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A Simulation-Based Analysis of Campus Characteristics and Free-Floating Bike-Sharing System Design on Accessibility and Usage

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Abstract

In the design of free-floating bike-sharing systems (FFBSS), understanding potential usage patterns is essential for capturing dynamic fluctuations in shared bicycle demand. This study investigates the effects of campus characteristics and FFBSS design variables on the accessibility and usage rate of shared bicycles. A multi-method approach was employed to evaluate accessibility and utilization within a university campus, with undergraduate students identified as the primary user group. An online survey was conducted to examine students' travel preferences and typical destinations within the campus. Discrete-event simulation models were then developed to estimate system accessibility and usage rates under varying levels of key design parameters. Regression analysis and t-tests were subsequently applied to assess the statistical significance and magnitude of the effects of campus and system design factors. Results indicate that population density (PD) negatively influences accessibility while positively affecting usage rates. The availability of parking spots (PS) near demand points significantly enhances both accessibility and usage rate. Fleet size (FS) exhibits a strong nonlinear (parabolic) relationship with accessibility, wherein increases in fleet size improve accessibility but lead to diminishing usage rates. Rebalancing activities (RA) provide only marginal improvements in both accessibility and usage. The regression models developed in this study demonstrate strong statistical significance and offer valuable insights into the interactions between campus characteristics and FFBSS design variables. These findings provide practical guidance for bike-sharing operators and campus planners in determining appropriate system configurations tailored to specific campus environments.

Keywords
FFBSS, shared bike usage rate, shared bike accessibility, multi-method study, campus bike-sharing

1. Introduction
Bike-sharing systems can be classified into station-based bike-sharing systems (SBBSS) and dockless or free-floating (FFBSS). In a station-based system, the rider will access the bicycle in a docking station through a mobile app, RFID, code, or membership card (Jara-Díaz et al. 2022). It will return to another or the same station after a trip. In a dockless system, the rider can locate a bike through a mobile application, unlock the bike, and then park it in a designated area after a trip without the need for a docking station because locking mechanisms are already integrated with each bike

(Kou et al. 2020; Xu et al. 2020). The primary attractiveness of FFBSS is its travel convenience, easy parking, ease of getting, convenient public transport connections, ease of pay, and green environmental protection .

The largest bike-sharing systems market is college students who help sustain and promote the service scheme (Chen et al. 2019; Manca et al. 2019; De Santis et al. 2022). Shared bikes can answer the need to access different areas within the campus or even do nearby errands (Rotaris et al. 2019; Sun and Duan, 2021). Students have low vehicle ownership rates and usually depend on allowances to pay for travel, which might also be one reason to use shared bikes aside from their health benefits (Mensah et al. 2019; Rotaris et al. 2019; Sun and Duan, 2021). Bicycle acceptance is higher on university campuses compared to the city level, and students have a higher usage rate than other population groups (Chevalier et al. 2019; Kellstedt et al. 2019).

The bike-sharing scheme has been successfully implemented in many universities to facilitate first and last-mile travel and trips within the campus (Mattson and Godavarthy, 2017; Scott and Ciuro, 2019). Students have unique user requirements because of their limited time finding bikes while transferring between classes and doing errands. Students differ from other users, such as an employee who only uses a bicycle to go to one workplace and stay there for an extended period. As such, there is a need to make the bikes accessible to the students whenever they need to transfer from one place to another.

While increasing the accessibility of shared bikes is essential, the usage rate of shared bikes is also significant when designing a bike-sharing system on a campus. The usage rate of shared bikes is a necessary measure to consider for utility efficiency and sustainability. In this study, accessibility is measured as the proportion of students who were able to use shared bikes and students who attempted to use shared bikes in the system whether they could access a shared bike or not. The usage rate of shared bikes can be clearly defined as the measure of how frequently each bicycle in the system is used within a given period, typically a day. The usage rate was based on the total number of daily bike trips over the fleet size. The result represents the average number of trips made per bike per day. A higher usage rate indicates that bicycles are being used more frequently, suggesting better system efficiency and demand utilization. Conversely, a lower usage rate may indicate underutilization of the fleet, possibly due to factors such as poor accessibility, insufficient demand, or suboptimal bike distribution.

2. Problem Formulation

Studies that considered factors such as campus and BSS characteristics included population and campus size, number of stations, location and capacity of stations are limited to SBBSS which correlates these factors to the daily number of trips and usage, respectively (Kutela and Teng, 2019; Stahley et al. 2022). Research by Celbiş et al. 2023 emphasized that distance and accessibility significantly influence bike-sharing usage, suggesting that stations should be placed closer to potential users to improve adoption.

