Chair of Transportation Systems Engineering
TUM School of Engineering and Design
Technical University of Munich

Creating a Predictive Model for the Traffic Impacts of Road Closures

A case study in Munich

A thesis presented in part fulfilment of the requirements of the Degree of Master of Science in Transportation Systems at the TUM School of Engineering and Design, Technical University of Munich.

Examiner Univ.-Prof. Dr. Constantinos Antonios
Chair of Transportation Systems Engineering

Supervisors Filippos Adamidis
Simone Aumann

Submitted by Tim Lindermaier
Matr.: 03687452

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Abstract

This thesis investigates the impact of Munich's aqt project, focusing on traffic effects in two areas with newly implemented car-free zones. Using historical open-source data, a Random Forest regression model was developed to predict traffic impacts for future similar projects. The study researched travel behavior changes due to road closures, including traffic, alternative transport, weather, and sports activity data. Results show no significant change in relative speed, indicating stable traffic conditions with minor improvements. The models, utilizing averaged historical data by weekdays for future feature values, achieved modest accuracy ($R^2 \sim 0.2$), surpassing linear regression models. Key features influencing accuracy included speed, day of the week, and weather, while non-time-dependent factors like demographics and amenities had negligible impact. These outcomes support existing literature on road closures, indicating an elastic reaction to reduced car infrastructure and confirming minimal observed traffic changes. Overall, the aqt project demonstrated a non-significant effect on traffic conditions, mitigating concerns about increased congestion from restricting car access.

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1. Introduction

1.1. Background

The concept of a 'car-free' environment describes various urban settings, each defined by specific characteristics and objectives. These definitions extend to entire cities, residential areas, and city centers, among others. In a car-free city, the use of private vehicles is significantly restricted or eliminated to prioritize sustainable modes of transportation (Topp & Pharoah, 1994). Car-free housing developments focus on reducing vehicular presence to enhance community interaction and environmental quality. Similarly, car-free city centers aim to transform urban cores into pedestrian-friendly zones with improved accessibility and reduced pollution. Each of these definitions reflects a commitment to rebuilding urban spaces for a more sustainable and livable future (Friedman, 2021; Nieuwenhuijsen & Khreis, 2016).

There are already many reasons to accelerate this development. In 2017, car traffic in Germany accounted for 94.5 percent of the 149 billion euros of external costs related to transportation. These external costs include environmental, accident, and health-related expenses (Sutter, 2019). Additionally, car traffic significantly contributes to climate change, responsible for 20 percent of Germany's 164 million tons of greenhouse gas emissions in 2019 (Umweltbundesamt, 2023). The importance of a more car-free oriented development underscores the significance of car-free zones and cities.

Car-free districts within cities represent a starting point for developing car-free urban areas. The aqt project in Munich is an initiative to create car-free urban areas, focusing on sustainable city development. Main participants are the Technical University of Munich and Munich's mobility department. Key objectives include reducing car traffic, improving urban living quality, and fostering efficient, climate-neutral mobility. Launched in October 2022 with planning and design, the project progressed in 2023 through community engagement and street experiments in the Südliche Au and Walchenseeplatz areas. Significant changes were implemented in Südliche Au from June 12th, like transforming a section of Kolumbusstraße, the Schlotthauer Platz and Entenbachplatz into a car-free zone and adding three mobility hubs. In Walchenseeplatz, the main activities began on July 5th with the closure of Landlstraße and the establishment of two mobility hubs. These mobility hubs offer residents alternative mobility options, providing a substitute for car usage. Originally planned to conclude on October 31, 2023, the project was prematurely terminated on October 25, 2023, due to legal challenges (Landeshauptstadt München, n.d.; Technische Universität München, n.d.). This thesis is fundamentally based on the aqt project, exploring its macroscopic impacts on mobility behavior to inform the development of similar car-free districts in the future.

1.2. Objectives

The motivation behind this report is to demonstrate that spatially limited car-free development initiatives are unlikely to significantly disrupt traffic conditions and may promote the use of sustainable transportation modes and increase active mobility. This research aims to accelerate the adoption of car-free projects by eliminating concerns about deteriorating traffic situations. The thesis provides evidence that fears of worsened traffic due to such developments can be effectively addressed and mitigated.

