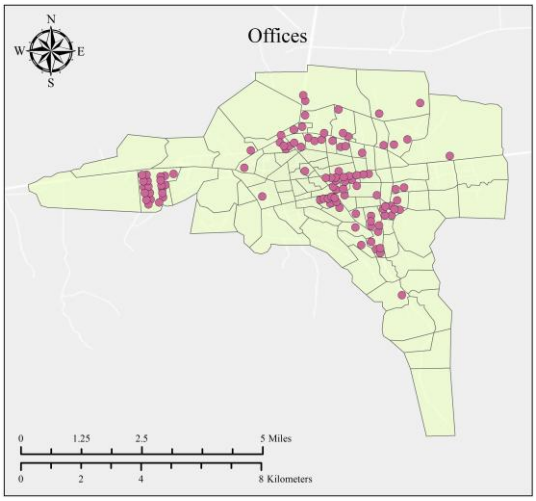
c. Transit stations



d. Universities



e. Mosques



f. Offices

424 *Figure 3. Distribution of study points in the city of Gorgan (Created by ArcMap 10.8)*

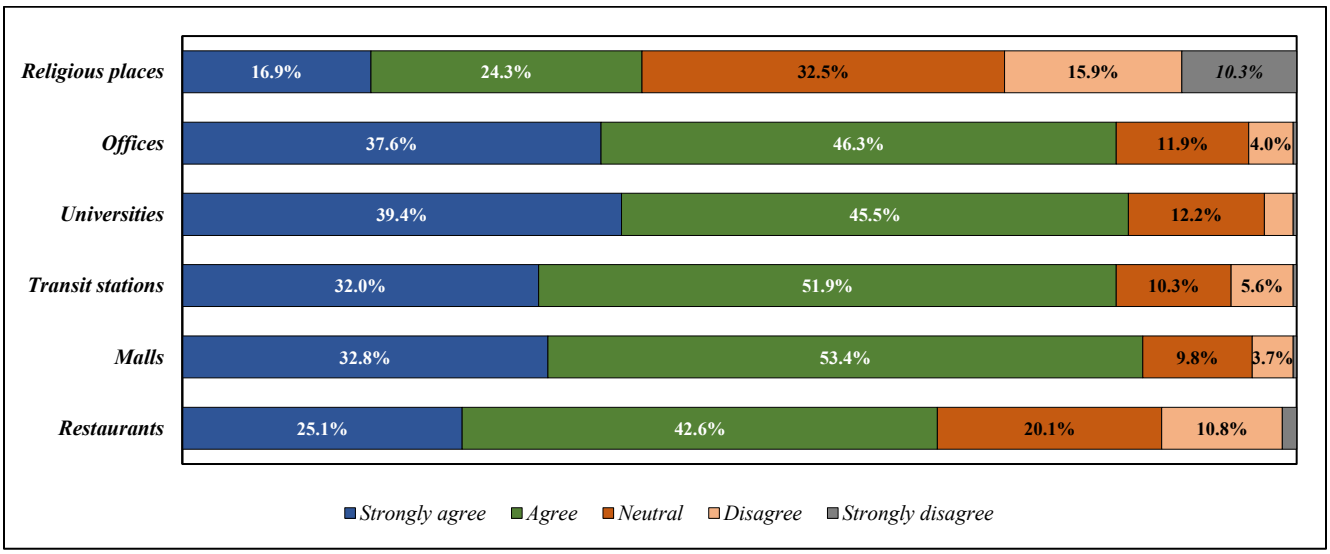


Figure 4. Average of the indicators studied

Among the 1,281 Gorgan residents approached for in-person data collection, participation was secured from 794 individuals, yielding a preliminary response rate of 62.0%. Subsequent administration of two screening questions led interviewers to exclude 90 respondents as ineligible, comprising 12 who had undertaken intercity travel the preceding day alongside 78 who fell outside the defined target population of employed individuals and university students, thereby reducing the eligible response rate to 55.0%. The remaining 704 questionnaires were then subjected to rigorous quality control procedures to identify and eliminate those compromised by internal inconsistencies, incomplete entries, or interviewer-induced errors, a process through which 622 instruments were deemed fit for analysis. Within this validated pool, 378 of the 439 questionnaires obtained from respondents expressing willingness to adopt BSS for their prior day's travel, as well as 244 of the 265 gathered from those disinclined to do so, met the requisite standards. Given that the research objectives centered on BSS adoption intention, the 378 questionnaires from willing respondents constituted the definitive analytical dataset. Notably, prior acquaintance with the BSS was reported by 251 of these participants, accounting for 66.4% of the final sample.

Figure 5 illustrates the modal shift of users (e.g., 378 respondents) before and after introducing BSS, revealing notable substitution patterns across all transport modes. Prior to BSS adoption, the dominant modes were car (46.5%), walking (21.7%), taxi (15.0%), and ride-sourcing (9.5%), with minor contributions from motorcycle (2.5%), bus (2.5%), and bicycle (2.3%). Following BSS introduction, BSS itself accounts for 37.0% of trips, drawing primarily from car users, whose share declined substantially from 46.5% to 31.9%, a reduction of 14.6%, indicating that private car trips constitute the single largest source of BSS substitution. Walking trips also declined from 21.7% to 13.8%, suggesting that a considerable proportion of short pedestrian journeys were replaced by cycling. Taxi usage fell from 15.0% to 9.4%, and ride-sourcing dropped from 9.5% to 4.5%, together reflecting a meaningful diversion of for-hire vehicle demand toward the shared bicycle system. Minor reductions were observed for motorcycle (2.5% to 1.0%), bicycle (2.3% to 1.2%), and bus (2.5% to 1.3%).