On the other hand, FFBSS studies on campus only used existing operators' bike-sharing data, failing to consider the potential demand in other locations within the campus. FFBSS studies focused on minimizing walking distance and travel time but did not explicitly address accessibility concerns due to the unavailability of shared bikes and probabilistic demand in every potential location (Guo et al. 2020; Wang et al. 2020; Mahmoodian et al. 2022). One FFBSS study examined the use of an electric fenced intelligent scheduling method for bike redistribution and found that scheduled rebalancing can increase both bike utilization and student satisfaction (Jia et al. 2022). However, the requirement for users to park only in designated areas may reduce convenience, particularly for users with limited time. Additionally, identified key determinants of user satisfaction, included designated bike return locations, availability of bikes, accessibility of the system, and the spatial distribution of bicycles (Xin Chen et al. 2022). Similar study investigated potential bike-sharing usage patterns and transportation mode preferences through an online survey but not captured students' travel modes throughout the day (Shahdah et al. 2025). Together, these studies indicate that accessibility, spatial distribution of bicycles, parking spots, and user travel patterns are critical considerations in designing efficient bike-sharing systems, which can be further evaluated through simulation-based approaches in campus environments.

The effects of factors on the accessibility and usage rate of FFBSS in a university campus have not been determined while considering the dynamic fluctuations of bike availability and demand in a day. The study aims to determine the effects of campus characteristics such as population density, number and location of parking spots, and FFBSS design, such as increasing fleet size and rebalancing activities on the accessibility and usage rate of shared bikes while considering the potential usage patterns of students and their preferences.

Determining the effects of campus characteristics on the accessibility and usage rate of shared bikes will help to determine the appropriate fleet size for a campus FFBSS to reach a target usage rate or accessibility to maintain customer satisfaction. On the other hand, understanding the effect of fleet size and the number of rebalancing activities on accessibility and usage rate aids in optimizing the design for campus FFBSS to increase the efficiency and profitability of shared bike operators.

3. Methods

A survey was done to determine the potential usage patterns of students which are not considered in bike-sharing trip data of BSS operators. After doing the survey, discrete-event simulation models were created; the output was used to make a statistical model to predict FFBSS performance on campus. Simulation modeling and statistical analysis were done in this study to derive systems accessibility and usage rate of FFBSS in a campus to determine the effects of PD, PS, FS and RA.

Discrete-event simulation is used for this study since it can model a complex system. It is a reliable and flexible way to analyze a system that can consider probabilities. It is a widely used tool in transportation systems that can analyze various scenarios to evaluate each factor's impact on the usage rate and accessibility of shared bikes. Three types of entities were used in the simulation models. First are the shared bikes that are distributed in designated parking spots for shared bikes in the hypothetical campus at the start of the simulation. The number of shared bikes determined the fleet size (FS) of the simulated FFBSS. Second to occur are the students who will assume to arrive with pre-determined distribution in different locations. Next is the truck that will distribute the shared bikes in different parking areas at the simulation's start and periodically redistribute or rebalance shared bikes. Figure 1 shows the entity flow diagram of each entity used in the simulation model in Figure 1.

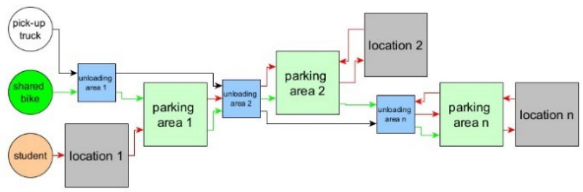

Figure 1. Entity flow diagram

The student arrivals was modeled as a piecewise-homogeneous Poisson process: hourly arrival counts were estimated from the departure-time survey and implemented in FlexSim as a day-table of hourly mean interarrival times, with exponential sampling within each hour. This approach is a standard practical approximation to a nonhomogeneous Poisson process (NHPP). Many simulation texts and recent studies approximate time-varying arrival intensity by piecewise constant rates and sample exponential interarrival times within each block (De Santis et al. 2022).

Simulation models were created using *Flexsim software* with the data from the online survey of the potential usage patterns of students within a day. Different assumptions were made for the simulation models, such as the capacity of locations, traveling, parking areas, entity arrivals, stay time and processing time and rebalancing activities. Table 1 shows the different time input and capacity constraints in the model that simplified the model in a way that it will still represent the complexity of the system. The simulation model also used a decision point for students to determine the available bikes accessible within 100 meters before balking to use the service if there is no available bike to use.