The primary aim of this thesis is to develop a predictive model designed to evaluate the travel impacts of car-free events within urban environments. This model will be built upon historical open-source data gathered during the aqt project, which will aid in comprehending the travel dynamics associated with such events. Furthermore, the model is intended to project travel impacts for future car-free events similar to the aqt project. The are two objectives of this thesis: firstly, to create an open-source model for future usage, and secondly, to analyze the gathered data which was collected relying solely on open-source data. This methodology is used to not only improve the model's utility and flexibility for subsequent applications but also to motivate its broader adoption by transparently describing the process and sources of data, thus establishing a framework for similar research projects in the future. This thesis aims to contribute to urban planning, transportation studies, and environmental policy by enhancing understanding of travel behavior dynamics in response to car-free initiatives, thereby enriching the discourse on sustainable urban mobility.

The scope of this study is geographically centered on Munich, particularly focusing on the areas impacted by the aqt project, and temporally confined to the duration of the project's implementation. While this specific focus allows for an in-depth analysis of the project's impacts, it also presents limitations. The findings might not be fully generalizable to other cities or regions with different urban layouts, cultural contexts, or traffic patterns. Additionally, the reliance on open-source data and the chosen modeling approach may constrain the comprehensiveness of the analysis. These limitations should be considered when interpreting the results and extrapolating the findings to other settings.

Based on the outlined motivation and objectives of this thesis, the central research question of the study is: How do road closures impact travel behavior, considering variables like traffic and active mobility data, weather conditions, infrastructure, and demographic characteristics, within the context of a car-free event in Munich?

1.3. Structure of the thesis

An in-depth literature review focuses on the design and concept of car-free streets, including their benefits and challenges. Research on traffic impacts of road closures draws on Cairns et al. (2002) work regarding the concept of evaporating traffic in response to reduced car infrastructure. This thesis also reviews specific case studies from Paris, Calgary, Oslo, and Seoul to pinpoint literature gaps and explore global approaches to car-free events and road closures, particularly their effects on travel behavior. Another significant aspect involves examining travel behavior models, beginning with more foundational travel behavior models and extending to data-driven modeling approaches in transportation research, with a brief discussion on the application of Random Forest (RF) regression and Deep Neural Networks in this field.

The methodology of this thesis focuses on developing a predictive model, incorporating data on motorized car traffic, alternative modes of transportation, sports-related activity, weather conditions, infrastructure, and demographics. It begins with an introduction to the study areas, followed by showcasing the collection of non-time-dependent data such as demographics and amenities. This is complemented by acquisition of time-dependent data using multiple APIs and open-source methods, allowing for the capture of transportation related impacts over various durations, from an hour to several days, as determined by the source of the data. This gathered data undergoes analysis and processing, serving dual purposes: visualizing changes over the project duration and contributing to model development of predicting traffic state. RF regression is selected as the modeling approach, with a focus on refining the model through hyperparameter tuning. The study also emphasizes evaluating feature importance and statistical metrics such as R^2 to assess the model's fit and accuracy. Additionally, the research considers the integration and effects of varying traffic patterns, weather conditions, and infrastructure changes to enhance the model's predictive capabilities in urban settings.

The results section of the thesis is divided into two main parts. The first part focuses on presenting and analyzing the collected data. This includes illustrating changes in relative speed within the study areas and examining the progression of the collected data throughout the timeframe. It features visualizations of activity-related data, weather conditions and the usage of alternative transportation modes. Non-time-dependent data, such as demographics and amenity distribution, is also presented. The second part delves into the specific models developed for the two primary study areas, Südliche Au and Walchenseeplatz. This section details the determined hyperparameters and discuss the feature importances and correlations along with relevant statistical measurements for the model results. Visual representations, including scatterplots and time series comparisons of actual versus predicted values, is used to demonstrate the accuracy of the models. To contextualize the results and provide a comparative perspective, a linear regression analysis is also employed alongside the primary model. Moreover, the section includes a cross-model validation, where one model, trained on one study area, is tested on the other, with their results presented in the described format. This approach showcases the adaptability of the model to different projects.

