Welke factoren beïnvloeden het gebruik van de OV-fiets?

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Samenvatting

De OV-fiets is een succesvol onderdeel van het Nederlandse OV systeem. Tegelijkertijd is, vanwege het unieke karakter van OV-fiets binnen deelmobiliteit, wetenschappelijk onderzoek naar het gebruik van dit systeem beperkt. Met dit paper beogen we inzichten te verschaffen in de gebruikspatronen van OV-fiets.

Hiertoe zijn de verhuringen (meer dan 2.5 miljoen) in 2018 van de 48 grootste locaties geanalyseerd en gecombineerd met aanvullende informatie zoals het aantal uitstappende treinreizigers op het station, de weersomstandigheden en tijd-gerelateerde informatie zoals de dag van de week of vakantieperiodes. De identificatie van relevante factoren is gedaan op een uur-aggregatieniveau door gebruik te maken van multiple linear regression en beschrijvende analyses.

In een verklarend model over alle 48 stations gezamenlijk heeft het aantal uitstappende treinreizigers de hoogste verklarende waarde. 19% van de variatie in verhuringen per uur kan verklaard worden aan de hand van het aantal uitstappers. De gezamenlijke tijd-gerelateerde variabelen verklaren 22% van de variatie, en de weersomstandigheden verklaren 5%.

Wat betreft de weer-gerelateerde gegevens blijkt voornamelijk het aantal uren zon een bepalende factor te zijn. Regen lijkt geen invloed te hebben in het aantal verhuringen in de ochtendspits, hoewel het aantal verhuringen gedurende de rest van de dag wel enigszins terugloopt bij regen.

Ondanks dat er een aantal generieke trends waar te nemen zijn bestaan er grote verschillen tussen stations. Voor een selectie van acht stations is een meer gedetailleerde beschrijvende analyse uitgevoerd om ook deze verschillen te duiden. Zo is er voor de meeste stations een duidelijk maandpatroon, met in de zomer een laag aantal verhuringen, echter zijn er ook stations waar de verhuringen in de zomer juist hoog liggen, dit vanwege het recreatieve karakter van de reis. Gedurende de dag zijn twee verschillende patronen zichtbaar. Een deel van de stations heeft een duidelijk spits-karakter: ’s ochtends is een grote piek in verhuringen en de rest van de dag blijft het laag, dit zijn veelal verhuringen aan forenzen. Daarnaast zijn er stations die ook ’s avonds een piek in verhuringen hebben, veelal voor reizigers met een recreatief doel.

Met deze inzichten in de vraag naar OV-fiets kan in combinatie met een geschikt prognose-model de vraag en aanbod van OV-fiets per station verder geoptimaliseerd worden. Daardoor kan bijvoorbeeld onderhoud beter gepland worden of kunnen reizigers in de toekomst vooraf geïnformeerd worden over het verwachte beschikbare aantal OV-fietsen op enig moment.

1. Introduction

The rise of one-way bikesharing all over the world throughout the last decade led to an increase in data accessible for scientific research. Multiple studies use the available data to identify potential determinants for the usage of bikesharing schemes, with the various findings being summarized within multiple reviews (Eren and Uz, 2020; Gu et al., 2019; Todd et al., 2021). When it comes to round-trip bikesharing, to date limited research has been conducted (Nello-Deakin and Brömmelstroet, 2021). This might be reasoned in the limited availability of these schemes, as, to the authors' knowledge, only two SBRT systems exist allowing users to do round-trip bookings to get around at their PT trip destination: OV-fiets in The Netherlands and Bluebike in Belgium (de Visser, 2017). Different from one-way bikesharing, round-trip systems provide users with the certainty of having a bike available for a return trip, as a bike available exclusively for the user who rented it until being returned to its origin. So far, no research has been conducted on the determinants of demand for these SBRT-systems and the underlying usage patterns.

This paper[1] aims to fill this gap by providing insights into the usage patterns of the SBRT-system OV-fiets in The Netherlands in comparison to existing findings on one-way bikesharing schemes. To do so, the systems' booking data is complemented by further data sources such as historical passenger flows leaving the train stations next to the considered SBRT-stations and historical weather data to identify potential determinants for the number of bikes rented per hour. The identification of determinants of SBRT rentals is performed on an hourly level of aggregation using MLR and descriptive analytics. The results are then compared to the preliminary identified determinants for one-way bikesharing based on literature. The focus of this paper lies on weather-related, train traveler-related and temporal determinants.

This paper is organized as follows: Section 2 identifies weather-, time-, and train travel-related determinants for bikesharing demand and assesses them based on their applicability on SBRT. Section 3 elaborates the data collection and the methods used for the analysis of SBRT demand. In section 4, the results of the performed MLRs and the descriptive analysis are provided and discusses. Sections 5 and 6 discuss and conclude the findings of this paper. The final section 7 provides recommendations for future research.

2. Existing determinants for Bikesharing Demand

Many weather-related determinants exist which are found to have an impact on one-way bikesharing demand according to various studies compared by Eren and Uz (2020): For one-way bikesharing, it is found that sunny weather results in a higher usage, while rain and wind have a negative impact on hourly rentals. Also, individuals tend to use one-way bikesharing more in moderate temperatures between 0°C and 30°C. The usage is identified to be highest between 20°C and 30°C, while scorching heat and temperatures below 0°C are found to have a negative correlation with the number of rented bikes (Eren and Uz, 2020). Recent research also found that in cities with a higher share of young people and a

[1] This paper describes parts of the findings of the master Thesis of Florian Wilkesmann. The full thesis is publicly available at the repository of the TU Delft: https://repository.tudelft.nl/islandora/object/uuid%3Abfcc3224-d5e5-4c12-babc-5f5e64cfe6d8

high-quality cycling network, the bike usage is more robust to unfavorable weather conditions (Goldmann and Wessel, 2021).