Table 1. Simulation input for time and capacity constraints

Time constraints		
Input	**Time distribution (min)**	**Reason**
Location Stay time	Triangular (60, 180, 90)	representing lecture classes held for 1 hr, 1.5hr and 3hr laboratory classes
Time for renting bikes	Poisson (3)	based on 1000 samples: mean = 2.95 min and SD = 1.75 min
Bike unload	1	It will take only a minute to unload each bike in the parking area
Simulation run time	840	(from 6am to 8pm) based on the departure and arrival time of the students
Location Capacity		
Location	**Capacity**	**Reason**
Parking spots	400	to handle more bikes at a time
Building	5000	large enough to handle population of students going to each building/area

Minitab Statistical software was used to perform the statistical analysis. To validate the relationship between factors and FFBSS performance, regression analysis and a T-test were done to assess the strength and direction of the relationship between factors and FFBSS performance measure (Faraway, 2006; Montgomery et al. 2012).

4. Data Collection

The study's target population consisted of undergraduate students. The survey helped to determine the potential usage pattern of students as they tend to have different behavior compared to other users. University of the Philippines Los Banos (UPLB) campus caters to more than 8,000 undergraduates every semester. The total campus area is about 4,224 ha. however, only about 1,524 ha. is used for academic activities and experimental farms. The UPLB campus is an ideal test case for considering shared bike potential usage patterns since it has existing SBBSS and widely spread possible destinations dictated by their class schedules and residence. UPLB undergraduate students are only given 10 minutes to transfer between different classes that can be assigned to different buildings.

The survey aims to determine the possible routes of students, preferred mode of transportation, and willingness to walk. Twenty-five (25) students were selected to answer an initial survey to improve and test the validity of the survey. After testing and revising the survey, the online survey (using *Qualtrics*) was sent randomly to UPLB undergraduate students with the help of the university registrar's office and face-to-face contact in different colleges and dorms within the campus. Two hundred sixty-seven (267) students answered the survey (2 preview only and were excluded in the analysis, 90 using QR code, 175 using anonymous link). The students were asked about their preferred mobility options. They were also asked about their origins and destinations, their time of travel, and their willingness to walk to find and park a shared bike if they use it.

5. Results and Discussion

5.1 Numerical Results

The effect of campus characteristics and BSS design is determined using the simulation models of the selected university. The total student population (8,797) entering the system was multiplied by 20%, 40%, 60%, 80%, and 100% to analyze the effect of population density (PD) on the accessibility and usage rate of shared bikes. The increase in multiplier will change the PD of the campus, and it will also change the PD of every location in the model. In this study, the total student population was scaled from 20% to 100% in equal increments to represent varying levels of population density (PD) across the campus. It was assumed that each area within the campus experienced a proportional change in PD. This uniform-scaling assumption is a standard practice in transportation and simulation modeling (Ortzar and Willumsen, 2011; Law, 2015), where the total population is increased uniformly while spatial patterns remain fixed. In the context of a university campus with stable land use, consistent schedules, and evenly distributed academic activity, it is reasonable to expect that population changes would affect all zones proportionally. This allows the model to isolate the influence of overall population density on system performance (usage rate and accessibility) without confounding effects from localized variations. Table 2 and Table 3 summarize the effects of PD to accessibility and usage rate of FFBSS in campus, respectively.

Table 2. Effects of PD to accessibility with 5 replicates

Campus characteristics and BSS design				Accessibility				
Population Density	Parking Spots	Fleet Size	Rebalancing	AR1	AR2	AR3	AR4	AR5
20.0%	16	32	0	43.9%	46.6%	39.9%	43.4%	44.8%
40.0%	16	32	0	37.7%	42.9%	41.6%	38.0%	42.7%
60.0%	16	32	0	28.9%	39.5%	37.7%	35.8%	36.9%
80.0%	16	32	0	29.3%	34.6%	34.7%	32.5%	33.8%
100.0%	16	32	0	26.7%	31.9%	31.5%	31.2%	29.4%

Table 3. Effects of PD to usage rate with 5 replicates

Campus characteristics and BSS design				Usage Rate (%)				
Population Density	Parking Spots	Fleet Size	Rebalancing	UR1	UR2	UR3	UR4	UR5
20.0%	16	32	0	16.1	17.1	14.3	14.3	17.2
40.0%	16	32	0	27.7	30.8	31.8	27.9	30.6
60.0%	16	32	0	32.9	42.8	42.5	40.3	40.7
80.0%	16	32	0	44.4	51.4	52.3	50.1	50.4
100.0%	16	32	0	50.9	57.7	59.5	58.9	55.3

To determine the effect of several designated parking spots (PS), the model used the existing PS (16 areas) as the first level and ten additional parking spot locations (26 areas) as the second level. The additional PS makes the bike parking area accessible to all possible locations of students. Table 4 and Table 5 summarize the effects of PS to accessibility and usage rate of FFBSS in campus, respectively.

