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ORIGINAL ARTICLE

Investigating the temporal differences among bike-sharing users through comparative analysis based on count, time series, and data mining models

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Abstract Bike-sharing services provide easy access to environmentally-friendly mobility reducing congestion in urban areas. Increasing demand requires highly service planning methods based on bike-sharing user behavior. Negative Binomial, Poisson Regression, and Time Series models were elaborated considering the weather to reveal the differences between the members, occasional users, and visitor bike-sharing user groups. The negative Binomial approach is found to be superior to Poisson. Weather effects were varied in their influence on bike-sharing user classifications. In general, good weather conditions lead to more usage of bike-sharing. Weekends attract more occasional users and visitors than weekdays. In time series models, the seasonal trend of bike-sharing trips conducted by members was predicted without weather impact. According to the comparison, Random Forest performed better than SARIMA when the number of observations was low. Visitors are more influenced by temperature, wind and type of day. Occasional users are more subjected to precipitation. For members, it is found that the temperature, type of day are the most significant factors. The least factors for all are varied as well: precipitation for visitors, humidity for occasional users, precipitation and wind for members. The results help decision-makers predict the daily usage of bike-sharing for various user groups.

1. Introduction

Cycling is one of the most important elements of sustainable mobility for its numerous advantages, including its zero-emission status, low land use, and positive impact on general health [32]. The rising interest in cycling attracts more users to bike-sharing systems as well. Besides health and environmental benefits, transition to bike-sharing was also propelled by the COVID pandemic because many people found it as an adequate alternative of public transport to avoid virus transmission [49]. As more people are using bike-sharing new issues related to capacity planning arise. Namely, better understanding of user behavior helps operation planning and

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facilitates high capacity utilization. Previously, the fluctuation and the wide variety of demand were found to be the among the biggest challenges of bike-sharing system operators [50]. Thus, we focus on the various user groups' usage pattern of using bike-sharing systems throughout time. The user groups were considered to reveal the different impacts of weather and temporal variables on their travel behavior. The analysis is conducted based on several statistical methods. Count models (Negative Binomial Regression Model and Poisson Regression), Time Series model (Seasonal Auto-Regressive Integrated Moving Average), and Data Mining Techniques (Random Forest) have been used and compared. The novelty of our research is that per our knowledge no research has examined the effects of weather conditions on various bike-sharing groups, as well as, none compared the detailed performance of the above methods in bike-sharing use prediction considering different user groups. The need of such comparison is to find the best-fit method for each user category.

The structure of the paper is as follows: after a brief literature review, a description of the methodology and data set can be found in Section 2. Results and discussion are presented in section 3. Finally, conclusions are drawn, and future research trends are identified.

2. Literature review

Recently, traffic congestion and air pollution led to a rise of interest in eco-friendly transportation [23,57,11]. Thus, Bike-sharing (BS) has a good impact on economics, transportation, health, and enhances rider safety by raising driver awareness as well as helps tourists to explore and visit attractions [41,33,58,57,7] found that many visitors who use bike-sharing are cyclists who are unable to transfer their vehicles to their destination and prefer public transportation and bike-sharing. Thus, bikers can use bike-sharing to connect to public transit at a reduced cost [64].

Several review papers [26,23] investigated factors affecting bike-sharing demand, such as weather, built environment [27], land use, public transportation, spatial aspects [31], socio-demographics [9], temporal factors, and safety. Research on bike user characteristics was conducted using different approaches. For example, Maas et al. [39] used the Ordinary Least Square (OLS) regression model to reveal bike-sharing's spatial and temporal characteristics use in Limassol, Cyprus. Faghih-Imani et al. [24] explored the BS use temporality between April and August 2012 in Montreal, Canada, using a multilevel statistical modeling technique. Noland et al. [42] provided a set of Bayesian regression seasonal trip generation models for New York City bike-sharing stations. It was found that the most weather-sensitive occasional users had lower usage than regular users. El-Assi et al. [22] applied a distributed lag model. The results showed that members used the bike share system 60 % more on weekdays than on weekends. Using multilevel modeling, [46] found that precipitation affects bike ridership negatively. The findings also show that people cycle 25 % more on weekdays than on weekends. Using the autoregressive negative binomial time series model, it has been observed that people use BS more in good weather [16]. In contrast, bicycle use declines on weekends, indicating a significant share of work motivated trips. Close to our aims, Turoń et al. [51] carried out a statistical analysis using data acquired in 2017 and 2018 in Hungary. The results support predicting seasonal demand and estimating the attractiveness of individual docking stations. The main difference between our research and Turon et al. article is that the authors used monthly and yearly observations trends without investigating weather conditions. Moreover, Földes and Csiszar [28] noted the need for further studies related to bike-sharing availability, usage, navigation, and payment.

Thus, we categorized the studies based on their focus into the following groups: temporal and weather conditions, count (Poisson and Negative Binomial), ARIMA, and data mining techniques (Random Forest) models.