In terms of temporal differences, the usage of one-way bikesharing-schemes differs across seasons, with a higher usage in summer than winter (Eren and Uz, 2020). Most studies investigating the usage throughout the week for specific systems see a clear difference in usage patterns between weekdays and the weekend (Gu et al., 2019) The findings are confirmed by a cluster-analysis performed including 322 station-based free-floating systems (Todd et al., 2021): According to the authors, the distribution throughout the day slightly differs between systems (e.g., different starting time of morning peak), but recurring patterns can be identified: Distinct morning and evening peaks on weekdays and a moderate usage during afternoons on weekends. Furthermore, it is found that during peak hours bikesharing is more competitive to cars in terms of travel time due to congestion, making the modal shift towards cycling more attractive (Jensen et al., 2010). It is to be investigated to what extent the described determinants for one-way bikesharing can be translated to SBRT systems. The temporal use might differ from one-way schemes, as users do not end a booking after reaching their destination. Instead, their booking continues until returning the rented bike at the same station.

Regarding the integration of bikesharing into existing PT services, one-way bikesharing is used to substitute PT trips involving transfers (Leth et al., 2017). The proper integration of one-way bikesharing into the existing PT network is found to increase the added value of both modes for travellers instead of resulting in competition (Böcker et al., 2020). This is the case especially for longer trips and in times of reduced PT services, i.e. at night and on weekends (Fishman et al., 2013). Further, the added value of round-trip bikesharing lies in the egress leg after travelling by PT as it allows users to cover a higher distance compared to walking, while also allowing to reach destinations which might have limited accessibility by PT (Kager and Harms, 2017).

While determinants of one-way bikesharing demand are thoroughly investigated, little is known about the determinants of SBRT-demand. Preliminary conclusions made for one-way schemes might be applicable for SBRT, but there is no scientific evidence supporting this to date. It is likely that the use case of SBRT differs from one-way schemes due to the requirement of ending a booking at the point where it started. This makes the SBRT especially suitable for the activity-end of multimodal trips (Kager and Harms, 2017). This is supported by the rising number of rentals in the existing systems (NS, 2021).

3. Methodology

3.1 Data Preparation

Data is provided by the Dutch national train station operator NS Stations. Weather data is extracted from the website of the Dutch Royal Meteorological Institute KNMI for countrywide weather measurement stations. The national holiday calendars are used to include the national and school holidays. The provided SBRT dataset contains all individual bookings having the same origin and destination. Technically, trips between different SBRT stations are possible, but strongly discouraged by the operator by a fine if returning a bike at another station. These trips are excluded in this analysis for consistency. The rentals of the dataset are cleaned and aggregated on an hourly level per station for the year 2018. The resulting data is combined with a static dataset containing information per SBRT station on the related capacity, the corresponding PT station, and the provided service type. For further analysis, only staffed stations with a capacity of more than ten bikes are included. Also, information on the hourly number of travellers leaving the corresponding train station is included. This information is based on the nationwide smartcard check-in/-out system. Further, all three different school holiday periods are included for all stations as SBRT users might use the service for their last mile in regions different form the one they live in. Lastly, the SBRT stations are connected to the closest KNMI weather stations to obtain weather-related information. It is emphasized that a higher distance between weather stations and SBRT stations results in lower accuracy on determinants such as rain duration per hour. The final filtered dataset contains 2,646,657 bookings across 48 SBRT stations. These are 75.5% of all bookings performed in 2018 at 15% of all stations, suggesting that the stations with a comparatively high usage are used for further analysis.

3.2 Definition of Determinants

In preliminary research, meteorological and temporal factors are found to explain most variance in hourly one-way bikesharing rentals (Du et al., 2020). Other factors such as a SBRT stations accessibility, the surrounding cycling infrastructure, topography, and land use are defined by the circumstances in which a SBRT-station is located and thus are considered out of scope. The hourly travellers leaving the corresponding PT stations are included as the analysed SBRT system is integrated into the national train system. This allows for an assessment on whether hourly SBRT rentals depend on the number of train travellers leaving the corresponding train station, as identified for one-way bikesharing (Zhang et al., 2018). The specific variables used to represent the determinants are visualised in Fig. 1.

For time-related variables, it is decided to represent each characteristic with a separate dummy-variable to independently assess their explanatory power. To reduce the high number of the resulting dummy-variables, an aggregated representation of the temporal determinants is added: Hours are aggregated into five separate times of day (namely Night, Morning peak, Daytime, Evening peak, Evening). The weekdays are reduced into one dummy-variable indicating whether it is weekend or a weekday, and the months are aggregated on a seasonal level (Spring, Summer, Autumn, Winter). Holidays, national and school in the three holiday regions, are represented by one dummy-variable each. In total, this results in forty temporal variables on a non-aggregated level, and eight on an aggregated level.