Table 4. Effects of PS to accessibility with 5 replicates

Campus characteristics and BSS design				Accessibility				
Population Density	Parking Spots	Fleet Size	Rebalancing	AR1	AR2	AR3	AR4	AR5
88.2%	16	32	0	28.9%	32.4%	31.5%	32.8%	33.9%
88.2%	26	32	0	32.9%	35.7%	32.8%	33.9%	33.7%

Table 5. Effects of PS to usage rate with 5 replicates

Campus characteristics and BSS design				Usage Rate				
Population Density	Parking Spots	Fleet Size	Rebalancing	UR1	UR2	UR3	UR4	UR5
88.2%	16	32	0	48.4	53.0	51.7	55.0	55.4
88.2%	26	32	0	54.7	56.8	51.9	56.2	53.9

An increment of one bike per PS was used to determine the effect of FS on the accessibility and usage rate of shared bikes. Table 6 and Table 7 summarize the effects of FS to accessibility and usage rate of FFBSS in campus, respectively.

Table 6. Effects of FS to accessibility with 5 replicates

Campus characteristics and BSS design				Accessibility				
Population Density	Parking Spots	Fleet Size	Rebalancing	AR1	AR2	AR3	AR4	AR5
88.2%	16	32	0	28.9%	32.4%	31.5%	32.8%	33.9%
88.2%	16	48	0	37.6%	41.4%	39.3%	38.1%	41.8%
88.2%	16	64	0	44.3%	45.7%	43.1%	43.7%	46.0%
88.2%	16	80	0	48.1%	48.0%	49.8%	48.8%	50.4%
88.2%	16	96	0	49.9%	50.4%	52.2%	48.6%	51.4%
88.2%	16	112	0	49.7%	50.3%	50.0%	50.5%	54.0%
88.2%	16	128	0	51.8%	50.8%	52.5%	52.1%	51.7%

Table 7. Effects of FS to usage rate with 5 replicates

Campus characteristics and BSS design				Usage Rate				
Population Density	Parking Spots	Fleet Size	Rebalancing	UR1	UR2	UR3	UR4	UR5
88.2%	16	32	0	48.4	53.0	51.7	55.0	55.4
88.2%	16	48	0	42.6	44.2	43.5	43.1	45.9
88.2%	16	64	0	36.7	36.9	35.3	36.8	37.2
88.2%	16	80	0	32.4	31.0	32.6	32.8	33.1
88.2%	16	96	0	27.9	27.4	28.7	27.3	28.1
88.2%	16	112	0	23.6	23.5	23.6	24.2	25.0
88.2%	16	128	0	22.0	20.2	21.9	21.7	21.0

Lastly, an increment of one was used to determine the effect of rebalancing activities (RA) on the performance measure of the FFBSS. Table 8 and Table 9 summarize the effects of PS to accessibility and usage rate of FFBSS in campus, respectively.

Table 8. Effects of RA to accessibility with 5 replicates

Campus characteristics and BSS design				Accessibility				
Population Density	Parking Spots	Fleet Size	Rebalancing	AR1	AR2	AR3	AR4	AR5
88.2%	16	32	0	28.9%	32.4%	31.5%	32.8%	33.9%
88.2%	16	32	1	30.4%	32.1%	31.8%	32.4%	34.7%
88.2%	16	32	2	30.6%	31.5%	31.5%	32.6%	33.3%
88.2%	16	32	3	32.2%	33.8%	32.7%	32.8%	34.3%
88.2%	16	32	4	30.5%	32.3%	32.8%	33.7%	34.3%

Table 9. Effects of RA to usage rate with 5 replicates

Campus characteristics and BSS design				Usage Rate				
Population Density	Parking Spots	Fleet Size	Rebalancing	UR1	UR2	UR3	UR4	UR5
88.2%	16	32	0	48.4	53.0	51.7	55.0	55.4
88.2%	16	32	1	50.6	52.1	52.2	54.5	56.2
88.2%	16	32	2	51.4	51.4	52.3	54.7	54.1
88.2%	16	32	3	54.1	54.6	53.2	54.9	55.4
88.2%	16	32	4	51.3	52.2	54.5	56.5	55.4

5.2 Graphical Results

Figure 2 shows the fitted line plot and the result of a linear regression analysis between PD and accessibility. The accessibility is predicted by increasing the PD while holding the other factors at a minimum level. The graph indicates a negative linear relationship between PD and accessibility. Using the existing PS (16 areas), FS of 32 bikes (2 bikes per PS), and no rebalancing activity, as PD increases by 1 unit, accessibility is expected to decrease by approximately 0.17 unit. Different PDs can alter the accessibility of shared bikes based on their relationship. In this data with a low level of resources, it was expected that an increase in PD would lower the accessibility because more potential users would not find available bikes near them as the current system has low capacity.