2.1. Count models

Several articles elaborated count models to reveal the relationship between the demand and weather conditions. A four-year study [37] used the Negative Binomial (NB) model. Researchers found that fewer trips were made on weekends, public holidays, and during summer semesters, while the number of rides was positively correlated to the daily temperature. However, user groups were not analyzed. Similarly, Younes et al. [63] used a log-level Poisson model to analyze changes in demand on weekends and weekdays separately in Washington DC, US. Higher temperature and better visibility have a substantial and positive effect on bike-sharing trips, while wind speed has a significant negative impact. In Daejeon, South Korea, Kim [35] indicated that high temperature and non-working days have a negative impact on the demand. For the San Francisco Bay Area Bike Share System, Ashqar et al. [3] used a Poisson regression model (PRM) and the Negative Binomial regression model (NBRM) to predict the number of bikes in the network. The time of day, temperature, and humidity level were found to be significant count predictors. User groups, pressure, and solar radiation were not considered. Others used this approach to reveal the impact of socioeconomic and land-use characteristics on BS [40]. Age, income, education, transit stops, hub locations, offices, schools, trails, and sidewalk facilities were significant geographical variables in Poisson model, but the weather was not investigated. Finally, in Cologne, Germany, Schimohr and Scheiner [45] investigated the space–time patterns of bike-sharing utilization using Poisson regression and found that demand is the lowest on Sundays.

2.2. ARIMA models

Research on bike-sharing using ARIMA method was conducted with various objectives. Cho et al. [18] studied the connection of public transportation to BS. The results implied that the bike-sharing demand is higher at bus stops than at subway stations. ARIMA was also used to determine how the built environment affects bike ridership in Houston [5]. It was found that the trips were two times greater in numbers on weekends than on weekdays. Temperature and wind did not affect the daily average trip counts. However, precipitation reduced the average number of trips. ARIMA was found to be a good predictor of bike-sharing demand in small areas according to a comparison with machine learning-based models [54,59,36]. Feng et al. [25] estimated bike availability at bike stations based on historical data using ARIMA and Markov queueing approaches. ARIMA was better in the performance of estimation. Dias et al. [21] forecasted the bike availability in the BS stations in Barcelona. The authors employed publicly available data, such as the weather forecast, to categorize the state of the stations using the Random Forest algorithm. Yoon et al. [62] proposed a personal journey adviser for BS users to assist navigation in cities. In terms of trip time, the authors modeled the behavior of real mobile bikers using ARIMA.

2.3. Data mining models

Ashqar et al. [3] used the Random Forest to anticipate bike counts in San Francisco Bay Area Bike Share stations. Time, temperature, and humidity were found to be the most significant count predictors using Random Forest. In the same line, Sathishkumar and Cho [52,53] predicted the hourly rental bike demand in Seoul Public Park. Temperature outperformed other weather variables like humidity, wind, visibility, dew point, solar radiation, snowfall, and rainfall. Moreover, Sathishkumar and Cho [52,53] used the same method of random forest in addition to the linear regression for the Capital Bike share program in Washington, D.C. The findings indicated that the descending order of impact variables are temperature, time, humidity, rain, and wind. In Europe, Ruffieux et al. [44] predicted bike and space availability at bike-sharing stations in real-time based on Random Forest algorithms and Convolutional Neural Networks. Again, the temperature was on the top, then wind, humidity, and type of the day. Lathia et al. [38] noted that bike usage varies significantly according to the time of day, the day of the week, and the type of day, such as holidays using data mining approach.

In summary, most of the previous studies focused on overall bike-sharing users as one group, influenced by temperature, and type of the day. Thus, it is important to conduct a study that focuses on good predictions and comparisons of the various categories, which is missing. Moreover, no research compared count models, ARIMA, and Random Forest, the main research gap. In this study, the bike-sharing demand is modeled based on the weather and temporal variables. Furthermore, the performance of the models is compared.

3. Methodology

This section elaborates on the count models (NBRM and PRM), Time series model (ARIMA), and Random Forest model. The flowchart of the methodology, is given in Fig. 1.

3.1. NBRM and PRM

NBRM and PRM were elaborated to predict the discrete number of bikes in use and daily trips based on historical data. NBRM is applied if the dependent variable has a negative binomial distribution, and the variance does not equal the mean value. Similarly, PRM used if the dependent variable has a Poisson distribution, a specific negative binomial distribution where the variance equals the mean value. Accordingly, PRM includes one less parameter [60]. Equation (1) expresses the count models. Nowadays, PRM is the most commonly used method for count data modeling [48,43,65]. Further information on NBRM and PRM can be obtained in the literature [12].

