Examining the Impact of Weather, Temporal Factors, and User Traits on Multimodal Shared Micromobility Systems in Non-Urban Campus Environments: The MORE Sharing Case Study

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Abstract: Although shared micromobility systems in cities have been extensively studied, their potential for non-urban settings such as university campuses and rural communities has not been explored much yet. This study aims to fill this gap by examining a multimodal shared micromobility service that offers various options through a single app, such as city bikes, e-bikes, e-cargo bikes, e-mopeds, and e-scooters. The study analyzed this campus-based system's first four months, considering factors like weather, time, user demographics, pre-reservation duration, and vehicle types. Machine learning models like Negative Binomial Regression, Random Forests, Gradient Boosted Regression Trees, and Neural Networks were used to analyze the data. The study found that e-scooters were the most popular, followed by e-bikes. E-mopeds were used less but were reserved for more extended periods. Most trips were taken on weekdays, especially between 8 AM and 6 PM. Reservation numbers peaked in the first month, and subsequent months showed longer reservation durations and distances. Rain decreased trip numbers and distances but increased reservation durations. Reservations on Fridays, weekends, and holidays were shorter but covered more distance. Female users tended to travel longer distances. These findings can benefit similar non-urban environments, broadening the application of shared micromobility systems.

1 INTRODUCTION

The 21st century has seen a rise in shared micromobility as a form of urban transportation. While most research has focused on city-wide commercial projects facilitated by private mobility companies, there is potential for implementing shared micromobility solutions in smaller settings such as residential neighborhoods, non-urban communities, campuses, and corporate settings. These unique contexts present opportunities and challenges that require thorough investigation, as successful implementation requires a deep understanding of local dynamics and community requirements.

The University of the Bundeswehr in Munich, Germany, is a suitable case study for exploring shared micromobility in microenvironments. This 140-hectare campus is one of the largest campus-based institutions in Germany, with a diverse population of 5,300 members. This population comprises 72% students, 16% academic staff, 8% non-academic personnel, and 4% professors (UniBw, 2023b). The student body comprises military officers and civilians from various regions and countries, primarily aged 20-30, within the middle-income bracket, and predominantly residing on campus. Approximately 27% of students and 25% of academic staff are female (UniBw, 2023a).

To meet the transportation needs of this population, the university recently introduced "MORE Sharing," a micromobility sharing system operated by a third-party contractor (evhcle, 2023; Huber, 2023; MORE Sharing, 2023; Pobudzei, Kemmerzehl, et al., 2023). Users can book and access a variety of vehicles via a mobile app, which displays

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rental prices and automatically selects the most cost-effective rate based on the rental duration. Users are also provided with the option of a complimentary monthly mobility budget after registration and payment details submission. Additional credits can be earned by participating in surveys offered by the service (evhcle, 2023; Pobudzei, Wichmann, et al., 2023).

MORE Sharing users are not confined to the operating zone during their rides and can venture beyond it, with the app offering a park mode for breaks without terminating the rental. However, rentals must be concluded within the operating zone, requiring users to ensure sufficient battery charge for their return trip (evhcle, 2023). This integrated multimodal micromobility system, coupled with the unique offering of a free mobility budget, sets MORE Sharing apart from other platforms and represents an area of shared micromobility that has received limited exploration (Pobudzei, Wichmann, et al., 2023).

This study aims to provide insights into the utilization patterns and influential factors of shared micromobility systems, thereby contributing to the development of sustainable transportation initiatives in microenvironments like campuses, corporate landscapes, residential neighborhoods, and non-urban communities. Specifically, this paper evaluates metrics such as hourly trip counts, trip durations, and reservation lengths during the initial months of the micromobility sharing system's operation on the university campus.

The analysis considers variables such as weather conditions, time of day, vehicle type, reservation duration, and user demographics, considering their potential impact on these metrics. Advanced analytical techniques, including Negative Binomial Regression (NBR), Random Forests (RF), Gradient Boosted Regression Trees (GBRTs), and Neural Networks (NN), are employed for this analysis. The outcomes of this research provide valuable insights for policymakers, urban planners, and transportation providers, enhancing shared micromobility system design and implementation across various settings, including residential areas and large campus environments.

2 LITERATURE REVIEW

Shared micromobility systems are becoming increasingly common in urban areas. However, these systems are typically single-mode, meaning that each service provider's app only offers a specific mode of transport, such as city bikes, e-bikes, e-scooters, e-cargo bikes, or e-mopeds. Users must register with multiple providers to access different mobility options.

Users' demographics for each shared mode of transport vary depending on the provider and location (Pobudzei, Wichmann, et al., 2023). For example, shared city bikes, e-bikes, and e-scooters are more popular among younger adults and men, while women and older populations use them less frequently (NACTO, 2022; Rérat, 2021).

In the United States, e-scooter users and bike share members typically embark on rides lasting 11-15 minutes, covering up to 3 kilometers (NACTO, 2022; Younes et al., 2020). Station-based bike share users usually opt for longer trips, lasting 24-28 minutes and covering approximately 5 kilometers (NACTO, 2022). However, data on usage patterns for shared e-cargo bikes and e-mopeds is limited, indicating a gap in current research (Pobudzei, Kemmerzehl, et al., 2023).

