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Analytics: A Case Study Validation of Bike Share Users Parameters

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ABSTRACT: The evolution and escalation of bike-sharing programs (BSP) continue unabated. Since the sixties, many countries have introduced different models and strategies of BSP. These include variations ranging from dockless models to electronic real-time monitoring systems. Reasons for using these BSP include recreation, errands, work, etc. There are all indications that complex, more innovative rider-friendly systems are yet to be introduced. This paper aims to analyze current variables established by different operators and streamline them by identifying the most compelling ones using analytics. Given the contents of available databases, there is a lack of uniformity and common standard on what is required and what is not. Two factors appear to be common: user type (registered and unregistered, and duration of each trip). This article uses historical data from one operator based in the greater Washington, District of Columbia, USA, area. Several variables, including categorical and continuous data types, were screened. Eight of 18 were considered acceptable and significantly contributed to determining a valuable, reliable predictive model. Bike-sharing systems have become popular in recent years all around the world. Although this trend has resulted in many studies on public cycling systems, there have been few previous studies on the factors influencing public bicycle travel behaviours. This study has identified unprecedented functional and pragmatic parameters required to improve BSP ridership dynamics.

KEYWORDS: Bike-sharing-programs, user type, monitoring systems, analytics, predictive models, historical data, categorical and continuous variables

I. BACKGROUND

A bike-sharing system is a computer-controlled system in which individuals can borrow bikes for a fee or free for a limited period. Bicycles are offered for rent across a city through public bicycle share programs (PBSP). PBSP are executed for several purposes, including increasing cycling rates, facilitating the first and final kilometres of public transit journeys, and reducing traffic congestion (Ricci, 2015). These programs are used for transit and leisure journeys but are primarily designed to make short trips easier. Users of PBSPs are often charged an extra cost for every journey that exceeds the time restriction. Potential paths via which these projects may result in population growth Enhancing access to bicycles for people who do not possess one, increasing the ease of riding, and normalizing bicycling as a mode of transportation are all ways to improve cycling (Goodman et al., 2014). According to the data, bike sharing can raise riding levels, but it requires additional pro-cycling policies and broader support for sustainable urban mobility to thrive. While bike sharing is mainly used for commuting, it also allows riders to engage in other important economic, social, and recreational activities. , The advantages are improved health, expanded transportation options, convenience, decreased travel times and expenses, and a better travel experience (Ricci, 2015).

Bike Share Programs: According to Fishman (2015), BS has gained high and rapid popularity in the last decade. The concept of BS was introduced in the 1960s. However, the number of cities, which have been offering the service, has increased since the late 1990s. In this context, "Contemporary bike-share programs (BSPs) refer to the provision of bikes, which can be picked up and dropped off at self-serving docking stations. Typically, trips are of short duration (less than 30 min). The bicycles usually contain technologies allowing program operators to monitor activities in their respective docking station locations. Some are equipped with a global positioning system (GPS)" (Fishman, 2015, 2). Based on the study findings of Fishman, Washington, Haworth, and Watson (2015), the BS programs' key benefits include flexible mobility and physical activity benefits, emission reductions, reduced fuel use & congestion, financial savings, and multimodal transport connection support. Additionally, one of the main benefits of BS is that bikes are perceived as replacement cars.

On the other hand, the Institute for Transportation and Development (2018) report found that in the year 2016, BS systems rider trips in the US accounted for over 28 million. Ridership, specifically in North America, has increased significantly since 2012 due to yearly new BS systems. Since 2016, most new bike share systems operating in North America have used intelligent bikes.

Furthermore, as BS continues to evolve, new operating systems across the US have emerged using dockless and stationless bikes. Additionally, in 2017, many dockless operators installed bikes in the US, Great Britain, China, Singapore, Australia, and Italy, among others. Correspondingly, 'pedal assist e-bikeshare fleets have been launched in many North American cities since 2017.