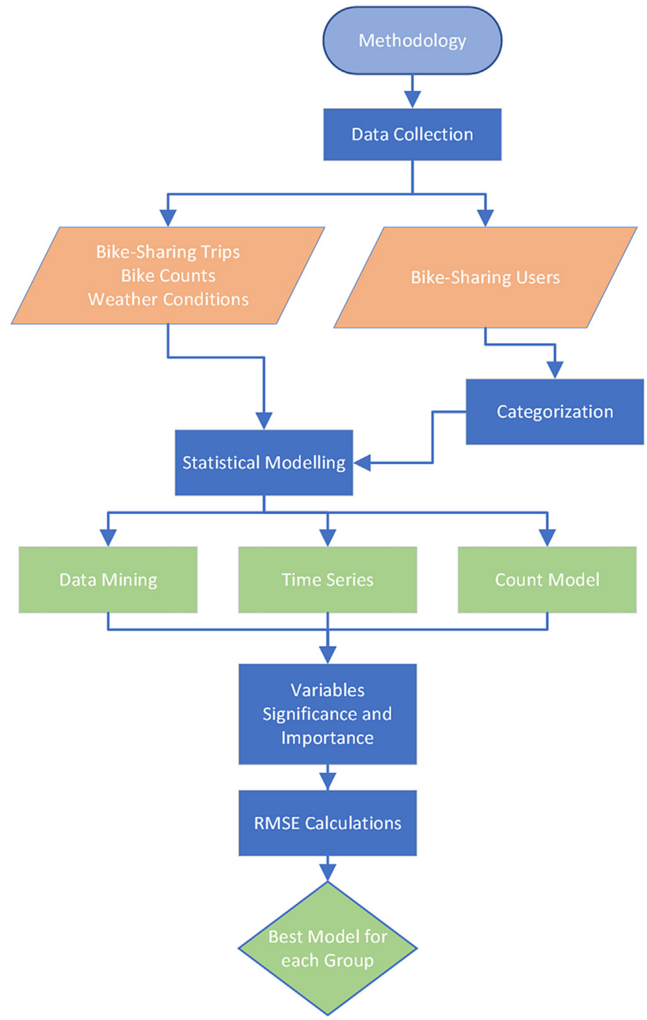

Fig. 1 Flowchart of the methodology.

$$\log(Y) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \tag{1}$$

Where:
Y : Bike counts or trips.
β_0: Constant.
β_i: Independent variable parameter.
X_i: Independent variables, including precipitation, wind speed, solar radiation, pressure, humidity, and temperature.

To evaluate the fitness of the models, we have applied the following common criteria to the data set [2]:

- Bayesian Information Criterion (BIC):
- The Akaike Information Criterion (AIC), and
- Likelihood Ratio (LR) test.

BIC and AIC consider the model fitness and the number of parameters. The only difference is, BIC considers the number of observations [65,4]. In general, the model with the lowest BIC and AIC is preferred [56,17]. LR test concentrates on the improvement concerning likelihood value. The higher the likelihood, the better is the fit of the model.

3.2. ARIMA model

Autoregressive Integrated Moving Average (ARIMA) models forecast time series considering periodicity and seasonality based on equally spaced univariate time series data, transfer function data, and intervention data. Because ARIMA was the most representative model in the time-series domain, many studies in the transportation field used it as a baseline. In this study, we applied the Seasonal ARIMA (SARIMA) on a weekly basis to consider weekly differences that may cause bias in regression models. The simplified notation for seasonal ARIMA is SARIMA (p,d,q)(P,D,Q), which is expressed in equation (2):

$$\begin{aligned}
&(1-\beta_1 Y_{t-1}+\beta_2 Y_{t-2}+\cdots+\beta_P Y_{t-P})(1+\beta_1 Y_{t-1}\\
&\quad+\beta_2 Y_{t-2}+\cdots+\beta_p Y_{t-p})(1-dY_{t-1})(1-DY_{t-1})Y_t\\
&\quad=\alpha+(1-\text{[03B8]}_1 Y_{t-1}+\theta_2 Y_{t-2}+\cdots+\theta_Q Y_{t-Q})\\
&\qquad\times(1+\text{[03}B\text{8]}_1 Y_{t-1}+\theta_2 Y_{t-2}+\cdots+\theta_q Y_{t-q})\varepsilon_t\\
&\qquad+\sum_1^n \varphi_n \qquad (2)
\end{aligned}$$

Where:

Y_t = dependent variables, which is daily bike counts or trips;

X_n = independent variables, including precipitation, wind speed, solar radiation, pressure, humidity and temperature;

$\varepsilon_t = Y_t - Y_{t-1}$;

α = constant;

β = coefficient in AR; θ = coefficient in MA.

p = the order of the AR; P = the order of the AR-Seasonal;

q = the order of the MA; Q = the order of the MA-Seasonal;

d = non-seasonal difference; D = seasonal difference.

φ_n = coefficient of independent variables.

3.3. Random Forest

The Random Forests (RF) approach is one of the top ensemble learning algorithms [8]. This methodology effectively deals with the enormous complexity of the input data and non-linearity aspects. However, because it recognizes the significance of each component, the random forest method is an extremely powerful tool for reducing dimensionality in any circumstance [15,1]. Random forest outperforms decision tree in terms of accuracy because of the use of Massive Numbers, yet it is more difficult to over fit than decision tree. Random forests can rank the impact of variables in a regression or classification problem more accurately than conventional methods. The improvement in the split-criterion at each split in each tree is the important measure given to the splitting variable. This measure is aggregated over all the trees in the forest separately for each variable [8,29].