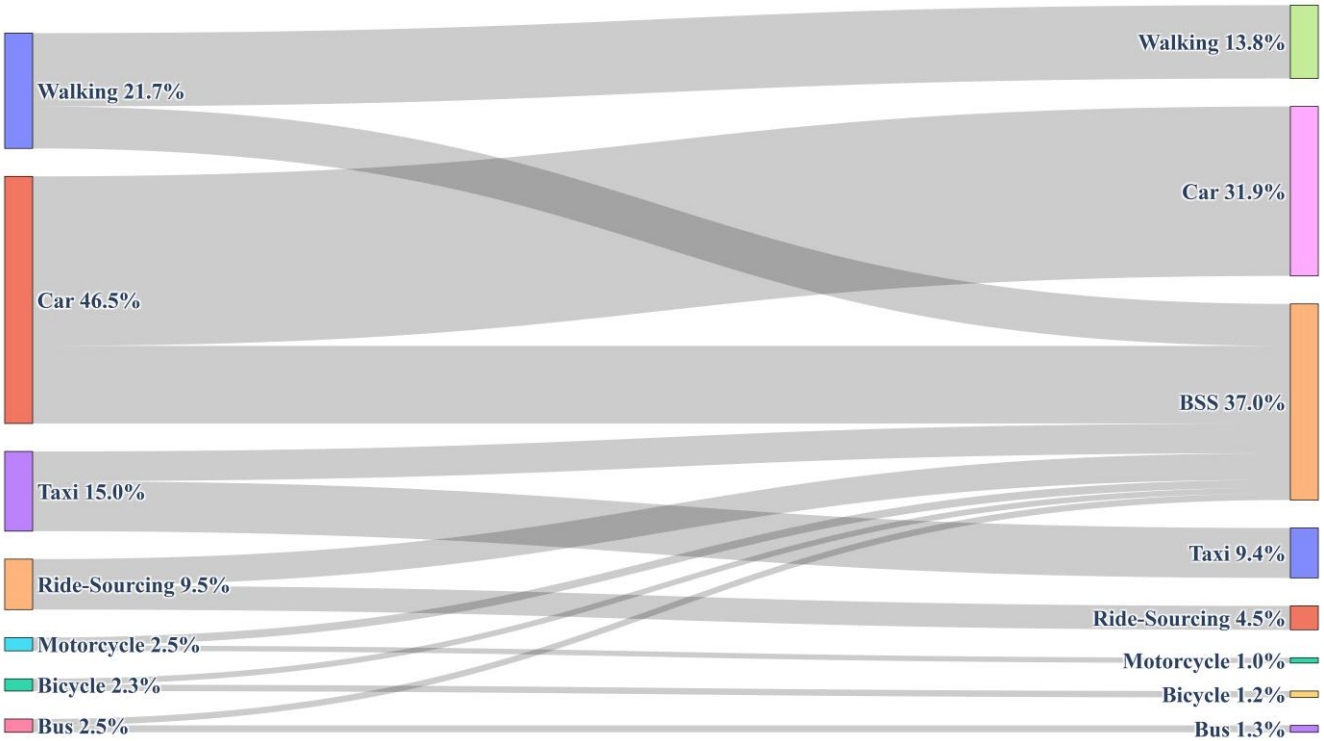


Figure 5. Modal substitution patterns before and after BSS introduction

A total of four distinct scenarios were presented to each participant, an approach that culminated in the assembly of a comprehensive dataset encompassing 1,512 observations (4×378), all of which were thereafter submitted to systematic analysis. Descriptive statistical characteristics pertaining to the surveyed sample have been consolidated and presented in Table 2. In order to gauge the extent to which the model is capable of generalizing to previously unseen data, the entirety of the collected observations was randomly partitioned into two non-overlapping subsets through the application of a uniform distribution function. Accounting for 20% of the total observations, a subset comprising 304 scenarios was set aside strictly for evaluation purposes, while the considerably more extensive remaining portion, representing 80% of the data and totaling 1,208 scenarios, was allocated for the purposes of model training and development.

Table 2. Descriptive statistics of the respondents across the sample datasets

Attribute		***Sample (%)***	***Behavior*** BSS	No change
Gender	*Male*	76%	66%	34%
	Female	24%	69%	31%
Marital status	*Single*	50%	69%	31%
	Married	50%	66%	34%
Age	*18-25*	35%	67%	33%
	26-35	29%	64%	36%
	36-45	23%	68%	32%
	46 ≤	13%	67%	33%
Household	*1-2*	13%	62%	38%

Attribute		Sample (%)	Behavior (BSS / No change)
	3	29%	70% / 30%
	4	42%	67% / 33%
	5 ≤	16%	67% / 33%
Education	No collage degree	53%	68% / 32%
	Undergraduate degree	31%	65% / 35%
	Postgraduate degree	16%	68% / 32%
Occupation	Self-employed	57%	67% / 33%
	Employee	23%	69% / 31%
	University student	20%	68% / 32%
BMI	Under weight (< 18.5)	3%	67% / 33%
	Normal weight (18.5-24.9)	54%	69% / 31%
	Pre-obesity (25-29.9)	34%	65% / 35%
	Obesity (30 ≥)	8%	65% / 35%
Number of adult bikes in household	0	62%	67% / 33%
	1 ≤	38%	66% / 34%
Car ownership	0	20%	70% / 30%
	1	65%	65% / 35%
	2 ≤	15%	72% / 28%
Driving license condition	Owner	78%	65% / 35%
	Not owner	22%	75% / 25%
Total daily travel time (min)	< 30	33%	68% / 32%
	30-59	35%	67% / 33%
	60-89	21%	66% / 34%
	90 ≤	11%	64% / 36%
Tour pattern	Simple tour	45%	72% / 28%
	Complex tour	55%	63% / 37%
Current transportation mode	Active	17%	70% / 30%
	Private	36%	63% / 37%
	Transit	47%	69% / 31%

5. Result

Given the significant correlation between the independent and target variables, while ensuring that no correlation exists between the independent variables, candidate variables for the modeling stage were selected. The HCM was developed following the method outlined in Section 3. Equation (19) represents the structural equation for the latent variable, while Equations (20) to (26) describe the measurement equations for the latent variable descriptors. Furthermore, Equation (27) defines the utility function for the desire to use BSS. Table 3 illustrates the optimal model, based on the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values at the 0.1 significance level.

$$LV_{nt}=A_0+A_1ABSc_{nt}+A_2NoCar_{nt}+A_3Bike2M_{nt}+A_4BMI_{nt}+A_5CTour_{nt}+A_6UStudent_{nt}+\omega_{nt} \quad (19)$$

$$ResArea_{nt}=C_{ResArea}+\lambda_{ResArea}LV_{nt}+\vartheta_{ResArea,nt} \quad (20)$$

$$EduCent_{nt}=C_{EduCent}+\lambda_{EduCent}LV_{nt}+\vartheta_{EduCent,nt} \quad (21)$$

$$Office_{nt}=C_{Office}+\lambda_{Office}LV_{nt}+\vartheta_{Office,nt} \quad (22)$$

$$ShCent_{nt}=C_{ShCent}+\lambda_{ShCent}LV_{nt}+\vartheta_{ShCent,nt} \quad (23)$$

$$TrSta_{nt}=C_{TrSta}+\lambda_{TrSta}LV_{nt}+\vartheta_{TrSta,nt} \quad (24)$$

$$Rest_{nt}=C_{Rest}+\lambda_{Rest}LV_{nt}+\vartheta_{Rest,nt} \quad (25)$$

$$RePla_{nt}=C_{RePla}+\lambda_{RePla}LV_{nt}+\vartheta_{RePla,nt} \quad (26)$$

$$U_{Bike\text{-}shared,nt}=\beta_0+\beta_1 Median_bike_lane_{nt}+\beta_2 Curb_bike_lane_{nt}+\beta_3 Mixed_traffic_{nt}+\beta_4 NTrip_{nt}+\beta_5 Cost_{nt}+\beta_6 OBike_{nt}+\beta_7 Basket_{nt}+\sigma_{eta}\eta_n+\alpha LV_{nt}+\varepsilon_{Shared\text{-}bike,nt} \quad (27)$$

5.1. Structural model

The results of the study indicate that individuals with higher education levels (*ABSc*) are more likely to have a positive attitude toward BSS accessibility, which in turn increases their likelihood of using BSS. This can be attributed to their greater awareness of environmental issues and the negative impact of increasing car use. This finding is consistent with previous studies (Bergantino et al., 2021; Fishman, 2016a). Additionally, the *NoCar* variable indicates that individuals without a private car in their household are more likely to have a positive attitude toward BSS access, which may increase their use of this travel mode. This may be because individuals without access to a car are more inclined to adopt alternative transportation options. This finding supports the research by Barbour et al. (2019). Furthermore, the *Bike2M* variable suggests that individuals who use their household's private bike at least twice a week tend to have a more positive attitude towards BSS accessibility, which may ultimately increase their willingness to use BSS. This could be due to greater familiarity with bicycles and less concern about theft and maintenance. This finding is in line with previous studies (Böcker and Anderson, 2020; Curto et al., 2016; Fuller et al., 2013).