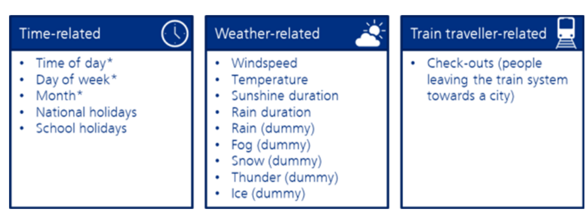

Fig. 1. Grouping of determinants considered for analysis (*exist on an aggregate and disaggregate level)

Regarding weather-related determinants, multiple determinants are selected for further analysis: Windspeed, Temperature, Sunshine Duration, and Rain Duration. These determinants are translated into variables using the interval scales defined by the KNMI: Windspeed and Temperature are assessed using averages for the last hour in in 0.1 m/s and 0.1°C, respectively. Rain and Sunshine Duration are indicated based on their occurrence, measured in tenths of an hour. Additionally, dummy variables are included indicating whether Rain, Fog, Snow, Thunder, or Ice occurred within an hour. Together, this results in nine different weather-related variables. It needs to be emphasized that this analysis only includes the weather within the hour a bike was rented. This assumes that the choice for a bike is based on the weather in that hour, leaving out the potential impact of weather forecasts for later hours. Lastly, the number of train travellers leaving a train station is used to assess its explanatory power on the hourly rentals of a SBRT-system. This determinant is included as nominal variable, i.e. the number of checkouts per hour. The assessment of the other side of train station-based SBRT-trips, namely the potential correlation between bikes being returned at a train station and the number of train travellers entering the train system, is considered out of scope to reduce complexity.

In total there are fifty different independent variables to assess their explanatory power regarding hourly SBRT-rentals. This number can be reduced to eighteen when using aggregated time-related variables instead of determining each temporal component independently. Both approaches are used to assess to which variable can capture most of the variance in the hourly rentals.

3.3 Identification of Significant Determinants

To assess the explanatory power of the different variables defined above, a Multiple Linear Regression (MLR) is applied using the hourly rentals across all stations as dependent and the previously defined determinants independent variables. To identify the most significant determinants, multiple backward searches are applied using the loss of R^2 as performance indicator to identify the most significant determinants. This indicator is used as a high R^2-value suggests that the selected variables can capture most noise within the hourly bookings throughout the assessed dataset. For further explanation of the applied methods, it is hereby referred to the related thesis (Wilkesmann, 2022). The variables contributing to a change of R^2 higher than 0.001 within the backward search application are selected for further analysis on station level. Station-specific MLRs are performed to examine whether differences exist in terms of the identified determinants' ability to explain the variance in the dependent variables across different stations. This is done as stations are found to have different usage patterns when it comes to the bike-train combination (Schakenbos and Ton, 2021). The results of the station specific MLRs are compared using the number of significant variables per station to assess how well the previously conducted variable selection explains the variance at a specific station. Also, the resulting R^2-value from each MLR-application is used to examine to what extent the noise in the data can be explained by using the identified variables.

3.4 In-Depth Analysis

Based on the performance of the different stations in the station specific MLRs, eight exemplary stations are selected and investigated in more detail to generate a further understanding of the determinants. The station selection is based on the distribution of the R^2-values of the station-specific MLRs. The selection of exemplary stations involves two stations with a low and a high remaining noise, selected using the highest and lowest R^2-value across all stations, respectively. Additionally, the stations being closest to the mean, the median, as well as the 25% and 75% quantile are selected to provide a wide range of exemplary stations. This is only a small selection of both the forty-eight stations filtered for analysis and the in total 313 SBRT-stations in the system, but is deemed sufficient to provide first insights into the data and reduces complexity of the research. The selected stations are then compared using a visual representation of the average hourly rentals across days and weeks in combination with the identified determinants. The aim of this descriptive analysis is to assess whether the determinants have a similar impact across different stations, or whether the patterns are so different that no overarching findings can be concluded.

4. Results

4.1 Identification of Significant Determinants

The backward searches using the previously described selection of variables is applied on the dataset to identify the most significant variables. The results for the different backward searches are visualised in Fig. 2, with each bar indicating the magnitude of drop in R^2 caused by the backward search removing the corresponding variable.

The number of hourly checkouts is found to have the highest explanatory power across all backward searches when determining the relative number of bookings per station, as 19% of the variance in the hourly rentals across all stations can be explained using this variable. Further, the multiple time-related variables are found to together allow for an explanation of 22% of the variance. The explanatory power is mostly covered by the disaggregated Hours 8-18 and the aggregated variables Morningpeak, Evening, Eveningpeak, and Night. Other considered variables are the time-related variables Saturday, Sunday and weekends, respectively, as well as both national and school holidays. The weather-related variables

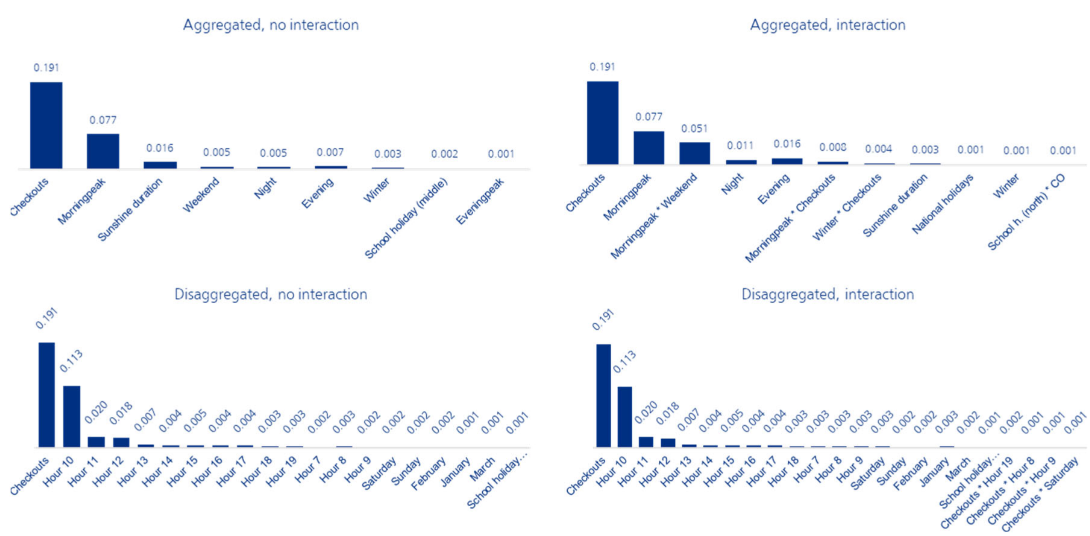

Fig. 2. Backward search –Change in R^2 per removed variable for the four different search methods