Additionally, Campbell, Cherry, Ryerson, and Yang (2016) stated that in the present scenario, China is the leading nation in the world in terms of the growth of public BS along with the private electric bike. The current projections confirm the feasibility of implementing large-scale shared e-bike systems nationwide. Public BS systems can be one of the fastest-growing public transportation modes in the world. The industry has been increasing at an average rate of 37% since 2009. In this context, "The current trajectory of bikeshare adoption, the popularity of e-bikes, and the presence of e-bikeshare pilot projects in other countries all support a future of e-bike sharing in China" (Campbell et al., 2016, 400). Given the rapid evolution of transportation in China, it is not well understood how such a system will differ from standard bike-share and how both types of shared bikes (hereafter "shared bike" are used to refer to both bike-share and e-bikeshare) systems can best address the needs of urban China" (Campbell et al., 2016, 400). Based on the study findings of Guo, Zhou, and Li (2017), bike-sharing growth is receiving attention as societies are becoming highly aware of the significance of 'active non-motorized traffic modes. Since BS is perceived as a sound transport system, it increases bicycle use, especially in the circumstances providing different pick-up and drop-off locations, self-service, etc., thereby making it convenient for users. Furthermore, bike-sharing offers an efficient solution to the transport system and thus can be perceived as an alternative to other transit systems.

Additionally, Kim, Ghimire, Pant, and Yamashita (2021) asserted that it is essential for riders to use a helmet while using a bike. A survey conducted in the year 2013 under the 'New York City's bike share program' found that about 85.3% of the riders did not wear helmets. This raises an important question – whose liability is it? Even though there are no statistics available on BS riders' accidents, a well-designed and comprehensive program should include access to helmets. The additional challenge is motivating riders to use these helmets. If current rider safety behaviours and awareness are any indications, there is a strong likelihood that most BS riders will use them. This is a challenge that policymakers need to consider and prioritize in their respective BS programs.

Bike-Sharing Models: Different bike-sharing models can be used to predict flows in every station. Contextually, Tran, Ovtrachta, and d'Arcier (2015), robust linear regression models are one such model that helps in predicting flows. The developed environment variables used in the model are often identified within a buffer zone (300 meters) in every bike-sharing station. Thus, linear regression can be used during the busiest time of a weekday to predict the bike-sharing flow. Integrating a robust linear regression method can help improve rider needs and program optimization in general.

Furthermore, the arrival and exit flow at the hourly level can be integrated into the regression model at each station. On the other hand, Yang, Li, and Zhou (2019) highlighted another bike-sharing model system dynamics simulation. In this context, the simulation method helps to model factors along with operations, processes, and policies to be considered in the dockless bike-sharing programs operations. It further helps effectively assess sustainable strategies that enhance the overall system performance. Maintaining an adequate balance between expenditure and revenue is essential, especially in the sustainable development of dockless bike-sharing programs in a specific area. Thus, both revenue and cost of the dockless bike-sharing programs need to be fully considered in the respective system. Additionally, the system model performs different simulations and further evaluates the dynamic behaviour of the individual system.

The study findings of Ottomanellia (2013, 204) further stated that the main objective of a dynamic simulation model is that it helps to minimize vehicle repositioning costs for bike-sharing operators, aiming at high-level user satisfaction. It increases with the probability of finding an available bike or an accessible docking point in any station at any time. The proposed model considers the dynamic variation of the demand". Based on the study findings of Soriguera, Casadoa, and Jiménez (2018), docking stations along with bikes are passive agents, while the amount and location are perceived as inputs to the simulation. Thus, it indicates that the simulation is dependent on the higher-level model for establishing the optimality in the respective inputs.
Furthermore, users and repositioning trucks are the active agents who make decisions, resulting in an efficient bike flow between stations" (Soriguera, Casadoa, & Jiménez, 2018, 140). For instance, the case study of Barcelona's Bicing can be considered, wherein a 24-hour simulation was performed with the inputs from a real case study. Bicing is a bike-sharing system in Barcelona, which was selected as a benchmark. Additionally, the open data policy of the Barcelona council, including Bicing's data, was decisive in such selection. The Bicing available data portal includes the real-time occupancy of every station with a one-minute update frequency. These data allow assessing some aspects of the simulator's performance" (Soriguera, Casadoa, & Jiménez, 2018, 142).

Significance of Research: The paper focuses on discussing, understanding, and identifying the association between bike share (BS) riders and compelling parameters using a live data set. Through this study, more in-depth knowledge can be achieved on bike-sharing models, thereby enhancing future applications' design, implementation, and utilization. Over the years, the concept of BS programs has increased globally. Thus, conducting this research paper has helped in understanding the arguments and theories which have been provided regarding the relationship between BS riders and compelling parameters. The research has also assisted in enhancing the developments made over the years on the selected topic and gaining insights regarding the gaps. Thus, understanding all these aspects will contribute to making a significant input in BS programming.