Figure 3 shows a linear relationship between PD and the usage rate of shared bikes. The graph shows a positive relationship between PD and usage rate. The increase in PD can be explained by increased demand per location on the campus, leading to a higher usage rate. The model suggests that higher PD values lead to a higher usage rate. It was hypothesized that PD of fewer than 1000 people per hectare positively affects the usage rate of campus FFBSS. The result confirms the hypothesis and supports the findings of Kutela and Teng, (2019) and Sun, Chen and Jiao, (2018) that higher population density near demand points will increase the number of trips of shared bikes. On the other hand, the result contradicts the findings of Scott and Ciuro, (2019), who state that population density is insignificant and does not affect shared bike usage.

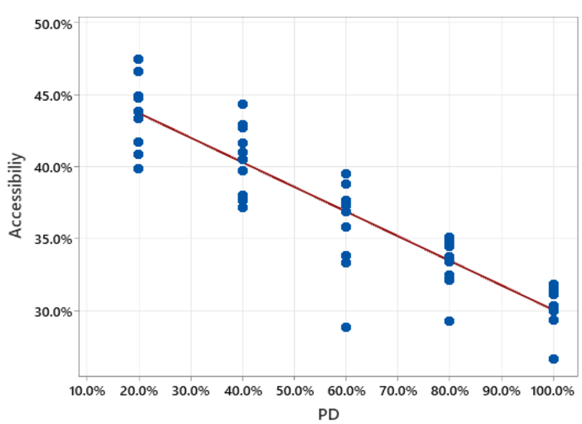

Figure 2. PD vs accessibility

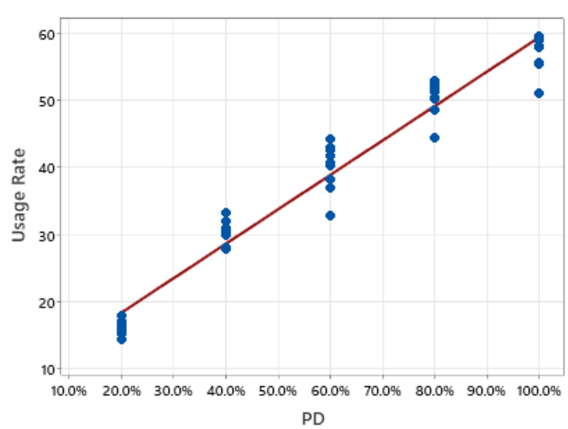

Figure 3. PD vs usage rate

The box plots visually represent the data distribution, including the median line (middle line), interquartile range (box), and potential outliers. When there are few PS, the median is lower for both performance measures. The data spread is smaller in a low level of PS accessibility, indicating less variability. The box plot (Figure 4) shows that having more PS will improve the FFBSS accessibility with the upward box shift. However, there is more variability because the median is higher, and the spread of the data is larger. On the other hand, usage rate has a broader spread of the data in low-level PS compared to a higher-level PS (Figure 5). The slightly tighter spread of data in higher levels of PS indicates more consistent usage rate performance across the group.