3.4. Data set

Despite the strong interest in BS, only a few studies focus on bike-sharing-related issues in Central and Eastern Europe [7]. Thus, Budapest is taken as a case study. After five million people received at least one dose of a COVID-19 vaccination, Hungarian authorities removed most of the country's COVID-19-related internal restrictions on 24 May 2021. Thus, our study focuses on the post-COVID era between June and October 2021 to minimize the effect of the pandemic. Studies [10,6] have found that the negative effects of the pandemic on the cycling were limited in Hungary, which means that bikers continued their increasing travel behavior. Therefore, the results are still relevant after the pandemic.

The dataset consists of BS use and weather conditions. A station-based BS operator gave BS use data. It has approximately 200 stations and bikes. The stations are in Budapest's downtown area and cover about 17 km^2. The data include the average number of daily bikes used of bike-sharing service and average daily trips of bike-sharing service per user group and day. The following user groups were distinguished:

- Visitors: people with foreign phone numbers and without monthly membership,
- Occasional users: people with local phone numbers and without monthly membership,
- Members: people with local phone numbers and monthly membership.
- Irregular users: Visitors + Occasional users.
- All users: Members + Irregular users.

Visitors and occasional members together are irregular users. The average values of these attributes are shown in Table 1.

Weather data contained temperature, humidity, pressure, wind speed, precipitation, and solar radiation. The weather conditions between June and October 2021 are summarized in Table 2.

To depict the trend of daily usage and trip of bike-sharing, see Figs. 2 and 3. We notice that the daily trips of bike-sharing service are increasing by time, while the number of bikes usage is decreasing. This means that people use bike-sharing more frequently but with less bikes. One possible reason for the increase in daily trips could be increasing traffic after COVID, due to home office individuals' trip occur within a more limited space that fits cycling [55], lower attractiveness of public transport due to COVID, or more people become aware of and interested in sustainable transportation. The decrease in bikes used could be attributed to a number of factors such as changes in user preferences, e.g. longer trips distances, or increase in number of couriers that usually use limited bikes in their daily rides which affect the average bike usage. The trend-line of bike-sharing trips (Fig. 2) is increasing by time. We used 1-week (7 days-period) moving average for better rep-

Table 1 Average Values of Daily Usage and Trips.

User groups	Average daily bikes used (bikes/day)	Average daily trips (trips/day)
Visitor (V)	20.9	52.6
Occasional (O)	9.6	17.6
Member (M)	167.4	1084.1
Irregular (V + O)	30.5	70.2
All Users (V + O + M)	189.5	1140.8

Table 2 Average, Standard Deviation, Minimum, and Maximum Vales of Weather Parameters.

Weather Parameter	Average Value	Standard Deviation	Minimum	Maximum
Precipitation	1.11 mm	0.31 mm	0.00 mm	33.5 mm
Temperature	19.4 °C	5.9 °C	6.0 °C	33.0 °C
Humidity	65.1 %	9.1 %	45 %	93 %
Solar Radiation	13.8 h	1.9 h	10.0 h	16.0 h
Pressure	1017.14 hpa	0.42 hpa	1005 hpa	1033 hpa
Wind Speed	6.8 km/hour	2.6 km/hour	3 km/hour	16 km/hour

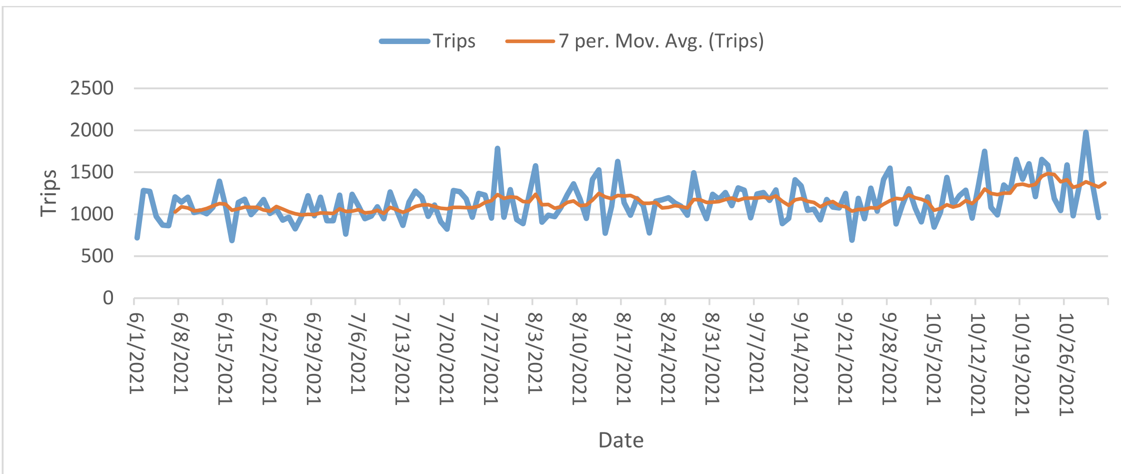

Fig. 2 Number of Bike-sharing Trips between June and October 2021.