Gaps: There is one significant gap in the research, as adequate information could not be found regarding the streamlining association between bike share riders and compelling parameters. To enhance the overall understanding and knowledge of these models, improved methodologies can be integrated, such as conducting interviews with bike-sharing operators. This is because it can help obtain insights from the participant, thereby enabling the understanding of the implicit relationship among different factors. Such a strategy, in addition to a more preliminary and comprehensively exhaustive analysis – addressing covariate independence, homoscedasticity, outliers, collinearity, etc. – is this research's central theme and focus.

Objective

This paper highlights specific arguments and ideas about designing, developing, and implementing bike-sharing models. The article further emphasizes understanding the aspects studied in the field, the weaknesses, and gaps or areas that need further study. Thus, the review focuses on demonstrating to the reader the reasons for conducting the research, including usefulness, necessity, importance, and validity.

Methodologies Used in Previous Literature: In the study conducted by Tran, Ovtracht, and d'Arcier (2015), the data were obtained from the bike-sharing trips from JC Decaux, the administrator of the Lyon bike-sharing system. This included data for every station during the year 2011. In this context, each trip helped provide information regarding the departure, the arrival station, the date, the hour of check-in & check out, and the subscriber type. Correspondingly, regarding the subscribers, Tran, Ovtracht, and d'Arcier (2015) focused on analyzing two different bike-sharing users, comprising short-term subscribers having a 'one-day bike sharing subscription' and long-term subscribers with yearly 'bike sharing subscription.' On the other hand, the research conducted by Kim, Ghimire, Pant, and Yamashita (2021) used the data gathered in June 2019. The authors selected a total of 25 sites located in urban Honolulu. In this study, stratified simple random sampling was integrated for selecting street segments with high, medium, and low traffic volumes that differed in lane configurations. This included multi-use paths, protected bikes, and shared and dedicated bike lanes. Visitors, shopping centers, attractions, activity generators, and commercial offices were also mapped and integrated into the sampling process.

Contribution to the Research Field: This study's importance or contribution will help better understand the global concepts associated with bike-sharing in the present scenario. This study will further enhance the knowledge regarding the potential challenges and can act as a source of information in the future. The paper will help policymakers generate policy based on the analysis results concerning bike share.

II. THE CAPITAL BIKESHARE STUDY

Setting: This study will be based on a US bike-sharing provider, Capital Bikeshare Company (CBC). A mountain bike guided tour and rental facilities are part of the business. The program is jointly owned and sponsored by the District of Columbia and Arlington County, VA, and operated by Alta Bicycle Share, Inc. Its coverage includes both regions (see figure 1). CBC provides rides for people of all skill levels. They will range from easy family rides to intense, fast-paced expert rides. These tours might take anywhere from a few hours to a week to complete. The company offers a package deal that includes bikes, transportation to and from the trailhead, lunches, and a personal tour guide to show them around the trails and provide information about the area. It also offers a complete bike rental fleet. The bikes range in price from low-cost city cruisers to full-fledged mountain bikes with full suspension. Customers are not required to be on tour to hire bicycles from the company. The company has 4500 bicycles and 500 stations.

Due to the ongoing Corona pandemic, the company's revenues have recently dropped significantly. In the current market environment, the company is struggling to stay afloat. As a result, it has decided to develop a thoughtful business plan to increase revenue as soon as the current lockdown ends and the economy returns to a healthy position. CBC hopes to understand better people's demand for shared bikes after the present Covid-19-related complications end across the country. They planned this to position themselves to meet people's needs whenever the situation improves, differentiate themselves from other service providers, and profit handsomely. They want to know what factors influence the demand for these shared bikes in the United States.