allow for an explanation of the variance in the data of around 5%, while the only weather-related variable resulting in a change of R^2 of more than 0.001 is the sunshine duration. All variables causing a drop of R^2 of more than 0.001 across all four different backward search applications are jointly shown in Fig. 3. The colour of the variables indicates the positive or negative correlation with the hourly bookings in relation to the reference variable. For example, when looking at the time-related variables on an disaggregate level, the hourly rentals in Hour 7-19 show a positive significant difference from the reference Hour 0. When aggregated, the reference variable is Daytime, to which hours in Morningpeak show a significantly higher number of rentals compared to the reference. The other three, Evening, Eveningpeak, and Night show significantly fewer hourly rentals. The interaction effects are read as a combination of two variables: For example, the negative significant interaction between Morningpeak and Weekend indicates that in weekend morning peaks fewer bikes are rented out per hour in comparison to morning peak hours during the week.

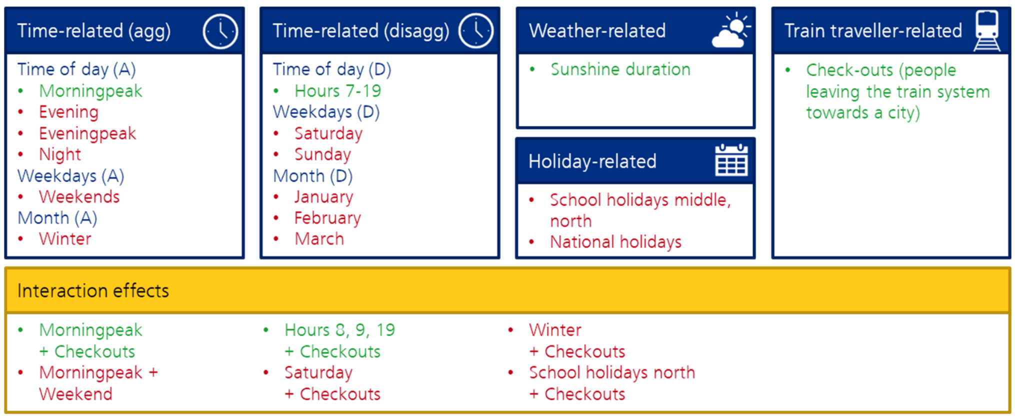

Fig. 3. Indication of correlations between the different variables (red indicates positive correlation, blue negative correlation)

4.2 Performance of Variables across all Station-Specific MLRs

While the findings are identified on a dataset across all stations providing general tendencies of the determinants, they provide limited information on which determinants can explain the variance of the hourly rentals on an individual station level. To assess their performance per station, station-specific MLRs are performed using the previously identified significant variables. 48 separate MLRs are performed using the defined variables, one per station. For each station, the reference variables for the dummy variables consist of the time-of-day Hour 0 (midnight), the season Autumn, and a day being not on a Weekend. The results are shown in Fig. 4, showing the count of the achieved significant levels across the 48 performed MLRs.

For train traveller-related determinants, checkouts show a high significance level on few stations only, while many stations show interaction variables including checkouts being highly significant.

Regarding weather-related determinants, sunshine duration is the only weather-related variable which is significant on a 95%-level (i.e., a p-value below 0.05) across 44% the MLRs. A similar result is shown by the interaction between sunshine duration and checkouts (50% of MLRs on 95%-level). The interaction variables representing sunshine duration and seasons is found to have a high significance across 36% and 39% of all stations for Spring and Summer on a 95%-significance level, respectively. This translates to spring being less different in terms of hourly rentals when interacting with sunshine duration compared to the reference level autumn. In Winter, 54% of all stations indicate the related interaction variable to be significant on a 95% significance level compared to the reference level.