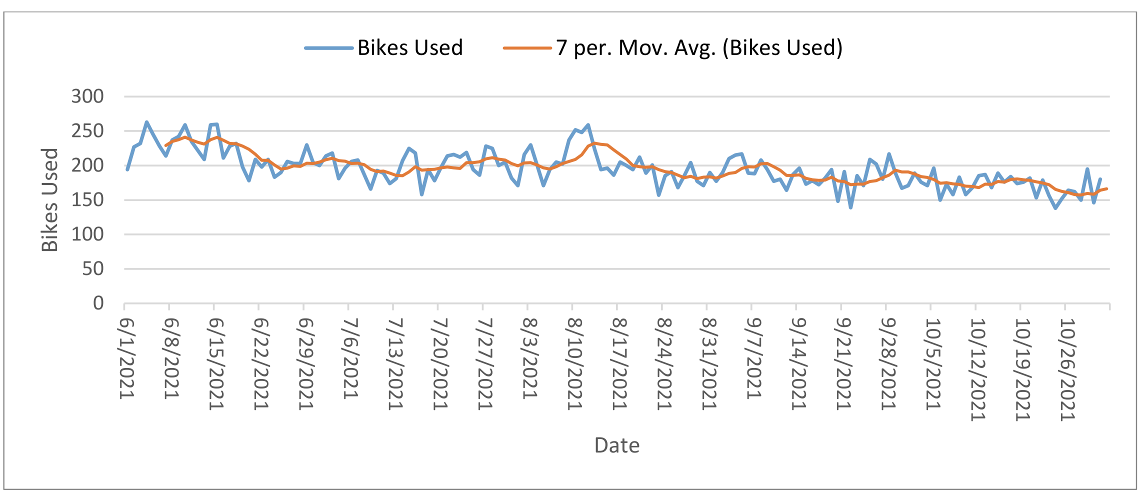

Fig. 3 Number of Bikes used in Bike-sharing service between June and October 2021.

resentation of the data. There are two observed peaks that could be explained as follows: the first in August were the weather is becoming better for tourists and occasional users, and the second in October were the weather is fluctuating and the couriers (e.g. food delivery) are working more with increased trips. On the other hand, as the bikes used are decreasing (Fig. 3, this is also explained by the same reasons above; more visitors with limited trips per bike daily in August (2.2 trips per bike), and more members with several trips using limited bikes daily in October (6.5 trips per bike).

4. Results and discussion

BIC, AIC, and Likelihood comparisons between NBRM and PRM were carried out. After getting the best-fit model, counts and trips are estimated through significant independent variables of weather conditions and weekdays/weekends. SARIMA models are developed based on AIC results and estimated independent variables for the time-series model.

4.1. Evaluation of distribution

The bike-sharing use data shows overdispersion and is closer to negative binomial distribution than to the Poisson distribution (Table 3 and Table 4) for lower BIC and AIC, and higher likelihood values [61]. Thus, the Negative Binomial model is chosen to estimate the number of bikes used and trips.

4.2. Parameter calculation using count models

The β_i parameters were calculated (equation (1). It was found that day type, and weather conditions have different impacts on user groups. The demand is higher on weekends than weekdays for occasional users and visitors. On the other hand, there is a drop in bike-sharing use for members, which is a line with [24,22]. Precipitation significantly affects only occasional users, which is explained by their choice of cycling that is somehow optional, and they have several transportation alternatives. This is in line with previous findings that occasional users are more sensitive than other users to precipitation [13]. Pressure and wind speed have negative impact on BS use in all user groups, which is supported by the findings of Zhou et al. [66] who found them to be unpleasant for bike-sharing users. Humidity only negatively affects members negatively and is not significant for other groups. The temperature has different impacts, as it is not significant for occasional users, positively affects visitors coming to the city, and negatively affects members. The positive effect of the temperature on visitors may be because tourists come to Budapest when the weather is good. At the same time, members do not prefer hot weather. Finally, the longer hours of sunshine lead to higher demand for occasional users and members, and lower demand for visitors. As Caulfield et al. [14] investigated, increasing hours of sunshine leads to more trips and bike-sharing usage. In general, good weather conditions, including pressure, wind speed, and humidity, positively impact BS use (Table 5).

It was found that day type has the same effect on the number of bikes used and trips. Precipitation is not significant for visitors, has a negative impact on occasional users, which is expected, and positively impacts members (Table 6). This indicates more trips of members on rainy days, which could be explained by the increased road congestion and demand for delivery services because many members are couriers. The temperature effect is varied. Pressure, wind speed, and solar radiation have a negative impact on trips. Finally, humidity is not significant for irregular users but has a negative impact on the members. Contrary to our results, Noland et al. [42] found that occasional trips are not sensitive to weather conditions. It may be because only a smaller range of weather conditions was observed during a shorter period (1 month). Compared to [16], this research shows similar findings in wind speed and the opposite for precipitation and temperature. Rainy day trips could be explained by courier members. Christie and Ward [19] conducted a study on the courier behavior and found that rainy days are popular among couriers due to several benefits such as incentives, tips, bonuses, etc. In addition, the low temperature range may explain the negligible effect of the temperature during the observed period compared to the high temperature range in Toronto.