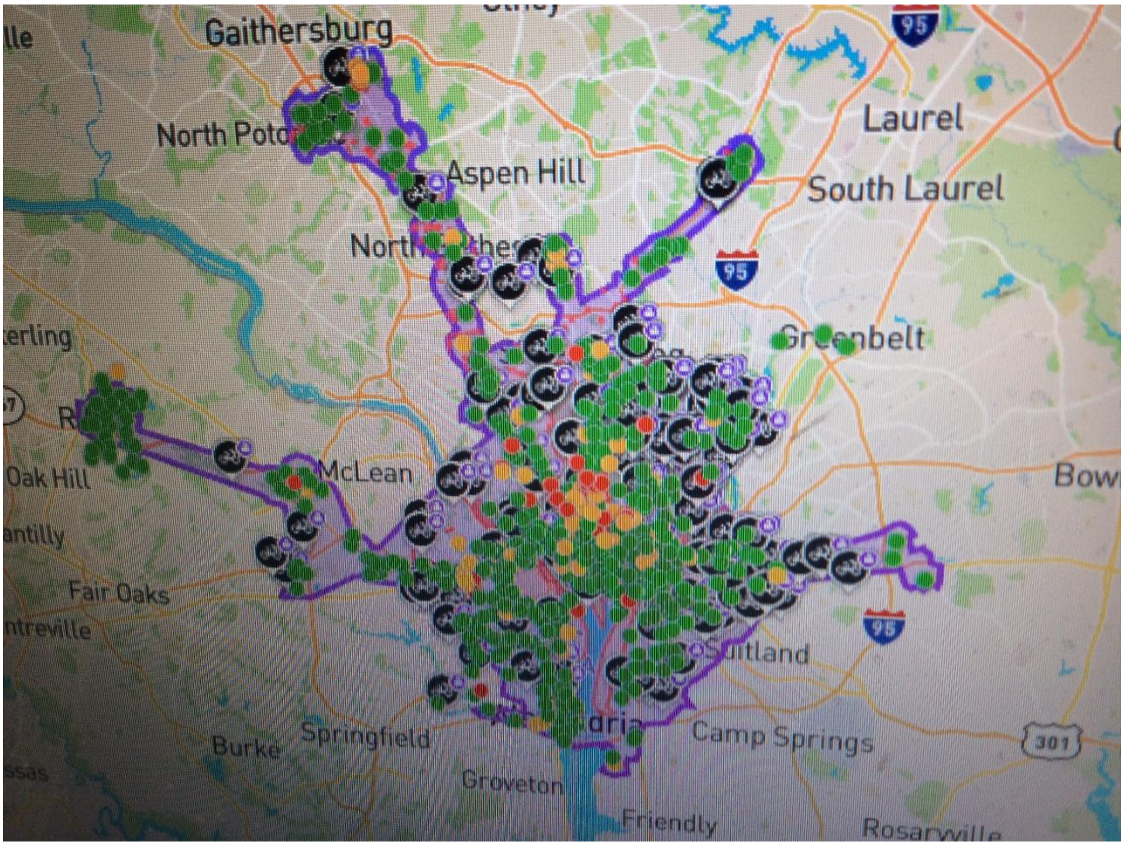

Figure 1. Capital Bikeshare (CB) Coverage: (Source: CB website).

III. RESEARCH LIMITATIONS

In general, many scientific research studies are prone to different limitations. This one is no exception. The inexhaustive list of this study's shortcomings includes:

- Existing data sets influence the study design.
- Lack of a sampling protocol. In this paper, there was a sampling protocol in place.
- A third party enhances the dataset. A third party did improve the data for this paper.
- Inability to verify inconsistent data points – wrong data entry, recording errors, etc. -: example following up outlier data. In this paper, the errors were checked, and outliers were removed.
- Inadequate data cleaning: This paper employed data cleaning, and the data were checked for missing values and redundancies removed.
- The data set used is old because no recent datasets measure variables like temperature, wind etc.

Data Management: A bike-sharing system refers to a service that makes bikes accessible for shared use to individuals for a fee or free on a short-term basis. Such systems let users rent a bike from a "dock," which is frequently computer-controlled and where the user enters payment information, and the system unlocks the bike. After that, the bike can be returned to another dock in the same system. The original database has N=731 observations. These have been reduced to 703 cases after adjusting for deleted cases identified as outliers. Table 1 shows the data dictionary that details the data set attributes used in the study. The data used are free and publicly provided by BSC and Hadi Fanaee-T Laboratory of Artificial Intelligence and Decision Support (LIAAD), University of Porto: original data provider and data compiler, respectively. As indicated earlier, one database limitation has been the inability to include a comprehensive data-cleaning strategy during this process. Data collection for the study was conducted between 2011 and 2012 inclusive. The data set is still relevant because the variables running the models have not changed over the years. Table 1 shows the descriptions of the variables measured in the dataset. The registered renters are those renters who have registered with the renting company.

Table 1. Study Database Dictionary (Source: Author).