The ensuing discussion interprets the results presented in this study. It starts with an analysis of the collected data, focusing on its project-specific impacts and interdependencies. The discussion also considers the actual project area and its main features regarding transportation, reflecting on the anticipated minimal changes observed. This aligns with the literature, which reinforces the findings and will be briefly examined. Further, the integrity and limitations of the collected data is analyzed, acknowledging the constraints given by open-source resources and computational limitations. The analysis extends to evaluating the features and target variables of the model, discussing their statistical measures, correlations, and factors contributing to the less-than-ideal model fit. A critical aspect of the discussion is the overall prediction power of the model, particularly addressing its lower accuracy and exploring the reasons behind this outcome with discussing methods to improve the accuracy. Finally, the methodological approach of the study is thoroughly reviewed and critiqued, ensuring a comprehensive understanding of the research process and its outcomes.

The conclusion summarizes the significant findings derived from both the presented results and the developed model. Additionally, the conclusion outlines the potential practical applications of the research, demonstrating how the findings and the model can be utilized in real-world scenarios. It also offers insights into possible future research directions, restricted by the limitations of this thesis.

2. Literature Review

2.1. Car-free zones and travel behavior

2.1.1. Designing car-free streets and their concept

Historically, cities have gone through different phases. Newman & Kenworthy (1999) defined the three city stages as “Walking City” until 1850, “Transit City” until 1950, and 1950 “Automobile City.” Until the first half of the 20th century, cities have been dense and traditional public spaces with walking as the primary mode of transport. Starting in the 1950s, health challenges changed the city’s development from a medieval dense structure to a more open and modern form (Doheim et al., 2020). Le Corbusier, a prominent French urban planner, envisioned a city that was both functional and accommodating for cars and people. His concept of an ideal city included towering buildings, expansive highways, and ample green spaces. In the mid-20th century, as economies grew, there was a notable shift from the dense urban neighborhoods to more spread-out suburbs, marking the era where automobiles became a crucial element of public life. However, this approach soon faced criticism, and around the 1960s, researchers began to delve into the intricate relationship between public life and urban spaces, questioning and re-evaluating Le Corbusier's urban planning principles (Gehl & Svarre, 2013).

Around 1990, conferences about car-free cities and sustainable transport began to spread. In 1992, the European Commission started the “Club of Car-free Cities” initiative, where around 100 cities showed interest (Topp & Pharoah, 1994, p. 233). In the new century, more and more cities are shifting their mobility solutions toward sustainable and environmentally friendly development (Nieuwenhuijsen & Khreis, 2016). Although there are many reasons on the environmental and health sites to reduce car traffic, the trend for cars is steadily increasing, and by 2023, 2 billion vehicles are expected in the world (Sperling & Gordon, 2008). Therefore, it is crucial to establish car-free areas, whether they be specific streets, designated zones, or entire cities, to mitigate the impacts of this trend.

Davis & Duany (2018) determined differences between the classification of a road and a street. In high-density urban areas, streets designed for slow-moving traffic serve as vibrant centers of activity, surrounded by a mix of offices, shops, and apartments. These multifunctional spaces not only allow for vehicular traffic but also provide a pedestrian-friendly environment, fostering interactions among residents, workers, and visitors that enhance social cohesion and community engagement. The focus on aesthetics and social integration distinguishes streets from mere thoroughfares, turning them into avenues of urban life. Conversely, roads are often found in suburban or rural areas, primarily designed for higher speeds and increased traffic volume. Focused on efficient vehicle movement, they emphasize unidirectional flow and provide direct routes with minimal interruptions. Unlike the multifaceted urban streets, roads typically lack a diverse mix of land uses and primarily serve a single function: facilitating vehicular traffic. While the distinction between roads and streets is evident, the definition of a street can vary among researchers and urban planners. Some emphasize the physical attributes of streets, describing them as narrower and more linear spaces compared to roads. Others emphasize the multifunctional nature of streets, which goes beyond their function as mere conduits for traffic (Ahmed, 2020; Rapoport, 1991).

In this thesis, the term "car-free street" refers to a specific type of street predominantly observed in suburban and residential areas near city centers. A car-free street emphasizes a local and socially oriented perspective, focusing on streets with restricted or limited motor vehicle access. These streets are designed to prioritize pedestrian and cyclist activities, creating a safer and more sustainable environment for residents and enhancing the quality of life.