In Munich, shared e-scooters are most frequently used on Friday and Saturday afternoons, with longer trips taken on weekends and holidays than on workdays (Pobudzei et al., 2022; Schreier et al., 2022; Tießler et al., 2023). The use of shared e-scooters witnesses an increase in frequency and duration from July to November, in contrast to the winter months (Pobudzei et al., 2022).

Shared city bikes and e-bikes see higher usage rates on weekdays, especially during peak commute hours (Fishman, Washington, & Haworth, 2015; Fishman, Washington, Haworth, et al., 2015; Rérat, 2021; Younes et al., 2020). However, some cities also witness a surge in usage during lunchtime and weekends, catering to recreational purposes (Pobudzei, Wichmann, et al., 2023). Shared e-cargo bikes are typically used on weekdays for commercial and delivery purposes (Becker & Rudolf, 2018), while shared e-mopeds e-mopeds are popular for weekday commuting and recreational use on weekends and evenings (Pobudzei, Wichmann, et al., 2023).

Weather conditions also play a significant role in the usage of shared micromobility. Extreme temperatures and adverse weather conditions like high winds, rain, snow, and other precipitation discourage users due to safety and comfort concerns (Gebhart & Noland, 2014; Noland, 2021; Pobudzei et al., 2022).

Despite the literature on shared micromobility in urban settings, more research should be conducted on systems deployed in non-urban settings and microenvironments such as university or corporate campuses, residential neighborhoods, or non-urban communities.

This paper addresses this gap by focusing on the shared micromobility service at the University of the Bundeswehr in Munich, where users can access multiple micromobility modes within a single application. The investigation aims to analyze hourly trip counts, trip distances, and durations for shared city bikes, e-bikes, e-cargo bikes, e-scooters, and e-mopeds within a micromobility sharing system in the campus environment. The findings of this study could be helpful in similar environments, thereby expanding the applicability of shared micromobility systems.

3 DATA AND METHODS

3.1 MORE Sharing Setup and Data

On the 6th of March, 2023, the MORE Sharing service was officially launched and communicated to the university community via email notification. Soon after, on the 15th of March, a launch event was organized to introduce potential users to the service. The event assisted with the app installation, a comprehensive tutorial on how to use it, and an introduction to the range of available vehicles. Additionally, a dedicated webpage with instructional videos and frequently asked questions was established and made accessible to help users understand the service (Huber, 2023; MORE Sharing, 2023).

The MORE Sharing service is only available to members affiliated with the University of the Bundeswehr, including students and staff. Upon registration, users can choose a mobility budget of up to 300 Euros, automatically renewing monthly. The unused monthly mobility budget cannot be transferred to the following months. Users can also earn extra credits by participating in surveys. The pricing structure for MORE Sharing is 0.13 Euros per minute for riding and parking any vehicle, with a daily cap of 25 Euros. The system applies the most economical rate, minute-based or daily, depending on the rental duration. Users can reserve a vehicle for up to 15 minutes at no cost before starting their ride.

From March to June 2023, MORE Sharing provided 94 vehicles, including 25 city bikes, 24 e-bikes, 7 e-cargo bikes, 9 e-mopeds, and 29 e-scooters. Users can start a ride by scanning a vehicle's QR code or selecting it directly from the map view in the app. After confirming the rental, the digital lock is activated. Users can pause and end their rides using the MORE Sharing app. For city bikes or e-cargo bikes, users need to manually secure the lock, while e-bikes, e-scooters, and e-mopeds use automatic locking mechanisms. People who want to ride e-mopeds must have a valid driver's license, which must be verified within the app, and are required to wear a helmet.

The MORE Sharing service operates within the university campus and extends to specific public transport stops within a 3-kilometer radius. Users can start or end their rides at these stops. However, they must finish their trips within the designated operational area, even if they travel beyond the 3-kilometer radius. Users can activate the parking mode if they need to park their vehicles outside the operational area (MORE Sharing, 2023a; Pobudzei, Kemmerzehl, et al., 2023).

The MORE Sharing app collects reservation details such as the reservation time, user ID, vehicle ID, start and end times of each journey, and the initial and final mileage readings of the vehicles. Between March and June 2023, we analyzed the data to calculate the frequency of trips, distance covered, and rental duration for each vehicle type hourly. Please note that the MORE Sharing service was not available on May 17th, 18th, and June 24th, 2023, due to local on-campus events.

Apart from the reservation data, we also collected meteorological data from weather station ID 3,379, located in Munich City at coordinates 48.16 latitude, 11.54 longitude, and an elevation of 515 meters. This weather dataset included meteorological parameters such as wind chill index, relative humidity, and recorded precipitation levels (DWD, 2023).

3.2 Modeling Methods

The study aims to analyze the patterns of hourly trip counts, trip distances, and durations observed during the initial four months of operation of a micromobility sharing system deployed on a university campus. The study's main objectives are to gain insights into user behaviors, evaluate the system's effectiveness, and comprehensively understand usage patterns.

In addition to descriptive methods, the study explored the application of various machine learning models, including Negative Binomial Regression (NBR), Random Forests (RF), Gradient Boosted Regression Trees (GBRTs), and Neural Networks (NN). The models were trained using 80% of the dataset and tested on the remaining 20%. The random seed was set to 42 to ensure consistent results.