As indicated by Table 3, the *BMI* variable suggests that individuals with a high BMI tend to have a more pessimistic view of BSS accessibility, which may reduce their likelihood of using BSS. This could be due to physical limitations that make using BSS more challenging. This result aligns with findings from the de Haas et al. (2021). The *CTour* variable indicates that individuals with more complex daily trip chains tend to have a more pessimistic view of BSS accessibility, ultimately reducing their willingness to use the system. This may be because such individuals must return bikes to stations, limiting flexibility and convenience compared to using a private car. This finding is consistent with prior research (Bordagaray et al., 2016; Zhang et al., 2018; Zhao et al., 2015). Lastly, the *UStudent* variable shows that university students have an optimistic attitude towards BSS access, which is likely to increase their use of BSS. This could be due to the affordability of BSS compared to other transportation modes and students' greater awareness of its benefits. This result is consistent with earlier studies (Du and Cheng, 2018; Mohiuddin et al., 2024; Torrisi et al., 2021).

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Table 3. The HCM of BSS usage

Variable definition	*Abbreviation*	*Estimate*	*t-value*
Constant			
Constant in the utility function of BSS.	*ASC_BSS*	*2.059*	*4.402*
Constant in the structural model of BSS.	*C_latent*	*0.153*	*2.801*
Constant in the measurement equation of EduCent.	*C_EduCent*	*1.129*	*26.162*
Constant in the measurement equation of ShCent.	*C_ShCent*	*1.006*	*26.134*
Constant in the measurement equation of Office.	*C_Office*	*1.046*	*27.655*
Constant in the measurement equation of Rest.	*C_Rest*	*0.621*	*16.383*
Constant in the measurement equation of TrSta.	*C_TrSta*	*0.977*	*26.945*
Latent and socio-demographic variables			
Latent variable for bike sharing accessibility	*LV*	*0.450*	*4.014*
The respondent has a B.Sc. degree or more (1= Yes, 0= No).	*ABSc*	*0.280*	*4.698*
There is no car in the respondent's household (1= Yes, 0= No).	*NoCar*	*0.326*	*4.421*
The respondent uses an adult bike in his/her household at least for 2 trips or more in a week (1= Yes, 0= No).	*Bike2M*	*0.548*	*4.671*
BMI of respondent (kg/m^2).	*BMI*	*-0.007*	*-9.757*
The respondent is a university student (1= Yes, 0= No).	*UStudent*	*0.291*	*3.902*
Trip variables			
The respondent has a complex tour on a working day before the survey (1= Yes, 0= No).	*CTour*	*-3.902*	*-6.022*
The respondent has a simple tour on a working day before the survey (1= Yes, 0= No).	*NTrip*	*-0.167*	*-3.053*
The cost of using BSS (Cent/hour).	*Cost*	*-0.383*	*-2.210*
Coefficients of latent variable in the measurement equations			
Indicator "How much do you agree with the proximity of bike-sharing stations to universities?"	*Uni*	*0.715*	*14.174*
Indicator "How much do you agree with the proximity of bike-sharing stations to malls?"	*Mall*	*0.663*	*15.203*
Indicator "How much do you agree with the proximity of bike-sharing stations to offices?"	*Office*	*0.757*	*16.252*
Indicator "How much do you agree with the proximity of bike-sharing stations to restaurants?"	*Rest*	*0.809*	*16.201*
Indicator "How much do you agree with the proximity of bike-sharing stations to transit stations?"	*TrSta*	*0.557*	*14.617*
Built environment factors			
The respondent chooses median bike lane (1= Yes, 0= No).	*Median bike lane*	*1.152*	*4.516*
The respondent chooses curb bike lane (1= Yes, 0= No).	*Curb bike lane*	*0.686*	*3.260*
The respondent chooses mixed traffic (1= Yes, 0= No).	*Mixed traffic*	*-0.969*	*-4.107*
Bike characteristics			

Variable definition	*Abbreviation*	*Estimate*	*t-value*
The respondent chooses a conventional bicycle type for the BSS (1 = Yes, 0 = No).	*OBike*	*-0.349*	*-2.127*
The respondent chooses a bike sharing with a front basket (1 = Yes, 0 = No).	*Basket*	*-0.295*	*-2.026*
Other variables			
The first threshold parameter for modeling thresholds of five points Likert scale.	*delta_1*	*0.349*	*25.059*
The second threshold parameter for modeling thresholds of five points Likert scale.	*delta_2*	*1.136*	*32.628*
The standard deviation of random terms in the equation of EduCent.	$\sigma_{EduCent}$	*0.701*	*20.777*
The standard deviation of random terms in the equation of ShCent.	σ_{ShCent}	*0.635*	*20.878*
The standard deviation of random terms in the equation of Office.	σ_{Office}	*0.722*	*22.063*
The standard deviation of random terms in the equation of Rest.	σ_{Rest}	*0.798*	*23.366*
The standard deviation of random terms in the equation of TrSta.	σ_{TrSta}	*0.686*	*21.042*
The standard deviation of common random terms in utilities.	σ_{eta}	*0.413*	*0.511*
Log-likelihood at null		*-9153.233*	
Log-likelihood at model		*-8933.441*	
Rho-square		*0.024*	
AIC		*17932.880*	
BIC		*18101.070*	

5.2. Measurement equation

Table 3 demonstrates that the proximity of bike-sharing stations to key locations, such as educational centers, residential areas, shopping centers, workplaces, restaurants, and transit stations, significantly influences perceptions of BSS convenience. Policies emphasizing land use planning and strategic station placement can enhance public attitudes and increase BSS adoption. This finding aligns with previous research (Faghih-Imani et al., 2014; Wang and Akar, 2019).

The results of this study suggest that the proximity of bike-sharing stations to restaurants can lead to more positive attitudes toward bike-sharing accessibility than proximity to other locations. This may be because restaurants operate over longer periods of time, unlike offices or universities, which are active during specific time periods (e.g., peak traffic hours). This reduces problems such as bike shortages or dock unavailability during rush hours, leading to smoother experiences and better accessibility.

On the other hand, according to the results of this study, the location of bike-sharing stations near offices can create a more positive attitude toward bike-sharing accessibility. The reason for this could be that many employees face short but inconvenient distances between PT stations and their workplaces. The presence of bike-sharing stations near their workplaces provides an efficient solution for these short distances and makes the BSS appear integrated with existing PT. Therefore, this increases citizens' positive attitude toward the accessibility of the BSS.

Furthermore, the presence of bike-sharing stations near universities can create a positive attitude toward the use of BSSs. This may be because students' travel patterns throughout the day are distributed, including commuting between university campuses, dormitories, and nearby uses (libraries and bookstores). Therefore, continuous access to bike-sharing is consistent with these flexible programs.

According to the results of this study, the presence of bike-sharing stations near shopping malls leads to a more positive attitude toward the accessibility of the BSS. The reason for this could be that users find the presence of bike sharing near shopping malls more accessible and useful, not only for commuting but also for everyday life. The feeling of being able to go anywhere and anytime from a shopping mall, where people already go for multiple purposes, increases the accessibility of the system. This broader perception leads to a more favorable attitude toward the overall accessibility of BSS.