2.1.2. Benefits and challenges of car-free streets

When vehicle access is restricted in certain areas, there's a shift towards non-motorized transport (NMT) and active mobility. This transition offers multifaceted benefits, broadly categorized into social, economic, health, and environmental aspects, as described by Mansoor et al. (2022). These categories are interrelated and contribute to reducing both internal and external transport costs. Internal costs in transportation include direct expenses like fuel, maintenance, insurance, and labor associated with vehicle operation and transport services. External costs, however, encompass broader societal and environmental impacts such as air pollution, traffic congestion, noise, and public health concerns, which are not typically included in the direct costs of transportation. By minimizing these internal and external costs, a transition to NMT and active mobility promotes a more sustainable and economically efficient transportation system (Friedrich, 2001; Jakob et al., 2006).

Encouraging active mobility, such as walking and cycling, has been shown to increase physical activity among individuals, which is important for preventing cardiovascular diseases (World Health Organization, 2009). Additionally, the National Public Health Partnership [Australia] et al. (2001) highlight the health benefits of increased physical activity. Implementing car-free zones also plays a significant role in reducing health risks associated with vehicle emissions, such as respiratory diseases like asthma. The absence or reduction of vehicle traffic in these zones leads to lower air pollution levels, thus enhancing air quality and fostering a healthier environment for both residents and visitors (Frank et al., 2006). Furthermore, car-free streets contribute to improved safety for NMT users, as they significantly decrease the likelihood of accidents involving vehicles and cyclists, thereby creating a safer urban environment (Vandenbulcke et al., 2009).

Car-free streets offer significant benefits for local communities, providing spaces for public gatherings and events that contribute to vibrant, livable neighborhoods, ultimately enhancing residents' quality of life (Gehl & Svarre, 2013). These pedestrian-centric areas also positively impact the local economy. They attract pedestrians and cyclists to nearby businesses, and studies have indicated that such pedestrian-friendly and bicycle-supportive environments can lead to increased foot traffic, higher sales, and the revitalization of local commerce. This transformation not only boosts economic activity but also fosters a sense of community and connectivity among residents and visitors (Bliss, 2021; New York City Department of Transportation, 2014; Thomson, 2018).

Vehicle usage significantly contributes to various forms of pollution, including air, noise, and water pollution, which harms the environment (Chester & Horvath, 2008). Emissions such as noise, carbon monoxide, and particulate matter, largely inevitable byproducts of vehicular traffic, predominantly affect local environments. Meanwhile, greenhouse gas emissions from vehicles have a broader, global impact on climate change (Litman, 2023). Consequently, reducing the number of vehicles on the road is an important strategy for primarily mitigating local pollution, thereby contributing to healthier and more sustainable urban environments.

In transitioning to a car-free environment, several challenges arise, ranging from the initial development of public spaces to the continuous monitoring and assessment of changes in and around the designated area. Chapter 2.1.3 of this thesis will specifically address challenges pertaining to traffic and travel impact, offering an in-depth analysis of these complexities. The success of implementing car-free initiatives depends on public acceptance and adaptability to change. The degree of public engagement and the quality of planning, particularly when driven by immediate needs without thorough consideration, are essential factors that influence community acceptance and attitudes towards change. Insufficient public involvement and hastily executed, imprecise planning processes often contribute significantly to resistance and reduced acceptance of car-free measures (Doheim, Farag, & Badawi, 2020).

A critical challenge in creating car-free environments is ensuring accessibility and ease of mobility for people with disabilities. Concerns arise that car-free zones might introduce additional barriers, worsen the long-standing issue of urban planning often neglecting the needs of disabled individuals. Addressing this challenge effectively requires providing fully accessible public transportation and adopting inclusive planning and development strategies that prioritize the specific requirements of people with disabilities. By incorporating inclusive design principles, the benefits extend beyond just supporting people with disabilities; such approaches also significantly improve the urban experience for other groups, including the elderly and children, fostering a more universally accessible and user-friendly urban environment (Verlinghieri et al., 2022).

2.1.3. Traffic impacts of road closures

Understanding traffic demand, especially in relation to infrastructure changes, requires a thorough examination of two key concepts: traffic evaporation and induced traffic. Induced traffic is essentially the converse of traffic evaporation, where improving and expanding transportation connections leads to increased traffic. However, it's crucial to differentiate induced traffic from just traffic generation. Induced traffic is better understood as a consequence of enhanced accessibility for residents in surrounding areas. This improved accessibility enables people to participate more frequently in a variety of activities, thereby affecting their travel behavior. Recognizing induced traffic as a reflection of increased access and activity options offers a more refined perspective on how transportation infrastructure impacts urban mobility (Bucsky & Juhász, 2022).