4.3. SARIMA models

The automatic function was used to achieve high goodness of fit. The function finds all possible models and chooses the best model along with the normalized Bayesian information criteria (NBIC). Ljung-Box (LB) statistic test was used to determine model fitness. Models with an LB significance value of more than 0.05 were considered suitable [34]. Tables 7 and 8 show the best-fit combination of (p,d,q)(P,D,Q) with normalized Bayesian information criteria as well as Ljung-Box test for both the number of bikes used and trips models for different user classifications.

As shown in Appendix 1, precipitation impacts occasional users only for the number of bikes used and trips. Wind speed has an impact on bikes used by visitors, while humidity influences their trips as well. The temperature and pressure affect members' trips. Finally, solar radiation has an impact on the overall bike-sharing trips. Moreover, only three models do not have weather parameters, which means they depend only on time seasonal effects without including exogenous variables (weather conditions). These models are bikes in use by members and all users and irregular trips. The latter predicts irregular users' trips with a temporal trend influenced by a lag of three days (p = 3). Namely, visitors' and occasional users' trips are affected by the trips in the previous three days. A detailed description of the AR, and MA parameters are given in Appendix 1.

4.4. Random Forest models

The suggested RF model design involves two parameters: the *number of trees (N)* and the *number of randomly selected variables* [47]. As further trees are added in the model, the prediction performance of RF is improved. On the other hand,

Table 3 Comparison between Poisson and Negative Binomial Models for Bike-sharing Counts.

Bike Counts	BIC		AIC		Likelihood	
	(P)	(NB)	(P)	(NB)	(P)	(NB)
Visitor	1212.41	**1058.97**	1188.16	**1031.69**	−586.08	**−506.85**
Occasional	820.25	**809.75**	796.01	**782.48**	−390.00	**−382.24**
Member	1329.24	**1320.66**	1305.00	**1293.39**	−644.50	**−637.69**
Irregular	1233.08	**1108.53**	1208.84	**1081.26**	−596.42	**−531.63**
All	1331.33	**1327.41**	1307.09	**1300.14**	−645.55	**−641.07**

Table 4 Comparison between Poisson and Negative Binomial Models for Bike-sharing Trips.

Trips	(P)	(NB)	(P)	(NB)	(P)	(NB)
Visitor	2850.31	**1422.71**	2826.07	**1395.44**	−1405.03	**−688.72**
Occasional	1494.86	**1071.68**	1470.61	**1044.41**	−727.31	**−513.20**
Member	6830.95	**2089.54**	6806.70	**2062.26**	−3395.35	**−1022.13**
Irregular	2769.21	**1462.00**	2744.97	**1434.73**	−1364.49	**−708.36**
All	6719.26	**2094.04**	6695.01	**2066.76**	−3339.51	**−1024.38**

Table 5 Calculated Parameters for Bike-sharing Counts.

	Constant	Weekday	Temp	Precipitation	Pressure	Wind	Humidity	Solar Radiation
Visitor	5.051	−0.364	0.037	N.S.*	−0.012	−0.028	N.S.	−0.181
Occasional	1.831	−0.641	N.S.	−0.248	−0.026	−0.028	N.S.	0.117
Member	4.577	0.114	−0.01	N.S.	−0.005	−0.004	−0.003	0.067
Irregular	4.712	−0.449	0.019	N.S.	−0.017	−0.027	N.S.	−0.084
All	4.969	0.041	−0.007	N.S.	−0.006	−0.007	−0.003	0.049

*N.S.: Not Significant.

Table 6 Calculated Parameters for Bike-sharing Trips.

	Constant	Day	Temp	Precipitation	Pressure	Wind	Humidity	Solar Radiation
Visitor	6.172	−0.332	0.056	N.S.	−0.007	−0.025	N.S.	−0.23
Occasional	2.314	−0.77	N.S.	−0.298	−0.024	−0.015	N.S.	0.094
Member	7.64	0.103	−0.002	0.019	−0.002	−0.007	−0.002	−0.036
Irregular	5.831	−0.435	0.04	−0.044	−0.011	−0.022	N.S.	−0.148
All	7.752	0.073	N.S.	0.016	−0.002	−0.008	−0.002	−0.042

Table 7 Goodness of Fit for SARIMA, Bike-sharing Count.

Count	(p,d,q)	(P,D,Q)	NBIC	Ljung-Box
Visitor	(0,1,1)	(0,1,1)	3.86	0.576
Occasional	(0,1,1)	(1,1,0)	2.77	0.257
Member	(0,0,1)	(1,0,1)	5.756	0.112
Irregular	(0,1,1)	(0,1,1)	4.213	0.585
All	(0,1,1)	(1,0,1)	5.878	0.368

Table 8 Goodness of Fit for SARIMA, Bike-sharing Trips.

Trips	(p,d,q)	(P,D,Q)	NBIC	Ljung-Box
Visitor	(0,0,1)	(0,1,1)	6.279	0.333
Occasional	(0,0,0)	(1,0,1)	4.67	0.873
Member	(0,0,6)	(0,0,0)	10.675	0.110
Irregular	(3,1,0)	(0,1,1)	6.639	0.129
All	(0,0,6)	(0,0,0)	10.710	0.165

increasing the number of trees in the model increases the model's run time. Namely, a small number of trees (N) saves calculation time, but the goodness of RF prediction decreases. Therefore, several computation tests are performed in this study to optimize N. Predicting accuracy doesn't improve significantly if N is equal to or greater than 150. Since the calculation time was acceptable, the optimal N was set to be 150, and it was used for each RF model development. Performance evaluation and testing are carried out with the various (M) combinations [52,53,30].