Finally, the location of bike-sharing stations in the vicinity of PT (bus) stations creates a positive attitude toward using the BSS. However, PT stations are less desirable than other locations among people. This may be because PT stations are often located in congested urban areas where parking and cycling spaces are limited. This situation can make access to bicycles less safe, which in turn reduces perceived ease of use and accessibility.

5.3. Choice model

According to Table 3, the *Median_bike_lane* and *Curb_bike_lane* variables suggest that providing dedicated bike lanes increases individuals' willingness to use BSS. This observation is consistent with findings from previous research (Amiri and Sadeghpour, 2015; Heinen et al., 2010). As shown, *Median_bike_lane* has a greater influence on individuals' willingness to adopt BSS compared to *Curb_bike_lane*. This disparity between the two variables may be explained by the proximity of curb bike lanes to motor vehicle traffic, which could increase the perceived risk of using BSS compared to median bike lanes (Amiri and Sadeghpour, 2015).

Additionally, the *Mixed_traffic* variable highlights that requiring individuals to cycle on mixed traffic lanes decreases their willingness to use BSS. This finding is consistent with results reported in prior studies (Chataway et al., 2014; Fitch and Handy, 2020). The LV_n variable underscores that an optimistic perception of BSS accessibility significantly enhances individuals' willingness to adopt the system. This conclusion supports the findings of Faghih-Imani et al. (2014). Time constraints, fatigue, physical limitations, and rising costs all intensify as people make more trips, which can reduce their likelihood of using shared bikes. More frequent trips increase total travel time and distance, making faster and more comfortable modes more appealing. Likewise, using BSS more often raises both physical effort and cost. Therefore, the negative coefficient of *NTrip* indicates that as daily trip frequency increases, willingness to use BSS decreases. This result is consistent with prior research (Politis et al., 2020).

Furthermore, the negative coefficient of the *Cost* variable indicates that higher usage costs of the BSS are associated with a lower willingness to adopt this mode of transportation, which is consistent with expectations. Similar findings have been reported in previous studies (Bergantino et al., 2021; Dill et al., 2022). Equipping shared bikes with a front basket (*Basket*) has been found to discourage potential users from opting for BSS. Counterintuitively, rather than being perceived as a convenience, the presence of such a fixture tends to heighten safety-related apprehensions among riders, given that an uncovered or inadequately secured basket may render belongings vulnerable to theft or accidental displacement during

transit. Finally, the *OBike* variable diminishes individuals' willingness to adopt BSS. Cyclists typically exhibit a preference for flat terrain, as conventional bikes provide no assistance on inclines or uneven surfaces, rendering travel on anything other than level routes physically taxing. Considering the semi-hilly topography of Gorgan city, this outcome is hardly surprising, corroborating the findings of prior research (Yang et al., 2024).

6. Implication

6.1. Model's constant recalibration

Since respondents express their preference rather than their actual behavior, which could differ, the predicted market share from models using SP data might not be an accurate reflection of the actual mode choice market share. A more precise estimate of the mode choice's market share is achieved by recalibrating the models with revealed preference data (Liu et al., 2019; Train, 2009; Zgheib et al., 2020). An effective method for recalibrating the constant for the BSS utility is to employ the approach proposed by Train (2009). This study employed the ratio of respondents intending to utilize a free BSS to the total number of respondents (0.608) as the model constant for the free BSS condition, owing to the absence of real BSS market share statistics. This amount is presumed to represent the market share of BSS among those doing non-discretionary trips. By using this method, the BSS share converged to 60.82% and the model's constant value to -0.3357 after 19 iterations.

A Receiver Operating Characteristic (ROC) curve was employed for both the training and test datasets in order to assess the precision of the model's predictions. Two parameters, the true positive rate and the false negative rate, are used to plot this graph (Flach, 2016). The sensitivity of the model in accurately and inaccurately forecasting positive findings is shown by the true positive rate and the false negative rate, respectively (Flach, 2016). In addition, the model's overall accuracy is shown by the area under the ROC curve (Bradley, 1997). There is a discrepancy of 0.036 between the test dataset's area under the curve (0.662) and the training dataset's (0.698). With only a little variation, we can see that the built model replicates the test dataset's performance on new data.

6.2. Effectiveness of protected bike lane development

Figure 6 illustrates how the probability of choosing a BSS declines as the cost increases from 0 to 15 cents per hour across three bike lane conditions: median bike lane, curb bike lane, and mixed traffic. At zero cost, the median bike lane starts at 78.2%, the curb bike lane at 76.1%, and mixed traffic noticeably lower at 67.8%. As cost rises to 6 cents per hour, the median bike lane drops to roughly 57.4%, the curb bike lane to around 54.6%, and mixed traffic falls more steeply to approximately 44.3%. Throughout the entire cost range, mixed traffic consistently shows the steepest rate of decline, suggesting that riders without dedicated bike lanes are considerably more sensitive to pricing compared to those using designated bike lanes.

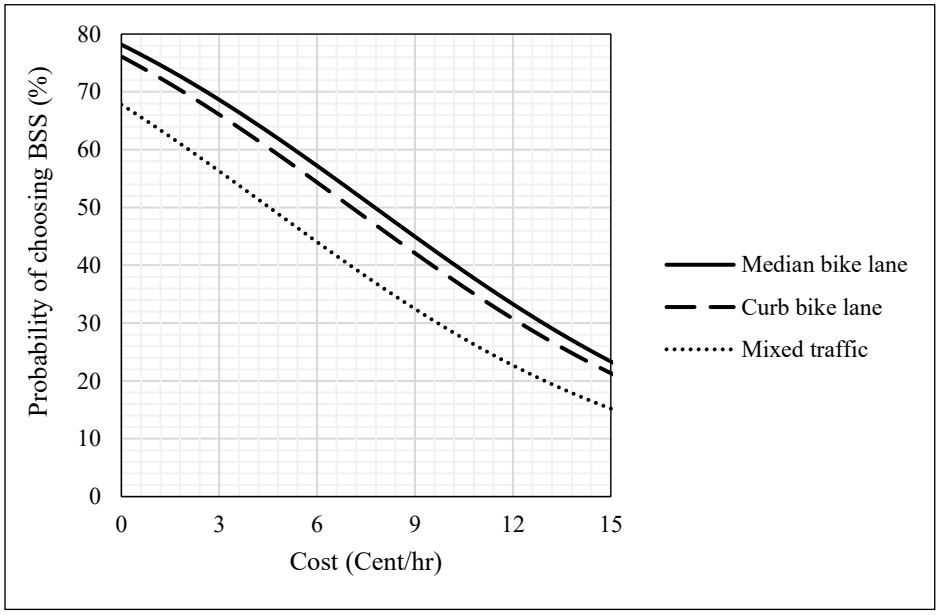


Figure 6. Probability variation of choosing BSS in various type of bike lane and cost

6.3. Evaluating accessibility preferences

Given the significance of the latent variable "accessibility of BSS," it is important to highlight that the accessibility of BSS directly influences the likelihood of its use. Figure 7 illustrates the effect of changes in accessibility indicators on the probability of using BSS with protected lanes. As depicted in Figure 7a, increasing agreement with the accessibility of bike-sharing stations to educational centers, such as schools and universities (*Uni*), from "*Neutral*" (level 3) to "*Agree*" (level 4) raises the probability of shared bike choice from 29.4% to 39.3%, reflecting a 9.9% increase. This indicates that the proximity of stations to educational institutions plays a significant role in promoting shared bike usage, particularly among students and staff commuting for short distances. The steep gradient in the probability curve also suggests that improved spatial integration between campus zones and BSS networks can notably increase system ridership during peak school and university hours.