The NBR model is suitable for counting data that shows overdispersion, where the variance exceeds the mean. It can effectively handle categorical and continuous predictor variables (Noland, 2021; Pobudzei et al., 2022).

RF constructs numerous decision trees by leveraging random data subsets and combines the predictions of individual trees to produce a final forecast. This approach mitigates overfitting and enhances the model's robustness by selecting random feature subsets for each tree. RF demonstrates proficiency in handling continuous and categorical variables, allowing it to model complex non-linear relationships (Breiman, 2001).

GBRTs adopt an iterative approach, initially fitting a simple decision tree to the data and then concentrating on the areas where the model exhibits weaknesses. These problematic instances are assigned higher weights, prompting the training of new decision trees to refine the model's predictions. GBRTs typically excel when dealing with smaller datasets, although they demand more computational resources for training compared to other methods (Davis, 2014).

Lastly, NN leverages a multilayered architecture comprising numerous interconnected neurons. During training, the weights that control the strength and direction of signal transmission between neurons are adjusted to enhance the model's predictive capabilities. NNs are proficient in modeling complex non-linear relationships and can handle diverse input data types, including images, text, and numerical data. It is important to note that they come with higher computational demands, mainly when applied to larger datasets (Analytics Vidhya, 2023).

4 RESULTS AND DISCUSSION

By June 2023, the number of registered users for MORE Sharing had grown to 2,379. There was a significant surge in registrations during the first three weeks after the service launch (Figure 1). All registered users received a monthly mobility budget of 300 euros that was automatically renewed monthly. The unused monthly mobility budget cannot be transferred to the following months. Figure 1 shows that the majority of users fall within their 20s, and 81.8% of users are male, 17.7% are female, and 0.4% identify as diverse, reflecting the demographics of the university community.

Between March and June 2023, MORE Sharing facilitated 25,742 distinct trips, with an average of approximately 238 daily trips. 66% of registered users utilized the service during this time, and 1,570 unique customers engaged with the service. Table 1 analyzes the cumulative trip count, distance traveled, and reservation duration for individual customers during the periods of March–April 2023 and May–June 2023. Specifically, during March–April 2023, 1,242 unique customers engaged with MORE Sharing, while the number increased to 1,333 customers during May–June 2023. Although May–June witnessed an increase in active customers, some users who had availed the service in March–April did not do so in May–June, resulting in a cumulative count of 1,570 customers encompassing both periods.

During the first two months, customers took an average of approximately 10.8 trips each. However, in the following period, the average number of trips per customer decreased to approximately 9.2. In the first two months of operation, 75% of customers made 15 trips or fewer. This number decreased to 12 trips or fewer in the following period. Despite this trend, some customers used the service much more frequently than the average. These observations indicate a broad spectrum of user engagement levels, behaviors, and preferences, ranging from less active members to prolific users.

Table 1 shows that the cumulative distance traveled and reservation duration per customer increased overall from the first to the second period. This suggests that users optimize their utilization within each trip, resulting in an overall increase in distance covered and reservation duration. A subset of users covered significantly longer distances in both periods, indicating potential usage of MORE Sharing for journeys beyond the immediate campus vicinity. Additionally, some users preferred reserving vehicles for extended durations, possibly for activities or events requiring prolonged mobility. Extended reservations per customer are also aligned with the fact that MORE Sharing users had a monthly mobility budget of 300 euros.

Between March and June 2023, MORE Sharing boasted a fleet comprising 94 vehicles, encompassing 25 city bikes, 24 e-bikes, 7 e-cargo bikes, 9 e-mopeds, and 29 e-scooters. To gauge the utilization rates for each vehicle type, we calculated the ratio of daily trips to the number of available vehicles of that particular type (Figure 2). These metrics revealed that e-scooters were the most frequently utilized vehicle type within the MORE Sharing system, with e-bikes closely following (Figure 2). This trend, especially evident in the initial weeks of system operation, indicates that e-scooters and e-bikes enjoy heightened popularity among users, presumably due to their convenience and ease of use. E-cargo bikes and city bikes exhibited similar utilization patterns, while e-mopeds recorded the lowest average utilization (Figure 2).

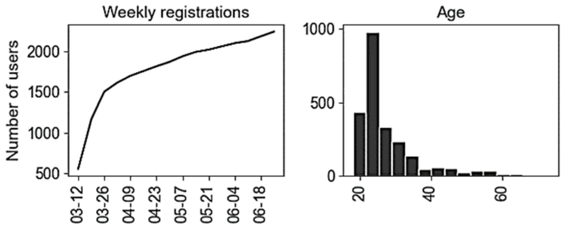

Figure 1: MORE Sharing user registrations and demographics

Table 1: Cumulative sum of trips, driven distance, and reservation duration per customer.