VARIABLE	DESCRIPTION	VALUE LABELS/VARIABLE TYPE
Independent variables		
season	Seasons of Year	1=Spring, 2=Summer, 3=Fall, 4=Winter
month	1=Jan, 2=Feb, etc.	Nominal-months of the year
holiday	Day Holiday or not	Nominal
weekday	Day of the Week	Nominal
Working day	Weekend or Holiday =0, Otherwise = 1	Nominal
Weather sit	1=Clear, Few Clouds, Partly Cloudy, Mist	Nominal
	2=Mist+Cloud, Mist +Broken Clouds, Mist+Few Clouds	
	3=Light Snow, Light Rain+Scattered Clouds	
	4=Heavy Rain+Ice Pellets+Thunderstorm+Mist, Snow+Fog	
temp	The temperature in Celsius. Normalized by division by 41	Scale
atemp	Temperature Feel Division by 50	Scale
hum	Humidity Division by 100	Scale
windspeed	Division by 67	Scale
Dependent Variable		
cnt	Total number of registered & unregistered bikers: renters	Scale

IV. METHODOLOGY

The research is motivated by the researcher's interest in learning more about the factors influencing the demand for these shared bikes. The study is interested in knowing what factors influence demand for these shared bikes. The study seeks to identify the variables that significantly predict the demand for shared bicycles. A multiple regression model is required to model the demand for shared bikes with the supplied independent variables. It will be employed to determine how needs vary depending on the attributes. According to Uyanık & Güler (2013), when there is a need to forecast a variable's value based on the values of two or more other variables, we utilize multiple regression. The dependent variable, the total number of registered & unregistered bikers: and renters, is the variable we want to forecast. The data are analyzed using Statistical Package for the Social Sciences (SPSS version 25).

Verifying Regression Assumptions: When a researcher decides to use multiple regression to analyze data, one step in the process is to ensure that the data the researcher intends to analyze are compatible with multiple regression assumptions (Ernst & Albers, 2017). This is necessary because multiple regression can only be used if the data "passes" – the study's outcome - the assumptions required to get a valid result. The first assumption is that the dependent variable has to have a continuous or quantitative level of measurement. In this study, the dependent variable, the Total number of registered & unregistered bikers: renters (cnt), meets this criterion. The second assumption is that there should be more than one independent variable, which can be either continuous or categorical; the independent variables in this study meet the criterion. The third assumption is that a linear relationship between the dependent variable and every independent variable should be assessed using a scatterplot matrix. Dummy variables were generated from the categorical variables.

Figure 2 shows that the dependent variable only has a linear relationship with variables temp and atemp.". "Figure 3 shows the relationship between the Response variable and the Categorical variables.

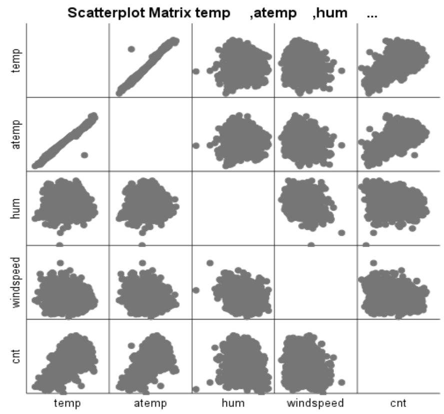

Figure 2. Scatter Plot with linear correlation between (cnt) and two Explanatory (tempt & attempt) Variables.

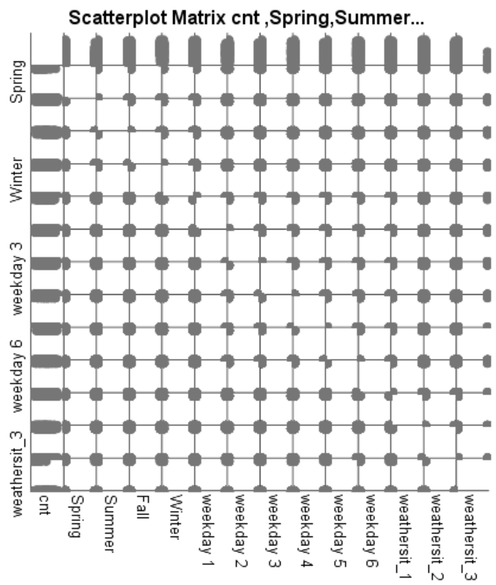

Figure 3. A linear relationship between the Response variable and the Categorical variables.