Figure 7b illustrates that enhancing accessibility to shopping centers (*Mall*) from "*Neutral*" to "*Agree*" increases the likelihood of BSS usage by 9.0%, from 24.4% to 33.4%. The positive association highlights that individuals are more inclined to use shared bikes for short leisure or errand-based trips when stations are located near retail and commercial hubs. However, the slightly lower sensitivity compared to educational centers implies that such trips may be more occasional, often influenced by trip chaining or weather conditions.

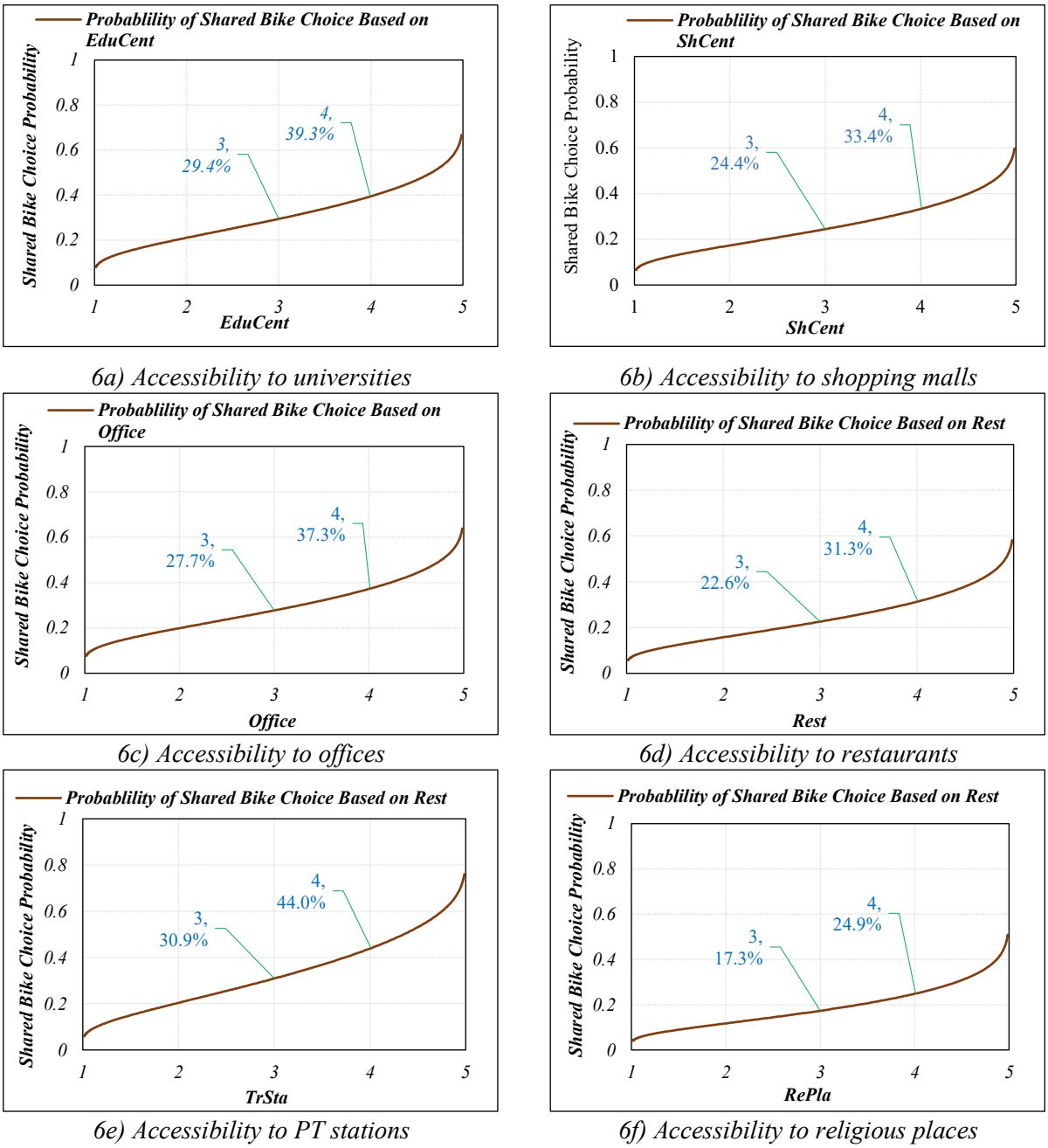


Figure 7. Changes in the likelihood of using the BSS

Similarly, Figure 7c shows that improving access to office areas (*Office*) increases the probability of shared bike choice from 27.7% to 37.3%, a 9.6% rise. This suggests that bike-sharing stations located near employment centers can substantially enhance first- and last-mile connectivity, particularly for workers seeking cost-effective and time-efficient alternatives to congested motorized travel modes. These findings reinforce the importance of coordinating BSS deployment with major office clusters and central business districts to capture regular commuter demand.

In contrast, Figure 7d reveals that improving accessibility to restaurants (*Rest*) leads to a smaller increase of 8.7%, from 22.6% to 31.3%. Although positive, this relatively modest effect implies that

dining-related trips are generally less routine and often undertaken in groups or at night, when BSS usage tends to decline. Consequently, while enhancing access to restaurants can marginally increase usage for leisure or social trips, it should not be a primary factor in network expansion priorities.

Figure 7e demonstrates that accessibility to transit stations (*TrSta*) has the most substantial effect, with the probability of BSS usage rising by 13.1%, from 30.9% to 44.0%. This underscores the synergistic relationship between BSS and PT, where shared bikes act as critical feeders that extend the effective catchment area of transit hubs. This integration improves overall system efficiency and promotes sustainable multimodal travel. From a planning standpoint, prioritizing BSS expansion around metro, bus, or rail stations can significantly enhance ridership and reduce dependency on private vehicles.

Conversely, Figure 7f shows that improving accessibility to religious facilities (*RePla*) results in the smallest increase, with the probability of BSS usage rising by only 7.6%, from 17.3% to 24.9%. This suggests that trips to religious places are more occasional and may involve family or group travel, making individual bike sharing less practical. Therefore, while accessibility improvements in these areas can support inclusivity, they are unlikely to yield large-scale ridership gains.

Overall, these results reveal that land-use accessibility plays a differentiated role in shaping BSS adoption patterns. Accessibility to educational centers and transit hubs exerts the strongest positive influence, highlighting the importance of strategic station placement near high-frequency, purpose-driven destinations. In contrast, accessibility to leisure-oriented or occasional destinations, such as restaurants and religious sites, contributes less to overall demand. These insights emphasize that BSS planning should prioritize functional connectivity, particularly educational and employment corridors.