Traditional traffic models have often operated under the assumption that reducing transportation space would always lead to increased congestion, based on the belief that traffic levels are inelastic. However, this notion was challenged in the mid-1990s, particularly when the UK government recognized that constructing new roads was not an effective solution for reducing motorized traffic congestion (D. Wood, 1994). In an effort to substantiate the significance of this perspective, a research study was conducted to examine the effects of reallocating road space. Contrary to initial assumptions, the study found that the impact on vehicular traffic from space reallocation was considerably less severe than anticipated. Furthermore, the results showed an actual reduction in traffic volume, indicating that the response of individuals to changes in road space is more complex than traditionally thought. This revelation suggests a need for a revaluation of traffic models and policies, taking into account the dynamic nature of traffic flow and individual travel behaviors (Cairns et al., 1998).

A subsequent study by Cairns et al. (2002) delved deeper into understanding the factors leading to traffic reduction following road closures. This comprehensive research analyzed approximately 100 case studies on traffic evaporation, revealing an average traffic volume reduction of 11%. The study identified three primary explanations for this phenomenon of road traffic reallocation:

1. Traffic Management and Route Changes: It was found that reducing road capacity on one route often led to adaptations in traffic management. This included increasing capacity on alternative routes or adjustments in driving styles to accommodate the new road conditions.

2. Route and Time Adjustments: The study observed that while users generally maintained the same number of daily trips, they often altered their routes or adjusted journey times to navigate the changed traffic landscape.
3. Adoption of Alternative Strategies: In situations where the road network could not support increased capacity or alternative journey times due to pre-existing congestion, individuals resorted to various adaptive strategies. These included shifting to alternative forms of transport like public transport, walking, and cycling; changing their destination; consolidating trips; modifying the frequency of their journeys; or, in some cases, choosing not to travel at all. It was in these scenarios that a significant reduction in traffic was most notable.

Understanding the impacts of road closures requires examining network characteristics and tracking traffic changes over time, as behavioral adaptations can range from days to years. Following a road closure, temporary congestion often intensifies in nearby areas, but early public engagement can mitigate these initial effects. Over the first year, traffic patterns undergo adjustment, influenced by seasonal factors, without showing a definitive trend of reduction or increase. However, long-term studies indicate two patterns: an initial reduction in traffic may be negated by subsequent increases, often linked to rising car ownership. This implies that short-term traffic decreases might be counteracted by longer-term trends. Conversely, the long-term elasticity of traffic often leads to a more pronounced overall reduction in volume, reflecting a gradual adjustment of travel behaviors to the new road layouts over time (Goodwin et al., 1998).

In exploring the scale effects on car-free projects, a study by Melia & Calvert (2023) assessed the traffic impacts of two different scenarios: a local small-scale road closure and the closure of a major traffic artery. The findings revealed that the small-scale road closure did not significantly reduce traffic. In contrast, closing a central bridge led to journey time reallocations and an overall decrease in network traffic. The study highlighted important research gaps in understanding traffic evaporation and the redistribution of car spaces, particularly in measuring residents' behavioral responses and analyzing traffic displacement on key city routes. This master thesis addresses these identified gaps by investigating traffic shifts in small-scale road closures and developing a predictive model for traffic conditions in more central car-free zones.

2.2. Case studies: Traffic impacts of road closures and car-free events

This chapter examines a range of case studies to explore the impact of road closures and car-free events on traffic dynamics. The analysis is structured into two primary sections: the first evaluates the effects of road closures due to construction or structural collapses, while the second delves into in-depth studies of areas implementing car-free initiatives aimed at reducing vehicular traffic.

2.2.1. Road closures

Chapter 2.1.3 delves into the study of road closures and their impact on traffic, a topic of research interest since the late 1990s. This chapter presents a thorough review of various case studies on road closures, examining their effects on traffic dynamics. It covers a range of events, including the 1999 Calgary bridge closure and the 2016 Oslo tunnel restoration, analyzing key findings from these studies. The objective is to collect deeper understanding of how road closures influence travel behavior and transportation systems. The investigated scenarios encompass full road closures and spatial reductions involving lane closures on major streets (Federal Highway Administration, 2023). Our focus centers on case studies of full road closures in Calgary (1999) and Mississippi (2007), as well as a spatial reduction closure in Oslo (2016), with the main findings shown in Table 1.