Fig. 4 shows the variable importance results of the RF models of booking numbers trained for visitors, occasional, irregular, members, and all users. The top three influential variables for irregular users are temperature, solar radiation, and day type. Precipitation is ranked as the least influential variable. The top three influential variables for the members and all users are temperature, solar radiation, and humidity, while the least ranked is precipitation. These results indicate the high importance of temperature and low importance of precipitation. No significant difference was found between bikes used and trip models. These results are in line with other research that used the tree techniques to investigate the bike-sharing usage. For example, Jaber and Csonka [30] found that irregular users are influenced mostly by temperature and type of the day in Hungary, Collini et al. [20] found that type of the day and temperature are the most important factor affecting bike-sharing trips in Canada. Sathishkumar and Cho [52,53] resulted that humidity and temperature are the most influencing variables on the bike-sharing usage in Korea.

Compared to other studies, temperature, time, and humidity were the most influential variable in the research of [3,52,44] Day type was consistent with [44]. Precipitation was not significant in any of these studies as well.

4.5. Models validation and comparison

For the validation purposes, we have compared our models with other predicted data that have not beed used for the esti-

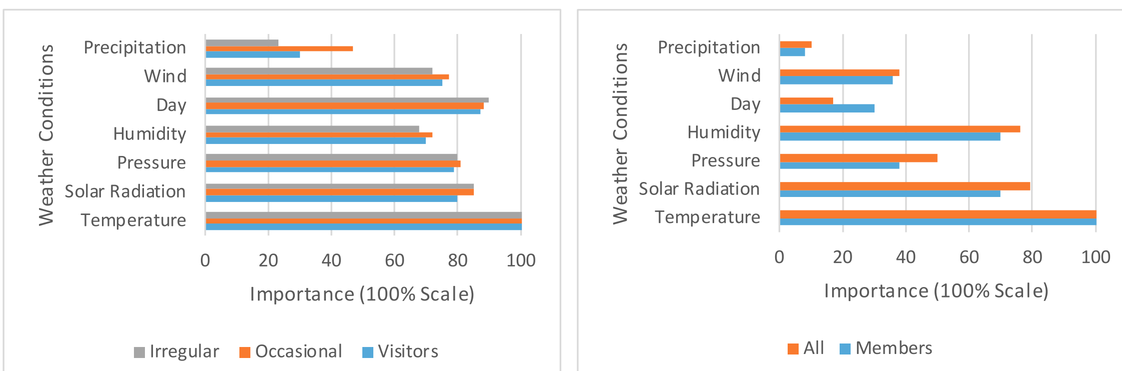

Fig. 4 Variables Importance of Bike-sharing Usage under Weather Conditions.

Table 9 RMSE comparisons among the models for the bike-sharing usage.

Group/Model	NBRM		SARIMA		RF	
	Training Set	Test Set	Training Set	Test Set	Training Set	Test Set
Visitors	4.98	5.20	4.42	4.36	**3.89**	4.21
Occasional	2.22	2.41	2.55	2.68	**2.15**	2.37
Member	15.76	14.98	**15.59**	16.81	18.65	18.02
Irregular	5.98	6.54	5.42	5.23	**5.27**	6.19
All	16.24	16.23	**16.11**	16.98	17.69	17.50

Table 10 RMSE comparisons among the models for the bike-sharing trips.

Group/Model	NBRM		SARIMA		RF	
	Training Set	Test Set	Training Set	Test Set	Training Set	Test Set
Visitors	19.59	20.10	17.57	16.74	**15.25**	17.66
Occasional	**5.35**	5.91	5.51	6.02	5.43	5.91
Member	199.12	202.33	**194.24**	192.15	198.67	195.72
Irregular	23.87	23.52	23.81	24.62	**20.57**	21.44
All	201.96	200.78	**198.15**	199.45	202.91	201.36

mation. This data is for November and Decemeber 2021. The Root Mean Square Error (RMSE) has been used for the comparison as metric for performance assessment as shown in equation (3), where A_i is the actual value, P_i is the predicted value, and n is the total number of cases (days). The results are shown in the Tables 9 and 10.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2} \quad (3)$$

At first, it is observed that the RMSE of the training sets and test sets is close among all the models. The small difference between the two RMSE values indicates the small produced training error and the high correlation between the trained and predicted data, thus acceptable performance of the trained models. Also, we noticed that the performance of the models is close among them for each user group. There are no major differences that make a bias towards such a model. With more focusing on the RMSE results, we can say that the NBRM is better in the case of occasional users. Random forest models performed better in the case of irregular users, while SARIMA performed better for members or all users as one group.