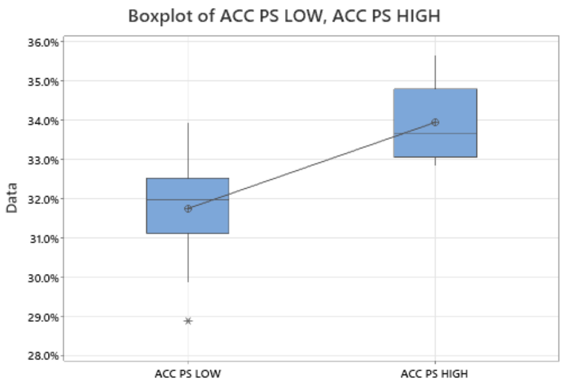

Figure 4. PS vs Accessibility

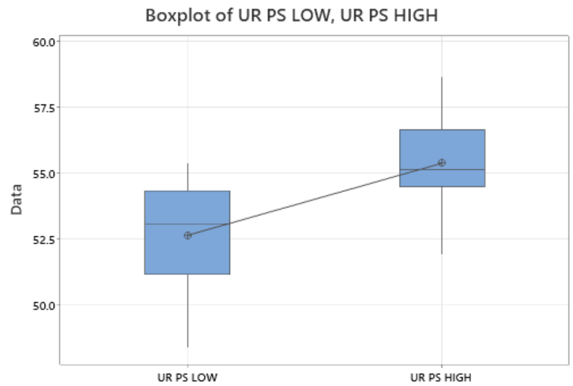

Figure 5. PS vs usage rate

The t-test and the graphical analysis suggest that a higher level of PS performs significantly better than a lower level of PS. The statistical output ensures that providing more PS near students' possible origins and destinations will increase the accessibility and usage rate of shared bikes. Shorter distances to PS correlated with a higher usage rate of shared bikes.

The fitted line plot (Figure 6) shows a quadratic relationship between FS and accessibility. The points are closely aligned along the fitted regression line. The slight downward curvature reflects the diminishing returns of FS on accessibility. Bigger FS provides more bike availability for potential users, leading to better accessibility, which explains the increase. However, after some point, FS will have a low effect on accessibility, as increasing the FS will no longer reach the demand points with a low level of PS, even with a higher level of FS. Additional FS yield diminishing returns on accessibility indicated by the negative quadratic term.

Figure 7 shows a fitted line plot with a downward concave curve. As the FS increases, the usage rate initially decreases sharply, and then the rate of decrease slows down, possibly stabilizing at higher FS. The results suggest that while the improvement in FS can initially reduce the usage rate, this effect diminishes at higher FS levels. It was hypothesized that a negative relationship exists between fleet size and the usage rate of shared bikes. The result confirmed this relationship. Usage rate will continue to fall with the increase in FS. However, there is a need to determine the optimal FS that will not overuse the shared bikes for sustainability and maintenance.

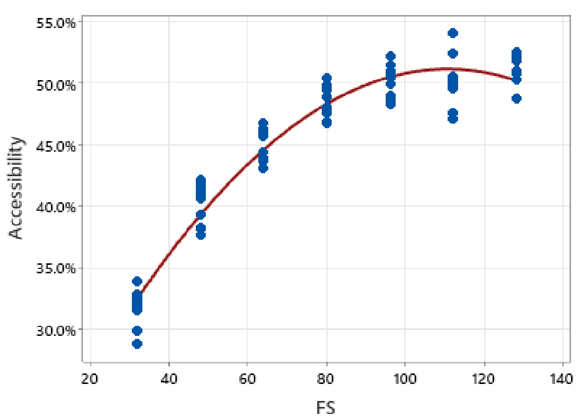

Figure 6. FS vs accessibility

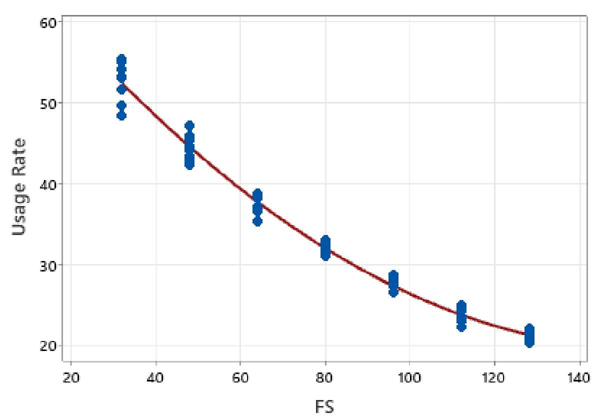

Figure 7. FS vs usage rate

The generated model of predicting accessibility and usage rate can assist in adjusting the FS to demand dynamically. For example, FS can be increased during peak seasons or events to cater to more demands. Areas with more demand can be allocated more bikes to maintain higher usage. Managing FS to align with demand can reduce capital expenditure and maintenance costs. Providing more bikes will surely increase accessibility, but the investment cost will increase to provide such a level. If bikes are overused, it may lead to faster wear and tear. If underused, it may indicate an excess capacity that increases capital costs.

The fitted line plot below shows the actual data points for RA versus accessibility. While there is a slight upward trend, the scattering of data points around the regression line overlaid suggests a weak correlation between RA and accessibility. Figure 8 shows that as RA increases, accessibility improves slightly. The positive coefficient in the linear term of the model reflects the relationship. Ideally, rebalancing helps ensure shared bikes are distributed evenly across the university, making them more accessible to potential users. However, since the model only used the lower-level FS and lower-level PS with the highest density in a week, rebalancing has little effect on the accessibility of shared bikes. It also added that the evenly distributed shared bikes in every parking spot will need to satisfy the dynamic changes of demand at different points on the campus. Excessive rebalancing does not contribute significantly to accessibility in this setup. This model can be used as a preliminary tool to assess the effect of RA on accessibility (Figure 8).