Parameters			Cumulative sum per customer					
Parameter	Period	Active customers	Min	25%	Mean	50%	75%	Max
Trips	3. - 4.2023	1,242	1	3	10.8	7	15	103
	5. - 6.2023	1,333	1	2	9.2	5	12	87
Driven Distance, Kilometers	3. - 4.2023	1,242	0.0	5	23	13	31	325
	5. - 6.2023	1,333	0.0	4	24	11	29	432
Reservation Duration, Minutes	3. - 4.2023	1,242	0.2	34	577	134	419	17,308
	5. - 6.2023	1,333	0.3	31	861	145	623	25,897

However, the lower average utilization of e-mopeds does not mean a lack of popularity. Users often reserved e-mopeds for extended periods compared to other vehicle types (Table 2). E-cargo bikes follow suit, with an average reservation duration approximately three times shorter than e-mopeds. E-bikes and e-scooters displayed comparable average reservation durations, while city bikes featured the shortest mean reservation duration (Table 2).

An analysis of driven distances, as presented in Table 2, indicates that e-mopeds typically cover the greatest mean distance, implying their use for longer journeys compared to other vehicle types. Nonetheless, it is crucial to note that half of the trips made on e-mopeds are less than or equal to 2 kilometers, suggesting a mix of shorter and longer trips. E-bikes, e-cargo bikes, and e-scooters exhibit comparable average distances traveled, while city bikes demonstrate the lowest mean distance traveled.

Figure 3 offers an overview of trip distribution across different distance and duration categories for each vehicle type. Predominantly, short trips in both duration and distance categories dominate the usage patterns across all vehicle types within MORE Sharing. This observation underscores the primary utilization of the service for brief journeys within the campus vicinity or nearby areas.

Extended reservation durations do not necessarily correlate with greater distances traveled, as these often involve extended idle times rather than continuous movement (Figure 3). This observation suggests that users reserve vehicles for longer durations to accommodate their needs, including extended breaks or multiple stops during their journeys, rather than solely focusing on covering longer distances. E-mopeds, e-cargo bikes, and e-bikes are utilized for longer distances during longer-duration rentals (Figure 3), indicating that users prefer these vehicle types for more extensive journeys or tasks requiring greater distances.

Kernel density estimate (KDE) plots (Figure 4) depict the distribution of trips across different micromobility modes throughout the week and at various times of the day. Most trips, irrespective of vehicle type, occur on weekdays, in line with the primary user base consisting of students, faculty, and staff members who are more active on campus during weekdays.

Trip numbers rise between 6 AM and 8 AM, corresponding to the morning commute on campus. From 8 AM to 6 PM, the trip counts for all micromobility modes remain consistently high. After 7 PM, the number of trips declines, indicating reduced demand during the evening hours when users likely conclude their campus activities. E-mopeds exhibit a distinct peak in usage between 1 PM and 6 PM, possibly due to various reasons, such as using e-mopeds for longer trips, leisure activities, or running errands during the mid-afternoon period.

The study investigated the effects of time, weather, user demographics, and vehicle types on MORE Sharing's hourly trip counts, reservation duration, and driven distance (Table 3). Results from the Negative Binomial Regression (NBR) model for hourly trip counts revealed that precipitation has a negative impact on the number of shared micromobility trips (Table 3).

Unfavorable weather conditions or safety concerns may decrease trip counts during wet conditions (Table 3). However, parameters like wind chill index and humidity level did not significantly affect hourly trip rates. Comparing the number of trips per hour for different vehicle types (Table 3), it was found that e-scooters, e-bikes, and city bikes had higher trip counts compared to e-cargo bikes. This discrepancy could be attributed to factors such as vehicle availability or specific use cases contributing to differences in trip counts.

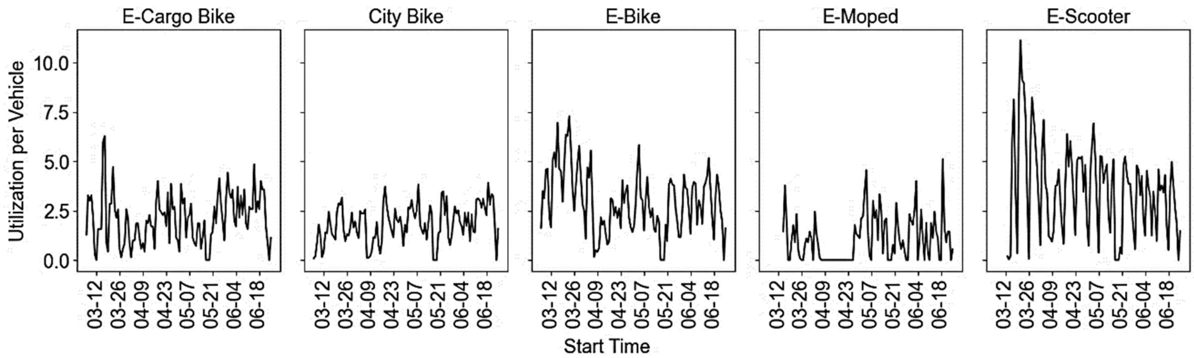

Figure 2: Daily utilization rate per vehicle type.

Table 2: Reservation duration (minutes) and driven distance (kilometers) per vehicle type.