5. Conclusions

This study investigates comparisons among count, time-series models, and data mining techniques in studying the weather and temporal variable impacts on various bike-sharing user groups. The negative Binomial approach was found to be superior to Poisson, thus it is used for parameter estimation. Weather conditions have a different effect on the user groups. In general, good weather generates higher demand for bike-sharing. Weekends attract more irregular users. Members' bike-sharing use was predicted for an extended period neglecting weather impact, as well as irregular trips of bike-sharing. The top influential variables are temperature, solar radiation, day type and humidity, while the least influential is precipitation. The analyzed period was 5 months, which affects the range of observed weather conditions (e.g., the temperature was between 6 and 31 °C). It was found that when the number of observations increases, the predictions are more accurate, and SARIMA performs better. While, for limited observations such as in irregular users, RF and NBRM performed better. We found similarities and differences between the models by exploring each group by itself. In common, it is found that visitors are more influenced by temperature, wind and type of day. Occasional users are more subjected to precipitation. For members, it is found that the temperature, type of day are the most significant factors. The least factors for all are varied as well: precipitation for visitors, humidity for occasional users, precipitation and wind for members. Comparing the investigated models with each other, it is found that they varied across each bike-sharing group. Time series models (SARIMA) performed better for members whom are continuous users, while the tree techniques (Random Forest) performed better for occasional users and visitors. Furthermore, the characteristics of the models confirm the results. Therefore, SARIMA is better for continuous events which is similar to the members usage.

Given that weather conditions affect various user groups differently, various targeted marketing strategies are needed to promote year-round bike-sharing use. For example, during rainy conditions, policymakers could promote bike-sharing services to occasional users. As the study found that the accuracy of predictions increased with the number of observations. It is recommended to consider increasing the availability of data on bike-sharing usage to improve the accuracy of predictions and enhance the effectiveness of bike-sharing services. Furthermore, it is recommended to consider weather conditions in bike-sharing service planning and ensure that the services meet the demand during different weather conditions. For example, policymakers could consider increasing the number of bikes during good weather conditions or providing sheltered bike stations to protect bikes from precipitation.

The main limitations of our study that we were not able to conduct a whole year analysis due to data availability, which could be invistagetd in the future. This is needed to gain a comprehensive understanding of factors affecting bike-sharing usage and develop more effective policies. These findings provide several options for researchers to predict bike sharing usage and trips for different user groups and enrich the empirical modeling-based daily usage prediction. In addition, this research study helps operators and decision-makers to expect the future demand on bike-sharing within forecasted weather. Future research will focus on spatial distribution, and could investigate the impact of bike-sharing infrastructure, such as the number and location of bike stations, on bike-sharing usage. Also, future research could investigate the impact of socio-demographic factors, such as age, gender, and income, on bike-sharing usage, as well as new artificial neural networks models could support a more comprehensive comparison.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A:.

- Bike-sharing Booking Counts SARIMA Models:

	(p,d,q)	(P,D,Q)	MA	AR Seasonal	Precipitation
Occasional (No Transformations)	(0,1,1)	(1,1,0)	Lag 1: 0.911	Lag 1: −0.539 (1)	−1.6

	(p,d,q)	(P,D,Q)	MA	MA Seasonal	Wind	Humidity
Visitors (Square Root Transformation)	(0,1,1)	(0,1,1)	Lag 1: 0.795	Lag 1: 0.832	−0.06	−0.022

	(p,d,q)	(P,D,Q)	Constant	MA	AR Seasonal	MA Seasonal
Member (No Transformations)	(0,0,1)	(1,0,1)	201.012	Lag 1: −0.352	Lag 1: 0.999	Lag 1: 0.977

	(p,d,q)	(P,D,Q)	MA	MA Seasonal	Wind
Irregular (No Transformations)	(0,1,1)	(0,1,1)	Lag 1: 0.874	Lag 1: 0.822	−0.601

	(p,d,q)	(P,D,Q)	MA	AR Seasonal	MA Seasonal
All (No Transformations)	(0,1,1)	(1,0,1)	Lag 1: 0.926	Lag 1: 0.997	Lag 1: 0.978

- Bike-sharing Trips SARIMA Models

	(p,d,q)	(P,D,Q)	Constant	AR Seasonal	MA Seasonal	Precipitation
Occasional (Square Root Transformation)	(0,0,0)	(1,0,1)	3.822	Lag 1: 0.999	Lag 1: 0.971	−0.689

	(p,d,q)	(P,D,Q)	MA	MA Seasonal	Humidity
Visitor (No Transformations)	(0,0,1)	(0,1,1)	Lag 1: −0.183	Lag 1: 0.790	−0.564

	(p,d,q)	(P,D,Q)	Constant	MA	Temp	Press
Member (No Transformations)	(0,0,6)	(0,0,0)	10910.86	Lag 6: −0.240	−20.14	−9.266

	(p,d,q)	(P,D,Q)	AR	MA Seasonal
Irregular (No Transformations)	(3,1,0)	(0,1,1)	Lag 1: −0.642 Lag 2: −0.415 Lag 3: −0.296	Lag 1: 0.832 (1)

	(p,d,q)	(P,D,Q)	Constant	MA	Sun Hour
All (No Transformations)	(0,0,6)	(0,0,0)	1611.807	Lag 6: −0.173	−34.667

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