When investigating time-related determinants such as hour-of-day and the interaction between hour-of-day and checkouts, it becomes visible that the timeslots of Hour 22, 23, and 1-5 are insignificant even on a 90%-significance level. It is important to mention that this does not necessarily translate to unreliable data for these timeslots, but instead means that the data does not provide sufficient information to distinguish the rentals in these timeslots from the rentals in the reference-timeslot Hour 0. This can be reasoned in the number of hourly rentals in these hours being similar, and much lower compared to the remainder of the day. In addition, for some stations no interaction variables could be assessed for the timeslots between Hour 1 and Hour 6, as either no checkout and/or no SBRT-booking data is available for these timeslots. This can be caused by the corresponding facilities being closed during that time. The timeslots in the morning peak (Hour 7-9) show a high significance among most stations when interacting with checkouts in that timeslot compared to their independent counterparts. The opposite effect can be seen for Hours during Daytime (Hour 12-18), which are mostly significant on an independent level and thus seem to be less explainable by an interaction with Checkouts. An exception can be seen for the evening timeslots (Hour 18-20), where up to 42% of the stations indicate a high significance of interaction variables with Checkouts. The fact of a timeslot being on a weekend has significant correlation with the hourly rentals across most stations, with 75% of the stations having a significance level >95%, and 56% even higher than 99.99%. The variables representing the seasons are found to be significant across few stations when considered separately but show a higher interaction when being combined with sunshine duration and checkouts (for the interaction with the sunshine duration, see above). The interaction with Checkouts is prominent for Winter, as for 92% of the stations this variable is significant on a >95%-level. Lastly, the variables representing the national and school holidays are found to be significant on a 95%-level for at least nine stations, but none of the variables is significant across more than 50% of the stations. Also, the interaction variables combining National Holiday and Seasons are found to be insignificant on a 95%-level for at least 83% of the stations, suggesting that the presence of holidays is only relevant for a small number of stations. There is no interaction variable between summer and national holidays as no national holidays take place in the summer period. An investigation on whether the correlation of the explanatory variables with the hourly rentals differs between negative and positive across the different stations or is the same across all stations is considered out of scope due to the expected

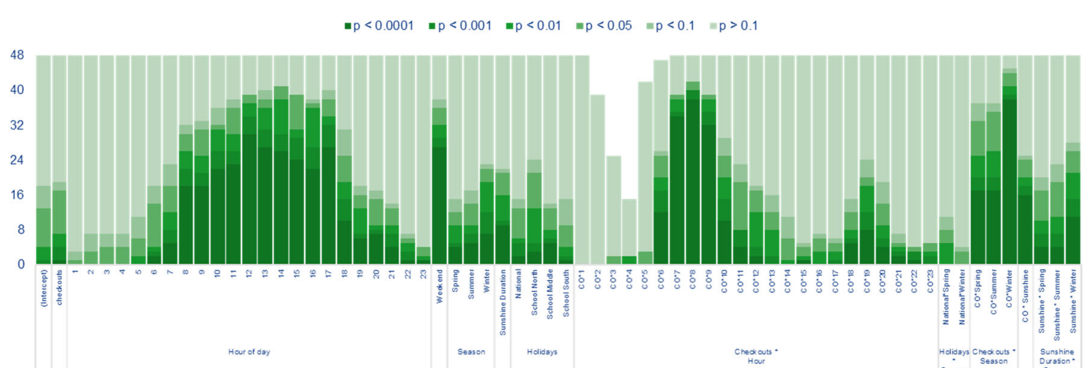

Fig. 4. Number of significant variables across significance levels and stations per variable (reference levels: Autumn, midnight, no weekend)

extensiveness. Nevertheless, such an analysis could provide additional understanding in the similarities and differences among the different stations.

4.3 Descriptive Analysis

The following section provides a descriptive in-depth analysis of different determinants using selected exemplary stations. This includes a discussion on potential causes when identifying recurring patterns among multiple stations. The exemplary stations are selected based on the performance of the station specific MLRs. Then, the determinants are descriptively analysed to unravel their potential dependency with the rental patterns, which are aggregated or averaged on a monthly, daily, and hourly level. Per determinant and level of aggregation, only a selection of the eight selected stations is shown to reduce the report's complexity. The selected stations are *Beilen*, *Vlissingen*, *Weesp*, *Rotterdam Centraal*, *Amsterdam Zuid Mahlerplein*, *Breda Centrum*, *Assen*, and *Apeldoorn*. The selection of determinants considered for comparison differs per level of aggregation: On a monthly and daily level, the aggregated rentals and checkouts are compared, while on an hourly level further time- and weather-related variables are analysed. This is reasoned in the time- and weather-related variables which cannot be compared on a daily or monthly level due to the potential loss of hour-specific information.

First, the monthly, daily, and hourly levels will be compared to identify recurring patterns across multiple stations. The aim is to investigate whether usage patterns are similar enough to allow for a generalisation of the previous findings across multiple stations. If it is found that the patterns are unique per station across multiple variables, distinct models per station would be required. The interpretation of the differences amongst stations were discussed with and confirmed by individuals working for the operational department of the SBRT-scheme. While the performed MLRs provide insights into these causalities allowing for a visual high-level analysis, the following results should be read with caution, as a descriptive analysis lacks the scientific foundation to confirm visually identified causalities.

Monthly Patterns
When comparing the distribution of rentals per month (see blue lines in Fig. 5), all selected stations apart from *Beilen* and *Vlissingen* show an increase in rentals throughout the first half of the year, followed by a decline in July and August in which the school summer holidays fall. This is in line with the decrease in the total number of checkouts at the corresponding train stations, visualised by the red lines in Fig. 5. In Autumn, the number of rentals rises again, which is in line with the increasing number of checkouts (with *Weesp* being an exception). This confirms the previous finding that checkouts can explain a high share of the variance in the hourly rentals.
The patterns of the other two stations, *Beilen* and *Vlissingen*, show limited similarity with the other stations. Due to the low amount of bike rentals (on average 3-4 a day) there is too much noise in the data for *Beilen* to look for patterns. For *Vlissingen*, the station being located close to outdoor recreation areas might suggest a higher usage throughout summer compared to winter. To conclude, the patterns of the stations themselves and in combination with the monthly checkouts provide little potential for generalisation.