Parameter	Vehicle type	Number of trips	Min	25%	Mean	50%	75%	Max
Reservation duration, minutes	City Bike	4,803	0.1	4.3	83.3	8.0	26.8	16,024.7
	E-Bike	7,769	0.0	4.3	55.4	8.2	32.2	8,924.7
	E-Cargo Bike	1,525	0.1	5.2	95.1	12.2	47.4	4,460.0
	E-Moped	977	0.1	2.2	262.1	20.9	107.1	9,796.7
	E-Scooter	10,668	0.0	4.4	59.3	8.5	33.5	10,197.8
Trip distance, kilometers	City Bike	4,803	0.0	0.5	1.6	1.0	1.7	38.5
	E-Bike	7,769	0.0	0.8	2.3	1.4	2.6	57.0
	E-Cargo Bike	1,525	0.0	0.5	2.3	1.2	2.7	63.5
	E-Moped	977	0.0	0.0	5.8	2.0	8.0	58.0
	E-Scooter	10,668	0.0	0.9	2.5	1.6	3.0	38.3

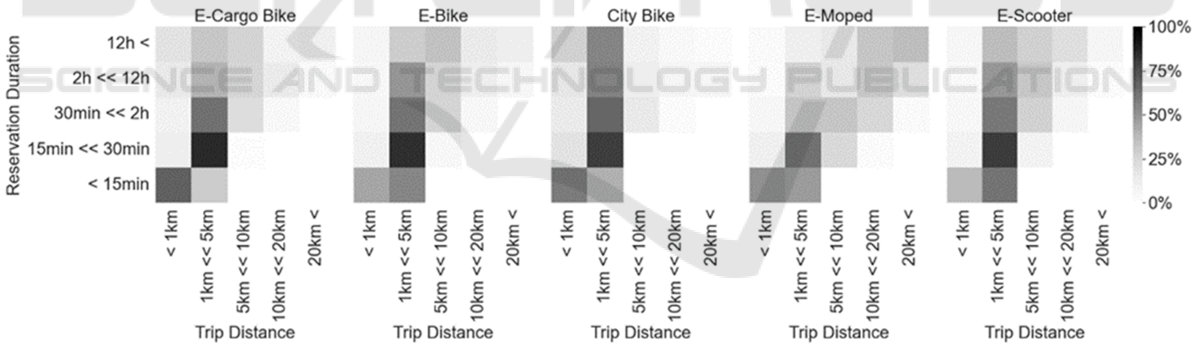

Figure 3: Distribution of MORE Sharing trips across different distance and duration categories.

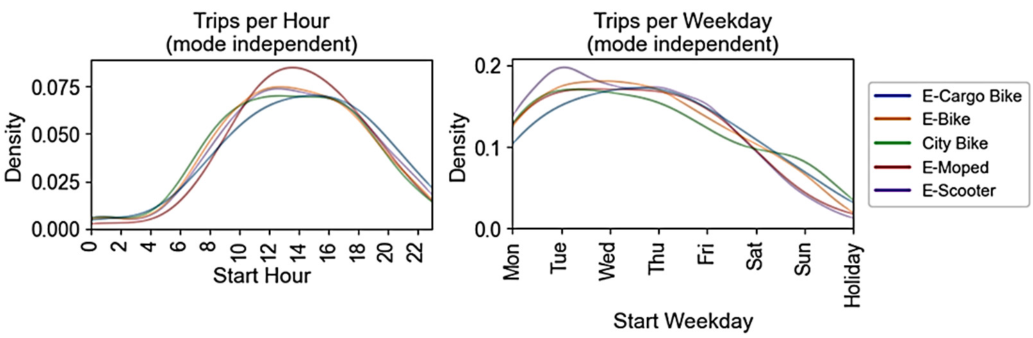

Figure 4: Kernel density plots (mode independent): distribution of MORE Sharing trips.

Table 3: Modeling hourly trip counts, reservation durations, and trip distances with Negative Binomial Regression (NBR). Bolded values indicate statistical significance at $p < 5\%$.