6.4. Station suitability index

In this study, five indicators were used to determine the SSI (shown in Equation (28)): 1) the total area of universities in each TAZ, 2) the total area of offices in each TAZ, 3) the total area of shopping malls in each TAZ, 4) the total area of the public bus station's catchment area in each TAZ, and 5) the total area of restaurants in each TAZ. Notably, TAZs are defined in the first phase of comprehensive transportation and traffic studies in Gorgan city.

$$\begin{aligned} SSI = {} & Uni.X_{Uni,\ Norm,\ i} \\ & + Office.X_{Office,Norm,i} \\ & + Mall.X_{Mall,Norm,i} \\ & + TrSta.X_{TrSta,Norm,i} \\ & + Rest.X_{Rest,Norm,i} \end{aligned} \tag{28}$$

Where *Uni*, *Office*, *Mall*, *TrSta*, and *Rest* are the coefficients obtained in the structural equation section of the HCM. Also, $X_{Uni,\ Norm,\ i}$ is the total normalized area of universities in TAZ i, $X_{Office,Norm,i}$ is the total normalized area of offices in TAZ i, $X_{Mall,Norm,i}$ is the total normalized area of shopping malls in TAZ i, $X_{TrSta,Norm,i}$ is the total normalized area of public bus stop catchment areas in TAZ i, and $X_{Rest,Norm,i}$ is the total normalized area of restaurants in TAZ i. In this study, the Z-score standardization method has been used to normalize the target indicators (area of universities, offices, malls, public bus stops, and restaurants). The Z-score is a measure of how many standard deviations an observation's value is from the mean value of what is being observed or measured. Observed values above the mean have positive

standard scores, while values below the mean have negative standard scores (Montgomery et al., 2009). Hence, the Z-score of each indicator is calculated through Equation (29), which represents the value Z_{ji} for indicators in zone *i*.

$$Z_{j,i\ .\ j=1,2,3,4,5}=\frac{x_{j,i}-\mu_j}{\sigma_j} \tag{29}$$

where $x_{j,i}$ is the value of the SSI for station *j* in zone *i*, μ_j is the average of the SSI for station *j* across all zones, and σ_j is the standard deviation of the SSI for station *j*. The averages and standard deviations of the indicators examined in this study, prior to normalization, are shown in Table 4.

Table 4. Statistic description of indicators

Parameter	*Mall*	*Office*	*Restaurant*	*University*	*Public transit station*
Average (m^2)	*531.74*	*1642.31*	*163.65*	*6915.97*	*109817.98*
Standard deviation	*1239.23*	*3880.32*	*256.84*	*32060.37*	*86608.08*

Based on previous research on the distance between public bus stops and bike-sharing stations, this study uses 130 meters as the radius of the buffer zone. Figure 8 shows the SSI within the TAZs of Gorgan City. As illustrated in Figure 8, 35.4% (34 out of 96) of TAZs have an SSI greater than 28, indicating moderate to high suitability for bike-sharing station allocation, while 64.6% (62 out of 96) exhibit an SSI below 28, suggesting lower suitability based on the evaluated factors. Geographically, the peripheral zones, particularly those in the eastern part of Gorgan, generally have a lower SSI compared to the western zones. This difference is mainly attributed to the concentration of universities and office spaces in the western section of the city. Moreover, certain TAZs, such as 68, 83, 84, and 86, display low SSI values despite their proximity to the city center. This can be explained by the lack of key amenities like malls, restaurants, offices, and universities in these areas. On the other hand, while TAZs 14, 20, 21, 22, 58, and 59 are categorized as peripheral zones, they feature several malls, universities, and offices, which significantly contribute to their higher SSI values.

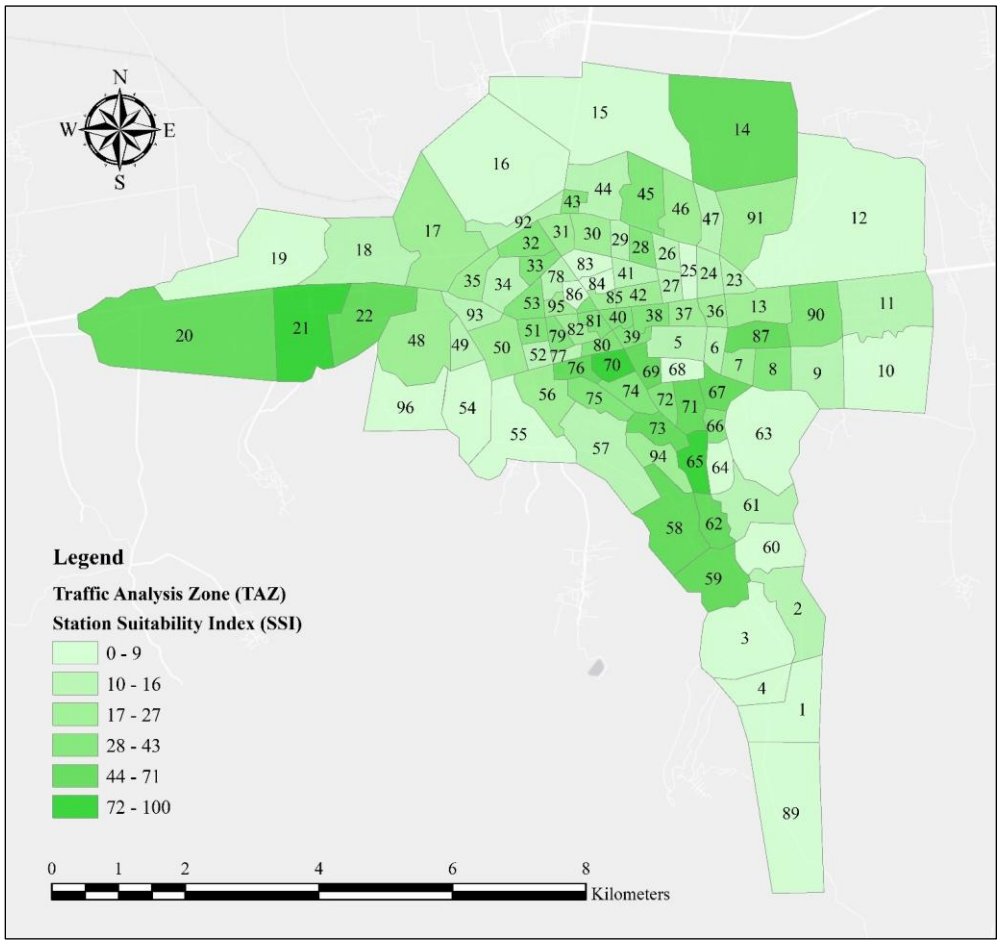


Figure 8. SSI of bike-sharing stations in Gorgan City (Created by ArcMap 10.8)

6.5. TAZ-level emission reduction

The adoption of BSS in Gorgan city generates a quantifiable and spatially distributed environmental dividend that, when monetized using US EPA damage cost estimates (EPA, 2023, 2025), yields a compelling economic rationale for sustaining and expanding the system. Table 5 presents the estimated annual emission reductions resulting from BSS adoption across all 96 TAZs of Gorgan, calculated based on the U.S. EPA framework (EPA Heavy-Duty, 2024; EPA Light-Duty, 2024), along with the monetary valuation of these reductions using the U.S. EPA cost framework. The pollutants covered, Carbon Dioxide (CO_2), Methane (CH_4), Nitrous Oxide (N_2O), Nitric Oxide (NOx), Particulate Matter ($PM_{2.5}$), Volatile Organic Compounds (VOC), and Sulfur Dioxide (SO_2), collectively represent the primary vehicle exhaust constituents displaced when private car trips shift to shared cycling. In total, BSS adoption is estimated to eliminate approximately 91.61 tons of pollutants per year across the city. The dominant share of this reduction, by mass, is attributed to CO_2 at 90.49 tons per year, reflecting the sheer volume of greenhouse gas associated with the motorized trips being substituted. VOC and NOx follow at 0.53 and 0.48 tons per year, respectively, while CH_4, SO_2, $PM_{2.5}$, and N_2O contribute smaller but non-negligible reductions.