Figure 3 shows the relationship between the independent and dependent variables and an approximately linear relationship between the dependent and the independent variables. The fourth assumption is that there should be independent observations; this is checked using the Durbin-Watson statistic. The model shows the value of the Durbin-Watson statistic as 0.452. This implies a positive autocorrelation; this means that the correlation between the data points is not modelled well enough. The fifth assumption is that the data should indicate homoscedasticity, which means that the variances remain similar as you move along the line of best fit. The scatterplots suggest homoscedasticity; the points should be about the same distance from the line. The sixth assumption is that there should not be multicollinearity. This occurs when there is a high correlation among independent variables - problem; this is assessed using the values of the Variance Inflation Factor (VIF). The acceptable values for VIF are those less than 10 (Hair et al., 2019). In this case, the independent variables with the highest values of VIF are; 'temp', 'atemp' and 'Winter'. The variables' atemp' and 'Winter' will be excluded based on the high VIF values. The variable 'temp' will not be excluded despite having a high VIF value since, based on general knowledge, the temperature is likely to be an essential factor for bike rentals. The seventh assumption is that there should not be outliers or points that are highly influential. Cook's Distance (see Table 4) was used to point out the influential data points; they were not included in the regression model because they have the propensity to reduce the predictive accuracy of the results and the statistical significance. And according to David G. Keinbaum et al., it also "measures the extent to which the estimates of the regression coefficients change when an observation is deleted from the analysis". The original data points were N=731; after removing the outliers, the number of observations included in the study was reduced to N=703 The eighth assumption is that the residuals should be approximately normally distributed (see figure 4).

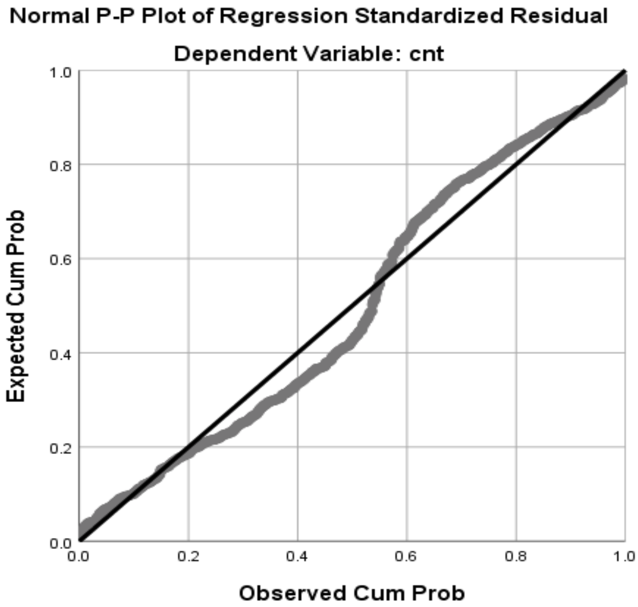

Figure 4: Normal P-P plots show that the residuals are approximately normally distributed.

Table 2 represents summary statistics of all the variables used in the study. Table 3 shows the coefficients for the final regression model. The R Square shows how much of the total variation in the dependent variable, the total number of registered & unregistered bikers: and renters (cnt), can be explained by the independent variables. In this case, 63.3 % can be explained. The F-statistic, $F(25,677) = 46.67$, $p<0.05$, suggests that the regression model is a good fit for the model, that is, the regression model statistically significantly predicts the total number of registered & unregistered bikers: renters (cnt). Table 3 shows that the variables that significantly predict the total number of registered & unregistered bikers: renters (cnt) include Temperature, humidity, wind speed, the month of September, Spring, Fall, all weekdays except weekday one and weather situation 3 (Light Snow, Light Rain with Scattered Clouds), $p<0.05$.

V. RESULTS AND DISCUSSIONTable 2 shows the descriptive statistics for the dependent and the dependent variables.

Table 3. Coefficients of Regression (Source: Author).