	Hourly trip counts		Reservation duration, minutes		Trip distance, kilometers	
N	5,325		20,516		20,516	
RMSE	2.63		324.7		3.24	
Variable	coef	z	coef	z	coef	z
Vehicle pre-reserved, minutes			**0.01**	**6.86**	**0.04**	**16.86**
User age			**0.02**	**12.94**	0.00	0.11
User registered since, days			**0.01**	**13.20**	**0.00**	**-3.60**
Female			0.04	1.48	**0.07**	**2.49**
Humidity, %	-0.01	-0.46	0.00	-0.76	0.00	-0.30
Precipitation index	**-0.19**	**-4.44**	**0.17**	**9.25**	**-0.10**	**-4.36**
Wind chill index	0.00	0.81	**0.01**	**33.72**	**0.00**	**7.08**
E-Bike	**0.95**	**17.00**	**-0.64**	**-20.37**	-0.01	-0.39
City Bike	**0.64**	**11.21**	**-0.21**	**-6.38**	**-0.39**	**-9.66**
E-Moped	0.11	1.40	**0.85**	**18.34**	**0.85**	**16.39**
E-Scooter	**1.32**	**23.73**	**-0.53**	**-17.29**	0.07	1.92
3-5AM	**-0.27**	**-2.21**	**0.97**	**12.70**	-0.09	-0.93
6-7AM	**0.47**	**5.06**	**0.15**	**2.74**	-0.07	-1.03
8-9AM	**0.89**	**10.16**	0.05	0.96	0.05	0.75
10-11AM	**1.02**	**11.71**	**0.17**	**3.43**	**0.13**	**2.20**
12AM-1PM	**1.12**	**12.69**	**0.26**	**5.22**	**0.14**	**2.26**
2-3PM	**1.02**	**11.44**	**0.11**	**2.09**	**0.21**	**3.46**
4-5PM	**1.06**	**11.89**	0.06	1.18	**0.22**	**3.60**
6-7PM	**0.93**	**10.35**	**0.25**	**5.00**	**0.15**	**2.37**
8-9PM	**0.54**	**5.87**	-0.02	-0.32	-0.05	-0.83
10-11PM	**0.38**	**4.02**	**0.12**	**2.25**	**-0.18**	**-2.64**
Tuesday	-0.06	-1.02	0.01	0.39	**-0.07**	**-2.49**
Wednesday	-0.09	-1.54	**0.18**	**6.97**	-0.04	-1.42
Thursday	-0.11	-1.89	0.05	1.82	**-0.13**	**-4.18**
Friday	**-0.15**	**-2.50**	**-0.15**	**-5.67**	-0.01	-0.20
Saturday	**-0.47**	**-7.38**	**-0.18**	**-6.26**	**0.12**	**3.34**
Sunday	**-0.67**	**-9.80**	-0.02	-0.58	-0.02	-0.40
Holiday	**-0.73**	**-6.14**	**-0.14**	**-2.15**	**0.19**	**2.61**
April, 2023	**-0.26**	**-5.62**	**0.29**	**14.82**	**0.08**	**3.39**
May, 2023	**-0.19**	**-3.55**	**0.40**	**16.51**	**0.11**	**3.68**
June, 2023	**-0.32**	**-5.42**	**0.53**	**19.51**	**0.17**	**5.25**

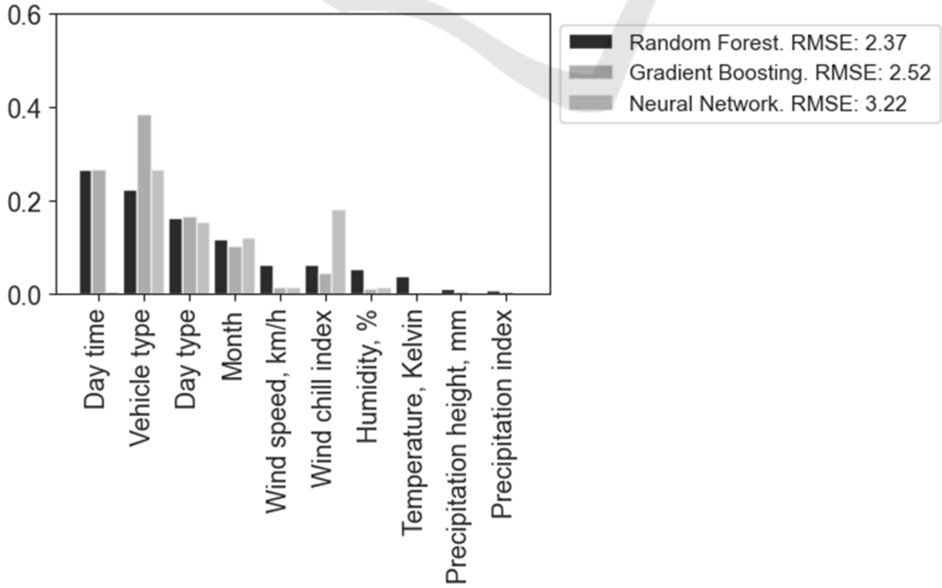

Figure 5: Feature importance for hourly trip count models

Analysis of the hourly trip rates throughout the day (Table 3) revealed an increase in trip counts between 6 AM and 11 AM compared to the period between 0 and 2 AM. This indicates higher demand during the morning hours, likely related to commuting and the start of daily activities. Most bookings occurred between 12 PM and 5 PM, reflecting lunchtime and mid-afternoon activities. After 6 PM, the trip rate started to decline, suggesting reduced campus activity during the evening hours.

Significantly fewer trips were observed on Fridays, weekends, and holidays than on Mondays. This pattern suggests that MORE Sharing experiences reduced usage during non-working days and weekends when the campus community may have fewer obligations or different transportation needs. The first month of MORE Sharing operations also had more hourly reservations than subsequent months.

When modeling hourly trip counts, the Random Forest (RF), Gradient Boosted Regression Trees (GBRTs), and Neural Networks (NN) models exhibited similar performance but varied in feature importance rates (Figure 5). RF placed considerable importance on parameters such as the time of day vehicle type, weekday type, and month when predicting hourly trip counts. GBRTs also considered vehicle type and time-related parameters as priorities. NN assigned the highest importance to vehicle type, followed by the wind chill index, day type, and month. These disparities in feature importance highlight the factors influencing trip counts and the potential of different models to capture and predict these patterns.