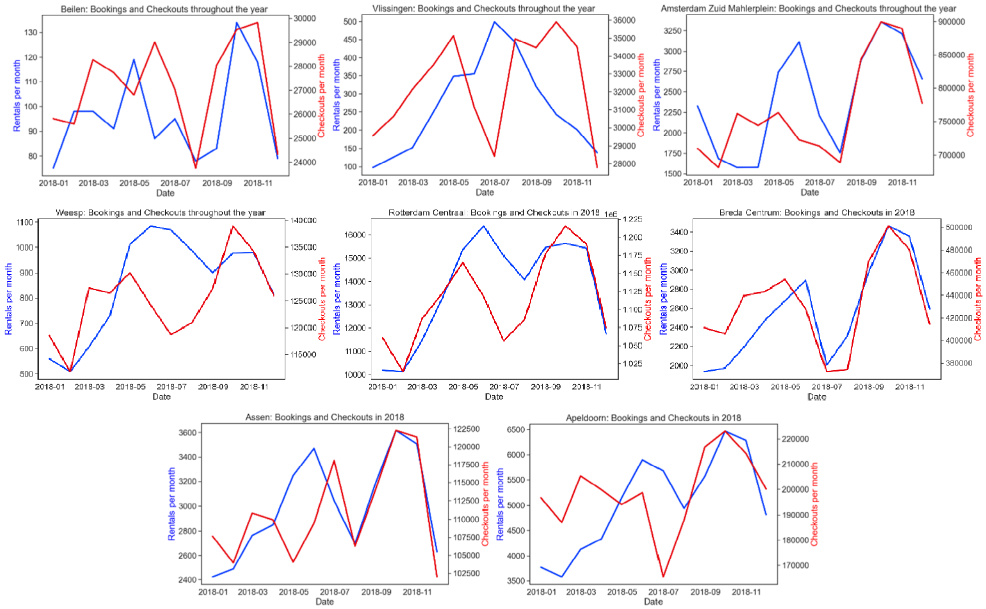

Fig. 5. Aggregated monthly rentals and checkouts in 2018 for the exemplary stations

Daily Patterns

To compare the average number of rentals per weekday throughout the week, two different patterns occur at multiple stations, as visualised in **Error! Reference source not found.** for three exemplary stations. The other exemplary stations are not shown to reduce complexity, and for further information it is referred to the corresponding thesis (Wilkesmann, 2022). Among the exemplary stations, the first pattern (*Beilen*, *Weesp*, *Breda Centrum*, *Assen*, *Apeldoorn*) follows a stable level of rentals throughout working days Monday to Thursday, with a small drop on Wednesdays and a sharp decrease from Friday to Sunday. The checkouts of these stations follow a similar pattern, suggesting that the dips in rentals on Wednesdays and Fridays might be caused by less commuters on these days, which use the SBRT to overcome the trip between workplace and train station. *Vlissingen* follows a similar tendency, but the high width of the confidence interval does not allow for an interpretation of an explicit pattern.

The second pattern occurs at both *Rotterdam Centraal* and *Amsterdam Zuid Mahlerplein*, showing an increase in rentals from Monday to Friday followed by a sharp decrease towards the end of the week. When comparing these daily rentals with the daily checkouts, checkouts show a similar pattern across all selected stations, with a stable level throughout the week and a drop towards the weekend. The difference between the two patterns might thus be reasoned in location-specific characteristics of the stations. For example,

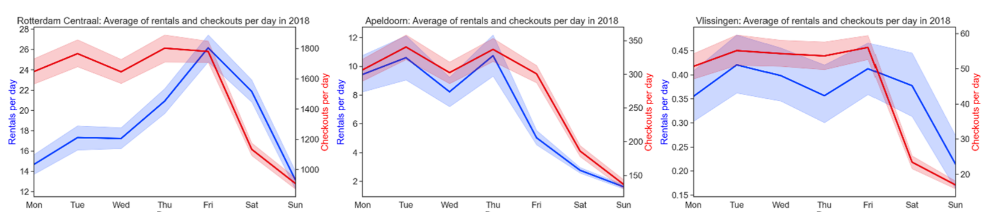

Fig. 6. Average hourly rentals and checkouts per day throughout the year 2018 for *Rotterdam Centraal*, *Apeldoorn*, and *Vlissingen*
(light filled areas indicate 95%-variance interval)

Amsterdam Zuid Mahlerplein and *Rotterdam Centraal* are located in the two biggest Dutch cities which attract both tourists and nightlife visitors using bikes to reach their destination (Jonkeren et al., 2021). An investigation of hourly rentals and the comparison between weekends and weekdays can provide additional insights.

Hourly Patterns

Two recurring patterns become visible when analysing the average hourly rentals per day, with *Vlissingen* being an exception (see Fig. 7 for *Rotterdam Centraal*, *Apeldoorn*, and *Vlissingen* as representative examples): While *Weesp*, *Breda Centrum*, *Assen*, and *Apeldoorn* show a high number of rentals in the morning peak hours, they remain low throughout the rest of the day. This pattern is different from the hourly checkouts throughout the day, which have an increase in the evening peak (4-7pm). These evening peak checkouts are train commuters on their way back home. While the SBRT-system is used on the activity-end of a trip and not on the home-end, this explains the difference between rentals and checkouts in the evening.

The high number of SBRT-rentals in the morning peak could be reasoned in commuters travelling by train to the corresponding city for work, using the SBRT-system for their last mile to reach their workplace. The second pattern occurs at *Rotterdam Centraal* and *Amsterdam Zuid Mahlerplein* showing a less steep decrease after the morning peak compared to the first pattern. Instead, the number of hourly rentals remains on an elevated level before displaying a second increase in the evening peak. Remarkably, for these two stations the hourly SBRT-rentals are following a pattern following the hourly checkouts. This suggests that SBRT-bikes are rented out for different purposes throughout the day. For example, the evening peak in rentals might be reasoned in a higher attraction of the corresponding cities to serve recreational purposes. This finding would be in line with previous findings on a daily level.