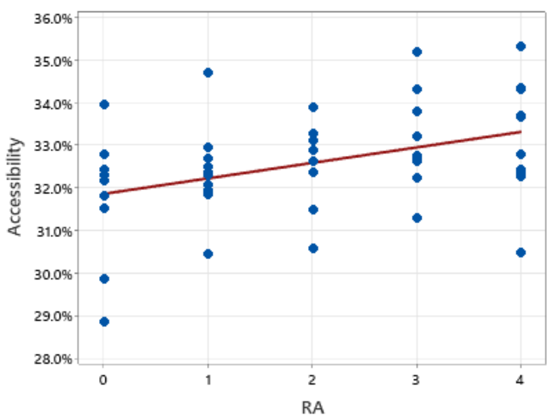

Figure 8. RA vs accessibility

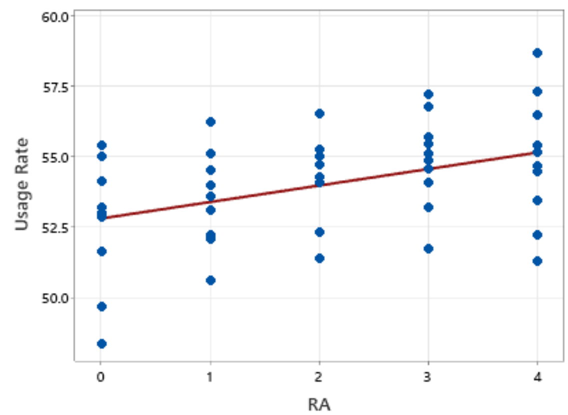

Figure 9. RA vs Usage Rat

Figure 9 shows that rebalancing also increases the usage rate as bikes are becoming more available where and when users need them, encouraging more frequent use. Like accessibility, rebalancing can increase usage up to a certain point, but a decrease in usage can be observed with excessive rebalancing that could disrupt the service. It was hypothesized that frequent rebalancing increases the usage rate of campus FFBSS. However, the result shows that increasing the number of RAs in a day only slightly increases the usage rate of shared bikes. The usage rate starts at around 53 for 0 rebalancing, then slightly increases for every additional rebalancing activity, and then increases to approximately 55.2 at 4 RA daily. The slight increase in usage rate should justify the additional effort of increasing the RA. RA will not increase the accessibility and usage rate if rebalancing still does not reach other potential demand points. Similarly, RA will not increase accessibility and usage rate further if the service capacity is less than the potential demand. These all explain why RA are sensitive to the PS and FS. Likewise, higher PS means higher demand in different locations. Operators can dynamically adjust the number of RAs based on demand patterns. For example, increasing RA can maintain high bike availability during peak hours.

5.3 Validation

The validation of the proposed models was conducted through a combination of statistical significance testing, goodness-of-fit evaluation, consistency with theoretical expectations, and comparison with existing literature. The objective was to ensure that the developed regression and simulation-based models reliably capture the relationships between campus characteristics, FFBSS design variables, and system performance indicators using additional 5 replicates.

Validation of Population Density (PD) Effects

Equations (1) and (2) validate the influence of population density (PD) on accessibility and usage rate under a baseline system configuration (16 parking spots, fleet size of 32 bikes, and no rebalancing activity). Equation (1) demonstrates a statistically significant negative linear relationship between PD and accessibility. The very low p-value (< 0.001) confirms that the observed relationship is not due to random variation. The high R-sq (81.5%) and adjusted R-sq

(81.1%) values indicate that PD alone explains a substantial proportion of the variability in accessibility. This validates the model's reliability in predicting accessibility changes as demand intensity increases. The negative coefficient aligns with system behavior under resource-constrained conditions, where higher population density leads to increased competition for a limited number of bikes, thereby reducing accessibility. The regression model is given by the equation:

$$Accessibility = 0.4715 - 0.1708 * PD \quad (1)$$

Equation (2) establishes a statistically significant positive relationship between PD and usage rate. The high F-statistic (1183.2) and very high explanatory power (R-sq = 96.1%) indicate excellent model fit. This result confirms that increased population density near demand points leads to higher bike usage, validating the demand-driven nature of FFBSS. Furthermore, consistency with findings from Kutela and Teng (2019) and Sun et al. (2018) strengthens external validity, while the divergence from Scott and Ciuro (2019) highlights contextual differences between campus-based and city-wide systems. The linear regression model for usage rate vs PD is given by:

$$Usage\ Rate = 8.121 + 51.22\, PD \quad (2)$$

Together, these results validate that PD exerts opposing but logically consistent effects on accessibility and usage rate, reflecting realistic operational dynamics in a constrained campus environment.