Table 1: Road closures and significant findings

Road closure/reduction event	Duration	Vehicles affected	Main findings
Street Bridge Restauration, Calgary (1999)	14 months	34,000 veh/day (closure)	4.4 % reduction in veh. Trips, 93% continued with the car and changed route, 3.6% increase in transit (Hunt et al., 2002).
I-35W Bridge Collapse Mississippi, Minneapolis (2007)	13 months	140,000 veh/day (closure)	No traffic reduction due to increased capacity on alternate routes, changing routes and journey time is the primary alternative, no increase in PuT (Zhu et al., 2010).
Tunnel Restoration, Oslo (2016)	14 months	70,000 veh/day (4 to 2 lanes)	Users shifted routes, journey times, and modes, and commute satisfaction remained high (Tennøy & Hagen, 2021).

In a comprehensive study conducted by Hunt et al. (2002), the travel impacts resulting from the closure of Calgary's Centre Street bridge for 14 months (from August 1999 to September 2000) were thoroughly examined. Through long ongoing 24-hour traffic counts and phone interviews, the research revealed a notable 4.4% reduction in vehicle trips along the north and east-west corridors, except for a slight increase during morning peak hours. Interestingly, despite the bridge closure, most users (about 93%) adapted their travel routes and times to evade congestion rather than discontinuing their vehicle trips altogether. Furthermore, the study unveiled a modest shift, with approximately 3.6% of vehicle users choosing public transport. In comparison, 0.8% chose active modes like walking or cycling during the closure period, highlighting the intriguing influence of infrastructure disruptions on travel choices. These findings shed light on the resilience of private vehicle use in the face of disruptions while emphasizing the importance of adaptable transportation systems to effectively manage congestion.

The collapse of the I-35W bridge in Minneapolis (US) in August 2007 resulted in significant disruption to approximately 140,000 daily vehicle trips. A comprehensive study by Zhu et al. (2010) was conducted to assess the traffic impacts, incorporating data from loop connectors, bus ridership statistics and a survey. In the wake of the bridge collapse, media projections speculated an immediate shift towards public transportation and a subsequent increase in congestion on alternative routes. However, the empirical findings presented a different scenario. While travelers experienced an overall increase in travel time, the congestion levels were not as severe as initially expected, indicating a certain degree of resilience in the transportation system. One notable finding was the considerable increase in public transport ridership immediately after the incident, exhibiting a significant rise of approximately 6.6%. However, this statistical significance diminished after a year, although the positive trend in public transport usage persisted. The primary reason for this sustained trend was expanding capacity on other bridges by implementing shoulder lanes, which mitigated the congestion and provided a viable alternative for commuters.

A lane reduction project took place in Oslo, Norway 2012, where four lanes in a main road tunnel were temporarily reduced to 2 lanes, impacting 70,000 vehicles per day. The research was conducted by Tennøy & Hagen (2021) from 2015 to 2018, involving traffic data collection for all modes during two weeks in spring and autumn, along with a survey and follow-up interviews for respondents. As expected, the reduction decreased average speed and increased volumes on alternative routes, particularly the most logical and closest ones. Residents reported that the reduction presented a significant disadvantage for vehicles and active modes, which were forced away from their usual paths.

The examined case studies focused on the travel impacts of several transportation infrastructure disruptions. Generally, these studies uncovered that, despite initial expectations of severe consequences, the short-term increases in travel time and congestion were more moderate. People displayed a notable adaptability, adjusting their routes and travel times to circumvent congested areas and the road closures. Moreover, a rise in public transport usage was observed following the disruptions, though this increment slightly diminished over time. These outcomes underscore the resilience of transportation systems and underscore the necessity of having flexible options in place to manage congestion efficiently.

2.2.2. Car-free events

While in the previous section, road closures happened due to construction or collapse, in this chapter car-free events and streets were built to ban traffic from the road. While there is less literature about car-free events, which occur quickly, more extended events are monitored more. Table 2 shows an overview of the main findings of road closures for the main purpose of developing a car-free area.