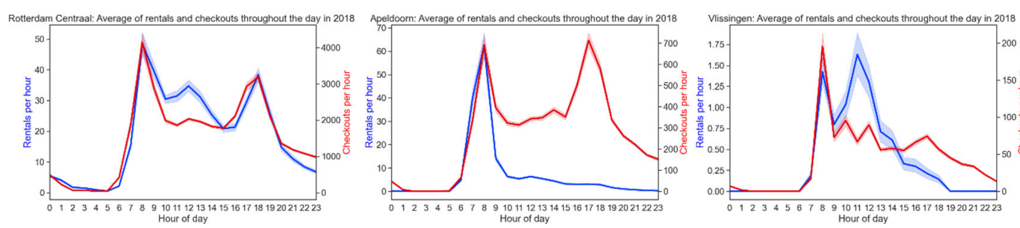

Fig. 7. Aggregated hourly rentals throughout the year 2018 for *Rotterdam Centraal*, *Apeldoorn*, and *Vlissingen*
(light filled areas indicate 95%-variance interval)

To assess the findings obtained from the daily and weekly patterns, the daily patterns are analysed based on the time-related determinants 'weekend', 'national holiday', and 'school holiday'. Exemplary results are visualised in **Error! Reference source not found.**. It is found that weekends and national holidays have a similar effect on the daily pattern, with morning and evening peaks being replaced by an increase in rentals around noon and the early afternoon. While this new peak is more elevated for stations located in big cities (Rotterdam Centraal and Amsterdam Zuid Mahlerplein), for stations located in smaller cities such as Breda Centrum, Apeldoorn, and Assen, the peak is less distinct. Amsterdam Zuid Mahlerplein, Weesp, Rotterdam Centraal, Breda Centrum, Assen, and Apeldoorn show similar effects of the different seasons, with an overall higher level of rentals per hour in Summer and Autumn and a lower level in Winter. An exception, again, is Vlissingen. There, in Spring and Summer an increase of rentals can be seen around noon, supporting the interpretation that in warmer seasons people are likely to use the SBRT for recreational purposes. It is found that at Amsterdam Zuid Mahlerplein, Rotterdam Centraal, and Vlissingen the presence of rain has almost no effect on the number of rentals within the morning peak among the selected stations, while leading to a slight decrease in other hours of the day, possibly because of greater demand elasticity. The other exemplary stations show no significant impact of occurring rain at all. This might be attributed to the lack of other options to reach the destination.

In summary, while some similar patterns among some exemplary stations are observed, the there are considerable variations in demand determinants across stations. It is therefore advised to apply models separately per station to allow for an appropriate representation of the local context.

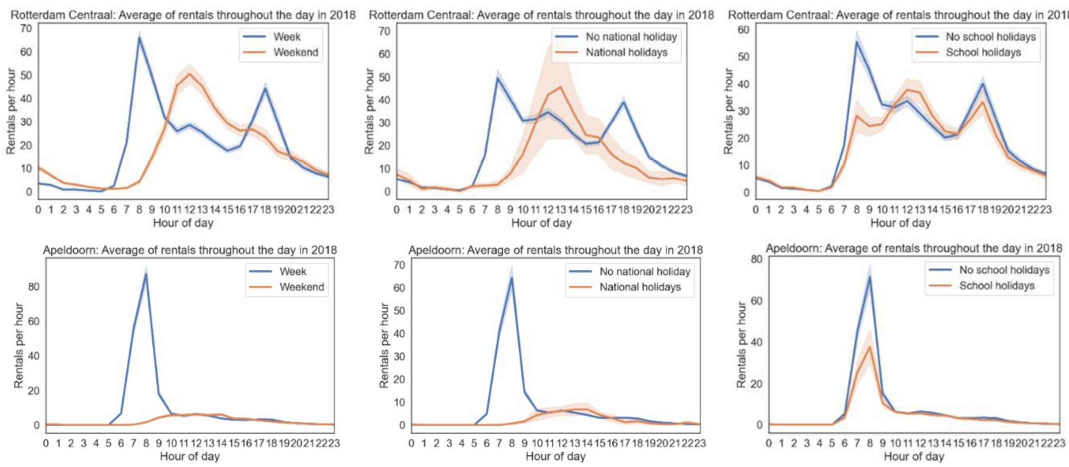

Fig. 8. Aggregated hourly rentals throughout the year 2018 for *Ro* and *Ap*, compared regarding the related days being on a weekend or a national holiday, or in school holidays (light filled areas indicate 95%-variance interval)

5. Discussion

Regarding weather-related determinants, the lack of impact of the occurrence of rain on hourly rentals in the morning peak differs from the negative impact of rain for one-way bikesharing systems (Bean et al., 2021). This might be caused by commuters relying on the SBRT-system for the egress leg of their trip as there might be no or few (less attractive) alternatives to reach their destination, making them less sensitive to occurring rain. Additionally, when renting an SBRT-bike the users are assured to also have it available for their return trip to the station. This results in a certainty of availability which differs from one-way bikesharing systems in which users cannot be certain that a bike will be available at a certain time and location when they need it. Regarding the positive correlation between hourly rentals and sunshine duration, this is in line with findings for one-way bikesharing (Eren and Uz, 2020). This finding is supported by the national train operator NS using a separate model to forecast train traveller demand for stations with a high recreational attraction in times of sunshine and elevated temperature, especially for destinations close to the beach.