When the reduction figures are translated into monetary terms using U.S. EPA pollutant damage cost values, the relative importance of each pollutant shifts considerably, revealing a hierarchy of

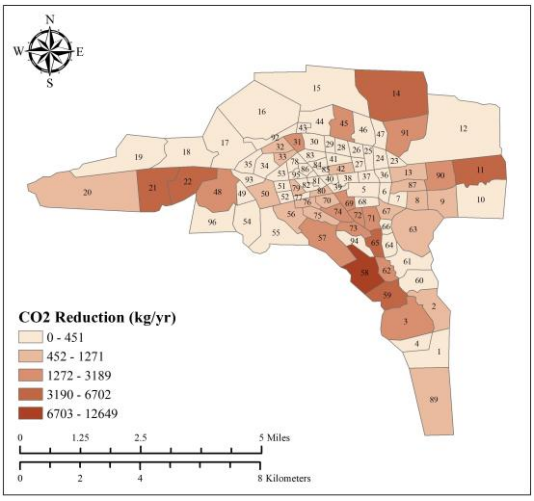
environmental harm that goes beyond simple mass comparisons. Although CO_2 is the most voluminous pollutant reduced, its social cost per ton is relatively modest, resulting in an annual benefit of approximately $30,766. In contrast, NOx, reduced by only 0.48 tons, commands the single highest monetary valuation at $33,796 per year, owing to its severe role in forming ground-level ozone and triggering respiratory and cardiovascular health impacts. Similarly, $PM_{2.5}$, though reduced by only 0.03 tons annually, is valued at $5,511, implying an extraordinarily high damage cost per unit mass — because fine particulate matter is among the most health-damaging air pollutants, capable of penetrating deep into lung tissue and entering the bloodstream. N_2O, a potent greenhouse gas with a global warming potential far exceeding that of CO_2, contributes $696 despite a reduction of just 0.01 tons, again demonstrating the power of the EPA's damage cost approach to capture long-term, disproportionate climate harm. VOC reduction yields $4,909, and SO_2 and CH_4 contribute $854 and $115, respectively. Taken together, the aggregate annual monetary benefit of BSS-induced emission reductions across Gorgan totals $76,646.27 per year. This figure is not merely academic; it represents a real and recurring societal saving that can be reframed as a subsidy source or cost-offset mechanism to support the operational and infrastructural expenses of the BSS service itself.

Table 5. Estimated annual emission reductions from BSS adoption

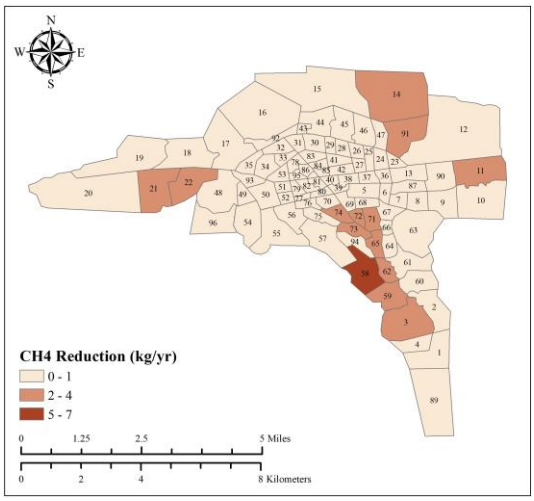
Pollutant	*Abbreviation*	*Total reduction (tons/yr)*	*cost ($/yr)*
Carbon Dioxide	*CO_2*	*90.49*	*30,765.92*
Methane	*CH_4*	*0.05*	*115.00*
Nitrous Oxide	*N_2O*	*0.01*	*696.00*
Nitric Oxide	*NOx*	*0.48*	*3,3796.00*
Particulate Matter (≤ 2.5 μm)	*$PM_{2.5}$*	*0.03*	*5,511.00*
Volatile Organic Compounds	*VOC*	*0.53*	*4,908.75*
Sulfur Dioxide	*SO_2*	*0.02*	*853.60*
Total			***76,646.27***

The spatial dimension of these emission reductions, illustrated in Figure 9, adds a critical layer of nuance to the city-wide totals. Figure 9 presents seven TAZ-level choropleth maps, depicting how annual emission reductions are distributed across Gorgan's 96 zones. The maps reveal a pronounced spatial heterogeneity that mirrors the city's land-use structure and BSS demand profile. TAZs in the western and central portions of Gorgan, which were identified earlier in the study as having higher SSI values, generally exhibit greater emission reduction potential across all pollutants. This is a logical outcome: zones with higher BSS ridership generate more vehicle trip substitutions, and therefore produce greater pollutant displacement. In contrast, peripheral eastern TAZs, characterized by low SSI scores and lower predicted BSS adoption, show correspondingly minimal emission reductions in all seven maps. This spatial alignment between BSS suitability zones and emission reduction hotspots validates the internal consistency of the study's methodology and reinforces the argument that strategically placed BSS stations not only maximize ridership but simultaneously concentrate the environmental and economic benefits where urban activity is densest. From a policy and financial standpoint, the monetized emission reduction of over $76,000 per year carries direct implications for the economic viability of BSS in a mid-sized developing-country city like Gorgan. BSS operations typically require funding for station infrastructure, bike maintenance, rebalancing operations, and digital management systems. In cities where public transit

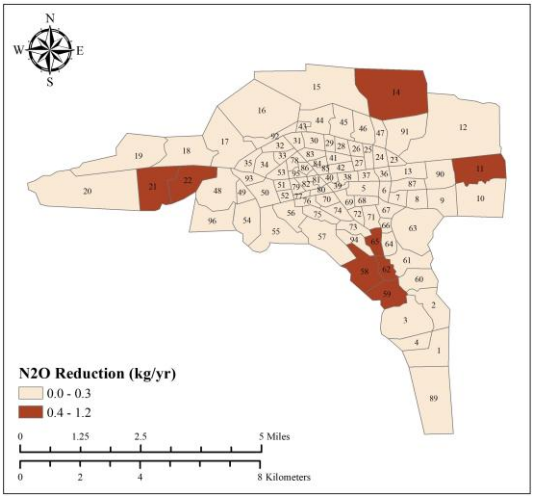
subsidies and dedicated cycling budgets are limited, identifying complementary revenue streams is essential.