To estimate reservation durations and traveled distances, additional parameters like pre-reservation duration in minutes, user age, and the length of user registration on MORE Sharing were included (Table 3). The NBR model indicated that these factors played a minor role in predicting reservation duration in minutes (Table 3). However, reservations made during rainy weather tended to last longer, suggesting that users prefer to reserve vehicles for extended periods when weather conditions are unfavorable, possibly to allow for flexibility or contingency plans.

E-cargo bikes had longer reservation durations compared to e-bikes, city bikes, or e-scooters, implying that users may require more time when using e-cargo bikes, possibly due to the nature of transporting goods or engaging in activities that necessitate the use of e-cargo bikes. E-mopeds had the longest reservations, potentially for more extensive trips or specific purposes (Table 3). Reservations between 3 and 5 AM consistently exhibited the longest durations, and daytime reservations generally surpassed those between midnight and 2 AM (Table 3). Furthermore, reservations on Fridays, weekends, and holidays tended to be shorter than on Mondays. The duration of reservations continuously increased since March 2023, with each successive month showing higher average reservation durations.

While the Negative Binomial Regression (NBR) model suggested only minor effects of user age, the length of user registration, and pre-reservation duration on predicting reservation durations (Table 3), both the Random Forest (RF) and Gradient Boosted Regression Trees (GBRTs) effectively utilized these parameters in predicting reservation durations (Figure 6). Weather-related parameters such as humidity and wind chill index also played a role in predictions, with the wind chill index demonstrating slightly higher feature importance than wind speed and temperature parameters alone. Vehicle type proved to be a relevant factor for RF and GBRTs in predicting reservation duration, suggesting that different vehicle types may exhibit distinct usage patterns that influence the duration of reservations. In contrast, the Neural Network (NN) model did not reveal particular features important for predicting reservation durations.

Concerning driven distances, users who pre-reserved vehicles tended to cover longer distances compared to those who made spontaneous reservations (Table 3). This suggests that individuals who plan their trips in advance may have specific destinations or longer journeys in mind, resulting in increased distances traveled. Additionally, female users traveled longer distances than their male counterparts, indicating potential variations in travel patterns, purposes, or preferences within the MORE Sharing system. Further exploration is necessary to elucidate the underlying factors driving these differences.

Distances traveled were generally shorter during rainy weather conditions (Table 3). This phenomenon could be attributed to users opting for shorter trips or seeking sheltered transportation alternatives during adverse weather. E-cargo bikes were consistently used for longer distances than city bikes, underscoring their suitability for transporting goods or engaging in activities necessitating extended travel. The longest distances were covered by e-mopeds, suggesting that users opt for e-mopeds when they require swift and substantial distance coverage. These results highlight the advantages of incorporating multiple vehicle types within a shared mobility system, as each type caters to distinct purposes and accommodates a broad spectrum of travel needs.

Distances traveled were higher during daytime and evening hours than nighttime (Table 3), aligning with typical travel patterns as users engage in various daytime activities. On Tuesdays and Thursdays, trips covered shorter distances, potentially reflecting specific weekday routines or shorter commutes. Conversely, trips on weekends and holidays tended to be more extensive, implying that users engage in extended leisure activities during these periods. Overall, the length of trips in kilometers has exhibited a steady increase since March 2023. Factors such as increased familiarity with the service, expanded usage scenarios, or evolving user preferences may contribute to this observed growth.

RF and GBRTs underscored the significance of vehicle type and the duration of user registration on the MORE Sharing platform in predicting the distance traveled (Figure 7). The wind chill index emerged as a significant distance predictor, representing the combined influence of temperature and wind speed. Additionally, GBRTs factored in whether the vehicle was pre-reserved, signifying the impact of this factor on the distance traveled.

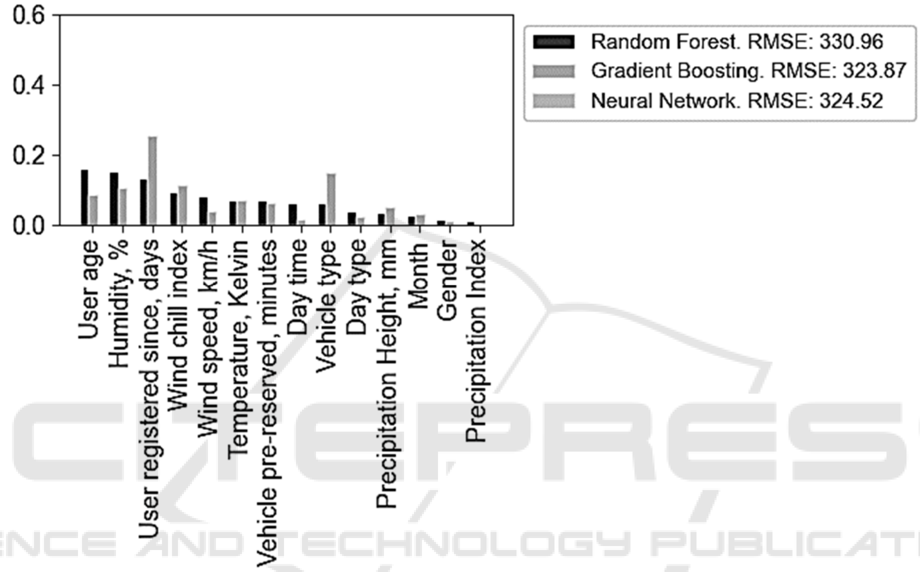

Figure 6: Feature importance for reservation duration models.