When looking at the time-related determinants, the findings on a monthly aggregation are to a certain extent in line with literature findings (Eren and Uz, 2020). Still, the present research identifies the highest number of monthly rentals during autumn, while preliminary one-way bikesharing-related research identified a peak of rentals during summer. This difference can be reasoned in lower numbers of commuters and train travellers during holidays, leading to a lower SBRT-usage. A special case, again, are SBRT-stations located at destinations with a high attraction for recreational trips: For example, Vlissingen has the highest number of rentals in summer, which is more in line with findings for one-way bikesharing. This might be reasoned in a similar trip purpose, namely recreation.

Regarding rental patterns aggregated per day throughout the week, some of the SBRT-patterns selected for the in-depth analysis are in line with preliminary findings (Todd et al., 2021): Both SBRT- and one-way bikesharing show a higher number of rentals on weekdays compared to weekends. But one pattern identified among the selected stations has no similar counterpart in one-way bikesharing literature: The peak of rentals at bigger stations such as *Rotterdam Centraal* and *Amsterdam Zuid Mahlerplein* between Thursday and Saturday. This might be caused by the 24-hour pricing scheme of OV-fiets making long-term bookings comparatively cheap. Another reason might be the round-trip nature of the system, making it more attractive to book a bike overnight and/or for an entire weekend in comparison to one-way bikesharing.
When comparing the literature findings for the distribution of rentals throughout the day, the distinct morning peak is in line with one-way schemes while the evening peak is less distinct. A potential reason is that individuals renting bikes in the morning have their rented bikes available to return to the station in the evening. In the one-way-schemes discussed in literature, these return-trips are separately booked, leading to distinct evening peaks (Todd et al., 2021). Still, evening peaks exist in the SBRT-system for some stations, but they occur later compared to one-way schemes and only at stations located in bigger cities such as *Rotterdam Centraal* and *Amsterdam Zuid Mahlerplein*. On weekends, the hourly patterns throughout the day show peaks in the early afternoon, which is in line with findings for one-way schemes.

Thus, while there exist determinants with similar effects on both SBRT- and one-way bikesharing schemes like sunshine duration, temperature and time of the year, other determinants show noteworthy differences such as the higher number of rentals on Fridays or the differences and/or the lack of evening peaks at many SBRT-stations. It therefore can be concluded that SBRT-usage requires research independent from one-way bikesharing schemes due to its distinct characteristics.

6. Conclusion

To identify significant determinants for bike rentals at SBRT-stations, the rentals done in 2018 throughout the Dutch SBRT-system OV-fiets are aggregated on an hourly level per station. The results are then filtered, normalised using the total capacity per station, and combined with information on national and school holidays as well as hour-specific information about the weather conditions. The latter is gathered from the national weather stations closest to each SBRT-station. The resulting dataset is used to perform MLRs across the entire dataset as well as per individual SBRT-station to identify significant weather- and time-related determinants. For some stations a high explanatory power can be achieved using few variables only, while others achieve a lower explanatory power even when having more significant variables. Thus, there is no clear set of variables being able to explain variance across the entire set of stations

To further investigate whether the available data can be used to identify temporal usage similarities and differences among SBRT-stations, a descriptive analysis is done using eight selected stations. The hourly rentals per station are then aggregated on a monthly, daily, and hourly level and compared with the previously identified determinants. When comparing the patterns of the different stations, it is found that while the patterns mostly differ across the stations, a number of general trends can be identified: For example, on average all stations have their highest number of hourly rentals in the morning peak between 7-9 am, and the two selected SBRT-stations located in bigger cities also experience a second peak in the afternoon between 5-7 pm. The latter suggests a different use case of the SBRT-system in the evening peak compared to the morning peak. Another identified difference becomes visible between the patterns of hourly rentals on weekends and weekdays, as on weekends neither morning nor evening peaks appear. Instead, the rentals either stay on a low level throughout the day or experience a peak during the early afternoon between 12-2 pm. Another finding is that the occurrence of rain is unlikely to impact the number of rentals in the morning peak, while the number of rentals throughout the rest of the day slightly drops when rain occurs.

For operators, the provided information on the determinants of a SBRT-system in combination with suitable demand forecasting methods might allow for an increase in efficiency in terms of staff scheduling, maintenance of bikes, and a potentially higher user satisfaction due to an improved match of supply and demand.

7. Recommendations

The present research does assess weather- and time-related determinants, while leaving out further location-specific and other external determinants such as events. The included determinants are also focussing on causalities and two-dimensional causalities only, while a higher dimensionality of interaction between determinants might be required to accurately explain the variance in the data. Further, the in-depth analysis only covers eight exemplary stations to provide a first insights into the system, while missing insights on the remaining forty stations included in the analysis and into the 265 SBRT-stations not included in this analysis. Furthermore, this research was conducted using data from 2018 to avoid the impact of COVID-19 related travel restrictions.

To conclude, this research provides new insights into a new, barely researched type of bikesharing. The learnings provide a first indication on where SBRTs have similarities and differences with the widely known one-way bikesharing and provides existing and potential operators new insights on how these learnings can be used to forecast the occupancy of their services to improve the service availability and efficiency. Further research can deepen the understanding of the system and help SBRT-systems to gain a wider acceptance by raising awareness on the added value of the system. Additionally, an investigation into whether the results of this work might be reproducible for different SBRT-systems or data for different timeslots, e.g. post-COVID-19 might be interesting to verify or neglect the present findings.

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