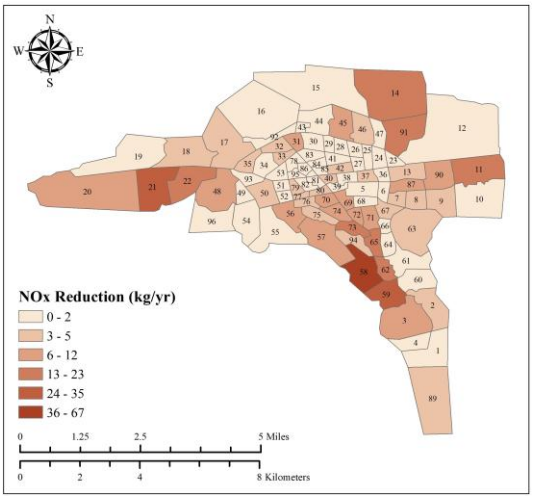
a. Distribution of Annual CO_2 Reduction



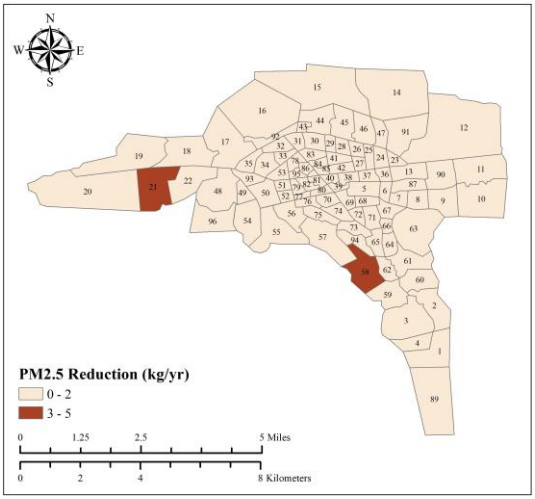
b. Distribution of Annual CH_4 Reduction



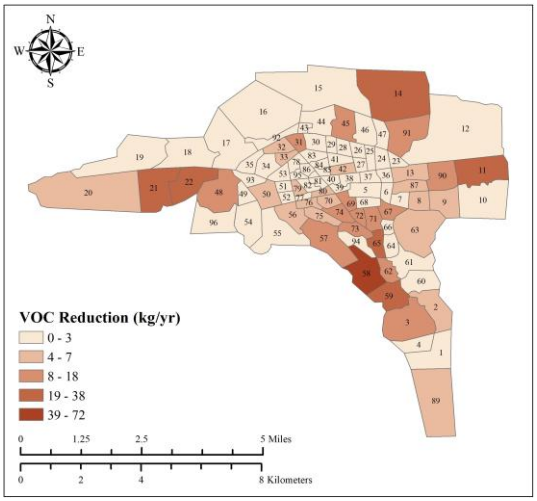
c. Distribution of Annual N_2O Reduction



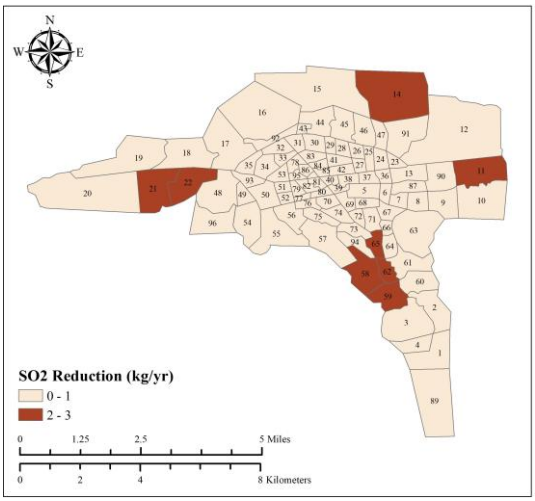
d. Distribution of Annual NO_x Reduction



e. Distribution of Annual $PM_{2.5}$ Reduction



f. Distribution of Annual VOC Reduction



g. Distribution of Annual SO_2 Reduction

Figure 9. Annual Emission Reduction Potential Across Gorgan (Created by ArcMap 10.8)

7. Conclusion

This study aims to identify factors influencing individuals' willingness to use BSS for non-discretionary trips as an alternative to cars. A SP questionnaire was used to examine the effects of bike-sharing station proximity to specific locations, the development and prioritization of bike lanes, and SDCs on individuals' willingness to use BSS. An HCM was employed to analyze these factors and assess the impact of station proximity.

The results demonstrate that the availability of dedicated bike lanes, particularly those segregated from motorized traffic, plays a crucial role in enhancing individuals' willingness to utilize BSS. Higher BSS usage was positively correlated with individuals undertaking short and straightforward trips, university students, private bike owners, and individuals without access to a private vehicle. In contrast, the absence of exclusive bike lanes, higher trip frequencies, having complex trip chain patterns, and a higher BMI were linked to a diminished willingness to adopt BSS.

Additionally, individuals with complex tours or a high BMI tend to perceive BSS accessibility negatively, reducing their likelihood of using the system. In contrast, individuals with higher education, no private car in their household, private bike users, and university students exhibit a more favorable view of BSS accessibility, increasing their likelihood of usage. Proximity to various land uses, including educational centers (universities), shopping malls, offices, and restaurants, positively influences BSS usage. Accessibility to PT stations, including bus stops, exerts a considerable influence, underscoring the necessity of prioritizing the placement of bike-sharing stations in proximity to these stations within the system of bike lane network development policies.

The SSI is crucial for enhancing the adoption of BSS by strategically positioning bike-sharing stations near key locations, including workplaces, universities, and PT hubs. By aligning the placement of these stations with targeted land-use objectives, transportation planners can optimize urban mobility systems, making them more effective in pulling the urban commuters to use the BSS. This research highlights that land uses like educational centers (e.g., universities), workplaces, and restaurants significantly contribute

to generating higher demand for BSS. These results highlight that integrating land-use patterns with bike-sharing infrastructure enables cities to enhance the adoption of BSS by commuters.

Beyond the demand-side analysis, this study quantifies the environmental and economic benefits associated with BSS adoption in Gorgan. The results indicate that widespread BSS uptake across the city's 96 TAZs can collectively displace approximately 91.6 tons of vehicle-related pollutants per year, encompassing CO_2, NOx, $PM_{2.5}$, VOC, CH_4, N_2O, and SO_2. When monetized using the US EPA social cost framework, these reductions yield an estimated annual economic benefit of approximately $76,646. The spatial distribution of these reductions mirrors the city's BSS demand profile, with the greatest environmental gains concentrated in the western and central TAZs, where higher SSI values and stronger ridership generate more vehicle trip substitutions. This monetized environmental dividend provides a compelling economic rationale for sustained investment in BSS infrastructure and can serve as a partial cost-offset mechanism for operational and maintenance expenses, an especially relevant consideration for mid-sized developing-country cities where dedicated cycling budgets remain limited.

This study acknowledges several limitations that should be considered for practical implementation. First, the absence of validation data from the study population limits the verification of the collected data. Second, the study did not account for the modal share of travel within the city. Third, the sample population was comprised solely of individuals engaged in non-discretionary trips, including employees and university students. This specificity restricts the universality of the findings to the wider population. As a result, policy recommendations must be approached with a degree of caution. Consequently, policy recommendations should be interpreted cautiously. To address this limitation, the ratio of respondents favoring BSS usage was integrated into the model as a proxy for market share. Future research should explore subjective factors (e.g., convenience, safety, security, and norms) to provide a more comprehensive understanding of individuals' willingness to use BSS. This study focused on existing facilities, leaving certain influential factors unexamined.

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