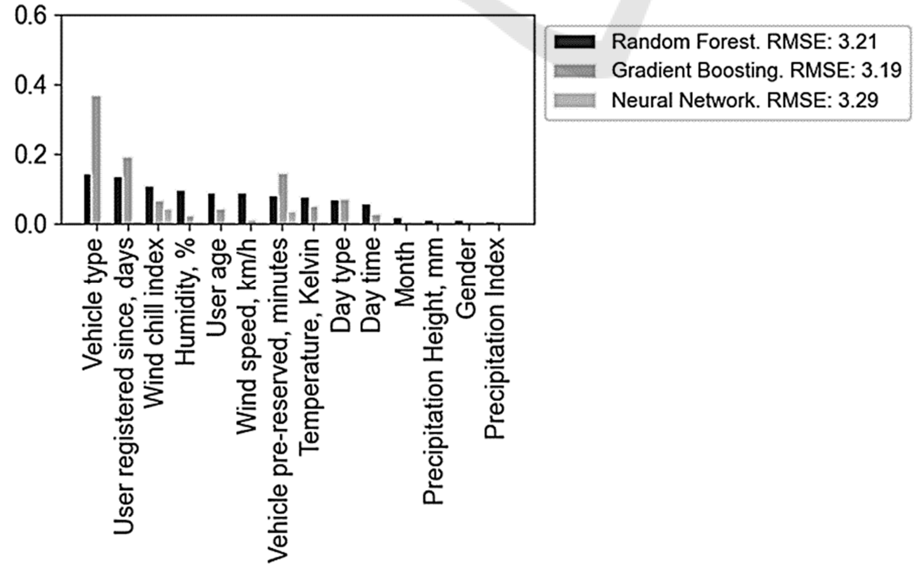

Figure 7: Feature importance for trip distance models

5 CONCLUSIONS

While shared micromobility systems in urban areas have been extensively researched, these systems still need to be studied more in non-urban settings and smaller contexts, such as university or business campuses, residential neighborhoods, and non-urban communities. This study aims to bridge this knowledge gap by investigating the multimodal shared micromobility service at the University of the Bundeswehr in Munich. This unique service allows users to access multiple micromobility modes through a single app and offers a complimentary mobility budget.

Our research focused on tracking hourly trip metrics, including trip counts, trip lengths, and reservation times, during the initial four months of this campus-based micromobility service. We considered factors, including weather conditions, time of day and week, lead times for reservations, user demographics, and various vehicle types such as shared city bikes, e-bikes, e-cargo bikes, e-scooters, and e-mopeds. To gain insights into usage patterns, we employed several machine learning models, including Negative Binomial Regression (NBR), Random Forests (RF), Gradient Boosted Regression Trees (GBRTs), and Neural Networks (NN).

Our findings revealed diverse user engagement levels, behaviors, and preferences within the MORE Sharing service. E-scooters emerged as the most frequently used vehicle type, closely followed by e-bikes. E-cargo bikes and city bikes exhibited similar usage rates, while e-mopeds had the lowest average usage. However, it is essential to note that lower average usage of e-mopeds does not equate to lower popularity; users often reserve e-mopeds for extended periods compared to other vehicle types. E-cargo bikes follow a similar trend, with e-bikes and e-scooters having comparable average reservation times, while city bikes recorded the shortest reservation durations. E-mopeds covered the most extended distances, with e-bikes, e-cargo bikes, and e-scooters showcasing similar average travel distances, while city bikes covered the least distance. These findings underscore the benefits of offering multiple vehicle types within a shared mobility system, catering to diverse travel needs and purposes.

Our research also highlighted that most trips, regardless of vehicle type, occur on weekdays. Furthermore, reservations on Fridays, weekends, and holidays tend to be shorter in duration compared to Mondays but involve longer distances during weekends and holidays. The peak in the number of trips typically falls between 6 AM and 8 AM, remains high from 8 AM to 6 PM for all micromobility modes, and decreases after 6 PM. Reservations between 10 AM and 7 PM generally exhibit the most extended reservation times and travel distances.

We observed more hourly reservations during the initial month of MORE Sharing operations than in subsequent months. However, since March 2023, both reservation durations and travel distances have steadily increased, with each new month surpassing the previous month's average reservation duration. Rainy weather decreased the number of shared micromobility trips and the distances traveled. However, during rainy periods, reservations tend to last longer. Users who reserve vehicles in advance tend to cover greater distances than those who make spontaneous reservations. On average, female users travel farther than their male counterparts.

This research underscores the significance of understanding local contexts and community needs when implementing shared micromobility systems in non-urban settings. Policymakers, urban planners, and transportation providers can leverage these insights to enhance the design and implementation of shared micromobility systems in various microenvironments, such as campuses, residential neighborhoods, and corporate settings. This study contributes to the broader objective of promoting sustainable transportation initiatives and environmentally friendly mobility options across diverse settings. Examining and optimizing shared micromobility solutions in various contexts can pave the way for more efficient and accessible mobility solutions.

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