Validation of Parking Spot (PS) Effects Using Two-Sample t-Tests

Two-sample t-tests were employed to validate whether changes in parking spot density lead to statistically significant differences in system performance. The resulting p-values (0.001 for accessibility and 0.008 for usage rate) confirm that increasing the number of parking spots significantly improves both performance measures.

This statistical evidence validates the simulation outputs by demonstrating that observed improvements are not attributable to random variation. The results also confirm that reduced walking distance to parking spots enhances both access to bikes and system utilization, supporting the structural validity of the model.

Validation of Fleet Size (FS) Effects Through Polynomial Regression

Equations (3) and (4) validate the nonlinear impact of fleet size on accessibility and usage rate. The inclusion of quadratic terms captures diminishing returns and saturation effects commonly observed in shared mobility systems.

For accessibility, Equation (3) exhibits strong statistical significance ($p < 0.001$), a high F-statistic (474.23), and an R-sq of 95.57%, confirming that fleet size is a dominant predictor of accessibility. The parabolic form validates that while increasing fleet size initially improves accessibility, excessive fleet expansion yields marginal gains.

$$Accessibility = 0.1424 + 0.006668 * FS - 0.000030 * FS\hat{}2 \quad (3)$$

For usage rate, Equation (4) similarly demonstrates strong statistical validity ($p < 0.001$, R-sq = 98.71%). The nonlinear relationship confirms that beyond a certain fleet size, usage efficiency declines due to oversupply, validating realistic demand–supply interactions captured by the simulation model.

$$Usage\ rate = 71.52 - 0.6637 * FS + 0.002119 * FS\hat{}2 \quad (4)$$

These results validate both functional form selection and predictive accuracy of the fleet size models.

Validation of Rebalancing Activity (RA) Effects

Equations (5) and (6) assess the effect of rebalancing activity on accessibility and usage rate. While both models are statistically significant (p-values of 0.004 and 0.003), their low R-sq values (16.3% and 17.26%) indicate limited explanatory power. This limitation can be explained by the used of low FS and limited number of PS in such a way that even in higher level of RA, it will still not reach other potential demands without PS and bikes availability due to lower level of FS.

$$Accessibility = 0.3185 + 0.003626\,RA \quad (5)$$
$$Usage\ Rate = 52.80 + 0.5853\,RA \quad (6)$$

This outcome validates the model by demonstrating that rebalancing alone has only a marginal influence under the studied campus conditions. The results suggest that rebalancing effectiveness is constrained when fleet size and parking infrastructure are limited, reinforcing the need to prioritize structural design variables over operational interventions in low-capacity systems.

6. Conclusion

Each regression model provided a strong, statistically significant tool for understanding the effects of campus and FFBSS characteristics on accessibility and usage rate of shared bikes. Still, FFBSS operators should determine the right design to ensure that bikes are well-utilized and not overused. Proper maintenance of bikes should be provided with more usage. Understanding the relationship between PD and usage rate can help maintain or increase the usage rate.

The designated PS should be positioned near the origins and destinations of students within the distance accessible to them, as they have limited time to find or park a bike going to their destination. Based on the survey result, the students were only willing to walk for about 50 meters to 100 meters to find a shared bike due to time or mobility constraints and preference. One parking area for each location is better for easy access and improved usage.

When there are fewer bikes available, each bike is used more frequently. Conversely, the total demand is spread across a larger number of bikes with larger FS, making the usage rate low but making it more accessible with more resources to use by the potential demand. Understanding the relationship between FS, accessibility, and usage rate of shared bikes can help fleet management balance the availability and utilization of shared bikes. Redistributing the bikes more often leads to higher accessibility, but excessive effort only slightly improves the performance. If a small number of RA is enough to maintain the availability of bikes, then a few RA in a day may suffice. Targeting an acceptable level of accessibility can be the next step to maintaining customer satisfaction and achieving higher sustainability.

Understanding the effects of each factor can lead to higher accessibility and usage rate of shared bikes. The result of the system simulation in this study will be used to perform the Design of Experiments (DOE) with response optimization to determine the desired levels of the independent variables to optimize the performance measure of FFBSS but will be included in the next part of the research. It can help bike-sharing operators determine the right design for a specific campus, given their characteristics.

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