Table 2: Car-free events and main findings

Road Closure/Reduction Event	Type of closure	Vehicles affected	Main Findings
Parisian Riverbank (2016)	Full closure	40,000 veh/day	Six-minute increase in travel time for direct users, 15 % increase in traffic congestion on main alternative route (Sleiman, 2021)
Georgetown, Malaysia	Simulated reduction	N/A	78 % increased travel distance and 28 % increase in travel time (Salleh et al., 2021)
Cheonggyecheon Stream Restauration Seoul (2012)	4 to 2 lanes reduction	168,000 veh/day	6% decrease in vehicle trips with a modest rise in public transport use and a slight increase in congestion (Chung et al., 2012)

The Parisian Riverbank street closure, initiated by George Pompidou, involved the closure of approximately 3.3 km of the expressway between the southwest and southeast of the Seine River, impacting around 40,000 vehicles daily (Willsher, 2016). In a study by Sleiman (2021) the effects of the road closure were investigated using traffic data from road sensors and public transportation records. The study's key findings include a reduction in travel speed by 3.1 km/h on the primary alternate route (South ring road) and a notable 15% increase in traffic congestion on the eastward Ring roads. Users who typically travelled on the now-closed road saw an average increase of six minutes in their travel time, while those using major alternative routes experienced an additional two-minute delay. There was also a slight rise in public transport usage. However, the study highlighted negative side effects, such as increased air pollution affecting residents near the alternative routes. Overall, the case study portrays the road closure as unsuccessful in meeting sustainable objectives like reducing traffic demand and encouraging sustainable transport modes, despite providing benefits to those using the reallocated road space.

In another case study by Salleh et al. (2021) GIS analysis was used to model potential car-free zones in George Town, Malaysia. The research utilized Google Maps Traffic Data to predict traffic patterns, focusing on rerouting vehicle data based on route, distance, and journey time. This approach assessed the traffic impact on alternative routes. The study's significant findings included identifying suitable car-free areas and predicting their effects on travel time and distance. It revealed an average increase of 77.7% in traveled distance and 28.3% in travel time across seven analyzed routes.

The Cheonggyecheon stream restoration in Seoul, starting in July 2003, reduced road lanes from four to two in each direction, leading to significant infrastructure changes. Chung et al. (2012) studied the immediate travel impacts and monitored the changes over several years.

Initially, mode shift effects were modest, with slight increases in travel time and mild congestion. Vehicle trips decreased by about 6%, while public transport saw a minor increase of 1.65% to 4.89%. Public transit ridership peaked in the third week post-construction, while vehicle trips dipped to their lowest. Long-term analysis up to three years post-restoration showed the auto mode share decreased by 4.0% in Seoul and 5.4% in Cheonggyecheon, with public transport usage increasing by 6% and 10%, respectively. Average speed near the site initially dropped but returned to pre-restoration levels within three years. The long-term public transport share remained relatively unchanged by the project. Overall, both short-term and long-term traffic impacts were less severe than expected, demonstrating commuter adaptability and eventual return to pre-construction travel patterns.

2.3. Travel behavior models

In transportation planning and urban mobility studies, travel behavior models are key for understanding individual travel decisions and their impact on traffic patterns, especially within infrastructure changes. The next chapter will specifically focus on discussing key travel behavior models, emphasizing on data-driven models which are used in this thesis.

2.3.1. Overview of travel behavior models

One of the foundational contributions to travel behavior modeling was made by McFadden (1974), who introduced the concept of discrete choice models. His work laid the groundwork for understanding how individuals make discrete travel choices based on travel time, cost, and mode availability. In subsequent years, numerous advancements have been made to enhance travel behavior modeling, particularly in the context of infrastructure modifications. Traditional models, such as the gravity model and the four-step transportation planning process, have been widely utilized to forecast traffic patterns and estimate the effects of new infrastructure developments, including road and public transit expansions (Wilson, 1971). These models have proven effective in capturing broad traffic trends and understanding the overall impacts of infrastructure changes on travel behavior (Ortúzar S. & Willumsen, 2011).

Another theory that has raised attention in the last decades is the agent-based modeling approach, a powerful tool on the microsimulation level. Agent-based models (ABMS) are computational models that simulate complex systems by representing individual agents and their interactions within a dynamic environment. By considering individual-level behaviors and interactions, ABMs capture real-world systems' heterogeneity, adaptability, and complexity (Bonabeau, 2002; Macal & North, 2010). ABMs are particularly valuable for studying traffic flow, travel behavior, and urban mobility in transportation. They can capture the complexities of transportation systems, including traffic congestion, route choices, and the interplay between different modes of transport. ABMs help understand how individual travelers decide their routes, modes, and departure times and how these decisions collectively shape the overall transportation network (Crooks et al., 2021).