		Unstandardized Coefficients (Response Variable = cnt)			
Model		B	Std. Error	t	Sig.
1	(Constant)	4567.157	406.058	11.248	.000
	temp	7031.969	648.074	10.851	.000
	hum	-3563.312	473.934	-7.519	.000
	windspeed	-3471.414	640.650	-5.419	.000
	Jan	235.395	279.960	.841	.401
	Feb	210.804	283.372	.744	.457
	March	352.045	288.488	1.220	.223
	April	-11.964	387.999	-.031	.975

May	153.040	410.860	.372	.710
June	-470.427	421.167	-1.117	.264
July	-759.841	449.189	-1.692	.091
Aug	-164.138	429.240	-.382	.702
Sept	751.276	358.066	2.098	.036
Oct	286.497	253.176	1.132	.258
Nov	-179.087	237.306	-.755	.451
Spring	-1688.589	280.589	-6.018	.000
Summer	-651.577	344.391	-1.892	.059
Fall	-1089.325	319.478	-3.410	.001
weekday 1	202.147	164.052	1.232	.218
weekday 2	368.900	167.036	2.209	.028
weekday 3	445.015	165.848	2.683	.007
weekday 4	420.350	165.636	2.538	.011
weekday 5	420.175	166.046	2.530	.012
weekday 6	386.971	167.072	2.316	.021
weathersit_2	-192.036	121.059	-1.586	.113
weathersit_3	-1891.411	339.817	-5.566	.000

Table 3: Regression Coefficients of Response vs Explanatory Variables (Source: SPSS Output)

The analysis in table 4 revealed that an increase in temperature by 1^0 Celsius will lead to a rise in the number of renters by 7032; it also revealed that an increase in humidity by one unit leads to a decrease in the number of renters by 3564. The analysis also revealed that an increase in wind speed by one unit will decrease the number of renters by 3471, consistent with Nosal and Miranda-Moreno (2014). They used hourly data collected from induction loop counters on cycle lanes to evaluate the impact of weather on cycling in multiple North American cities. They established that temperature and humidity have significant implications for renting. The analysis also revealed that Spring and Fall seasons have a statistically significant effect on the number of bike renters; this is consistent with Lyu et al. (2021), who determined that factors like spring festivals significantly affect biking. According to the researchers, these temporal characteristics suggest that the bike turnover rate could rise even higher if the efficiency of the bike supply is increased by proper bike relocation and location. The analysis also revealed that September significantly affected the number of bikers. It was also established that all the days of the week had a significant impact on the number of renters except the first day of the week; this is consistent with Lyu et al. (2021), who established those different days of the week attract other numbers of bikers, for instance in Ningbo, China, the weekend's register between 20%-30% lower rental numbers than the weekdays. The analysis also revealed that weather situation 3 (Light Snow, Light Rain with Scattered Clouds) had a statistically significant effect on bike rentals.

VI. CONCLUSION

Bike-sharing systems have become popular in recent years all around the world. Although this trend has resulted in many studies on public cycling systems, there have been few previous studies on the factors influencing public bicycle travel behaviour. A bike-sharing system is a service where individuals can borrow bikes for a fee or a limited period. Many bike share programs allow users to borrow a bike from a system which is usually computer-controlled. The user enters payment information, and the system unlocks the bike. After that, the bike can be returned to a system-wide dock. The study aims to determine the demand for shared bikes in Washington based on compelling parameter estimates. Rental firms arrange this to position themselves to meet people's requirements whenever the situation improves, allowing them to stand out from other service providers and earn handsomely. The study aims to discover which variables are essential in predicting shared bike demand. How well do those variables accurately characterize the bike's requirements? The service provider organization has amassed a vast dataset on daily bike requests across the market based on some parameters that can reliably be applied to predict potential demand.

The regression analysis carried out determined that the variables that significantly predict the total number of registered & unregistered bikers: renters (cnt) include Temperature, humidity, wind speed, the month of September, Spring, Fall, all weekdays except weekday one, and weather situation 3 (Light Snow, Light Rain with Scattered Clouds). Comprehending the temporal features of bike-sharing usage may aid service providers and policymakers in improving bike-sharing services. Temperature was the most significant factor in predicting the number of renters. The fact that bike sharing benefits from and is dependent upon clear political, policy, and public support for sustainable mobility in general and cycling, in particular, may be the most important conclusion to be derived from all of the research on impacts and processes reviewed. Building a supportive cycling culture, increasing the number of cyclists, and pro-cycling policy initiatives like the provision of high-quality infrastructure for cyclists is crucial and, in some cases, determining factors that can support bike sharing both during and after implementation. The findings offer a chance to create a policy that centres on the collaboration and ongoing participation of stakeholders and local communities as implementers of bike sharing. See the end of the document for further details on references.

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