In recent years, through advanced data analytics, data-driven approaches have significantly transformed transportation research by utilizing the wealth of available data. Leveraging empirical data from various sources, such as traffic sensors, GPS devices, and travel surveys, these methods enable researchers to develop models and make informed decisions in the transportation domain. In traffic flow forecasting, data-driven techniques have successfully predicted traffic conditions and congestion (Jiang & Luo, 2022). Urban traffic management has also significantly benefited from data-driven approaches, particularly in traffic prediction, control, and optimization, offering practical solutions to improve traffic flow and reduce congestion (Sikder et al., 2022). Moreover, data-driven methods have played a crucial role in understanding travel behavior and decision-making processes, providing valuable insights into travelers' preferences, choices, and travel patterns (Ton et al., 2018). With the loads of available data, these approaches have the potential to revolutionize transportation planning and management, paving the way for more efficient and sustainable transportation systems. As explained, data-driven models are a favorable approach for managing large volumes of data and complex interactions, and they have been selected for implementation in this thesis. Specifically, the following chapter explores data-driven modeling in transportation research.

2.3.2. Data-driven modeling in transportation research

One approach to handle big data and model transportation effects is RF regression. This machine learning technique has emerged as a powerful data-driven modeling approach in transportation research. Leveraging the principles of ensemble learning, RF combines multiple decision trees to make accurate predictions and handle complex relationships between variables through majority voting. This approach has found widespread application in various transportation-related tasks, owing to its ability to handle large datasets, capture non-linear patterns, and provide robust predictions (Cheng et al., 2019).

In traffic flow forecasting, RF regression has remarkably succeeded in predicting traffic conditions and congestion. Cheng et al. (2019) conducted a study on data-driven traffic flow forecasting, showcasing the effectiveness of RF models over linear regression. The study used traffic diary data and explanatory variables to predict accurate traffic patterns. Additionally, the model's capability to handle temporal dependencies makes it well-suited for predicting traffic flow in urban areas.

In a recent study by J. Wood et al. (2023), RF regression was employed to predict bus passenger occupancy. The analysis utilized real-time passenger data and weather information as input features. The RF model demonstrated lower Root Mean Squared Errors on the training data than linear regression and a R^2 between 0.64 and 0.78. However, due to data quality limitations, its performance could significantly improve the testing data. Nevertheless, the RF approach's ability to handle categorical and continuous variables makes it valuable for passenger occupancy prediction and transportation safety analysis. In another study conducted by Yang et al. (2023), RF was utilized to forecast road traffic accidents, incorporating various contributing factors such as road conditions, weather, and traffic volumes. The model researched accuracy in identifying high-risk locations and discerning factors associated with accidents, thereby providing valuable insights for safety interventions and accident prevention strategies.

Deep neural networks (DNNs), a deep learning method utilizing artificial neural networks, have become increasingly significant in transportation research. These networks, which mimic the human brain's structure, comprise multiple interconnected neurons capable of learning complex patterns from large datasets (Schmidhuber, 2015). Effective in tackling complex transportation issues, DNNs excel at processing large-scale data, understanding non-linear interactions, and providing accurate predictions. Their application extends across diverse transportation areas, such as travel demand modeling and accident detection (Haghighat et al., 2020).

For example, in traffic flow prediction, DNNs outperform traditional methods due to their superior handling of traffic's dynamic and non-linear characteristics. In safety applications, DNNs analyze historical accident data to identify potential hotspots, enhancing proactive safety strategies (Ren et al., 2018). Their role in autonomous vehicle technology, particularly in developing advanced driver-assistance systems, further exemplifies their transformative potential in transportation (Bojarski et al., 2016). The adaptability of DNNs across various transportation fields highlights their central role in advancing both the theoretical and practical dimensions of transportation research.

3. Methodology

This paper aims to predict traffic dynamics around road closures in Munich. This chapter delineates the development of the predictive model, utilizing publicly available data. It begins with a description on data collection and cleaning, followed by a discussion on the selection of the features from various datasets. The chapter concludes with an explanation of the model's development, testing, and evaluation procedures. Figure 1 provides an overview of the applied methodology.

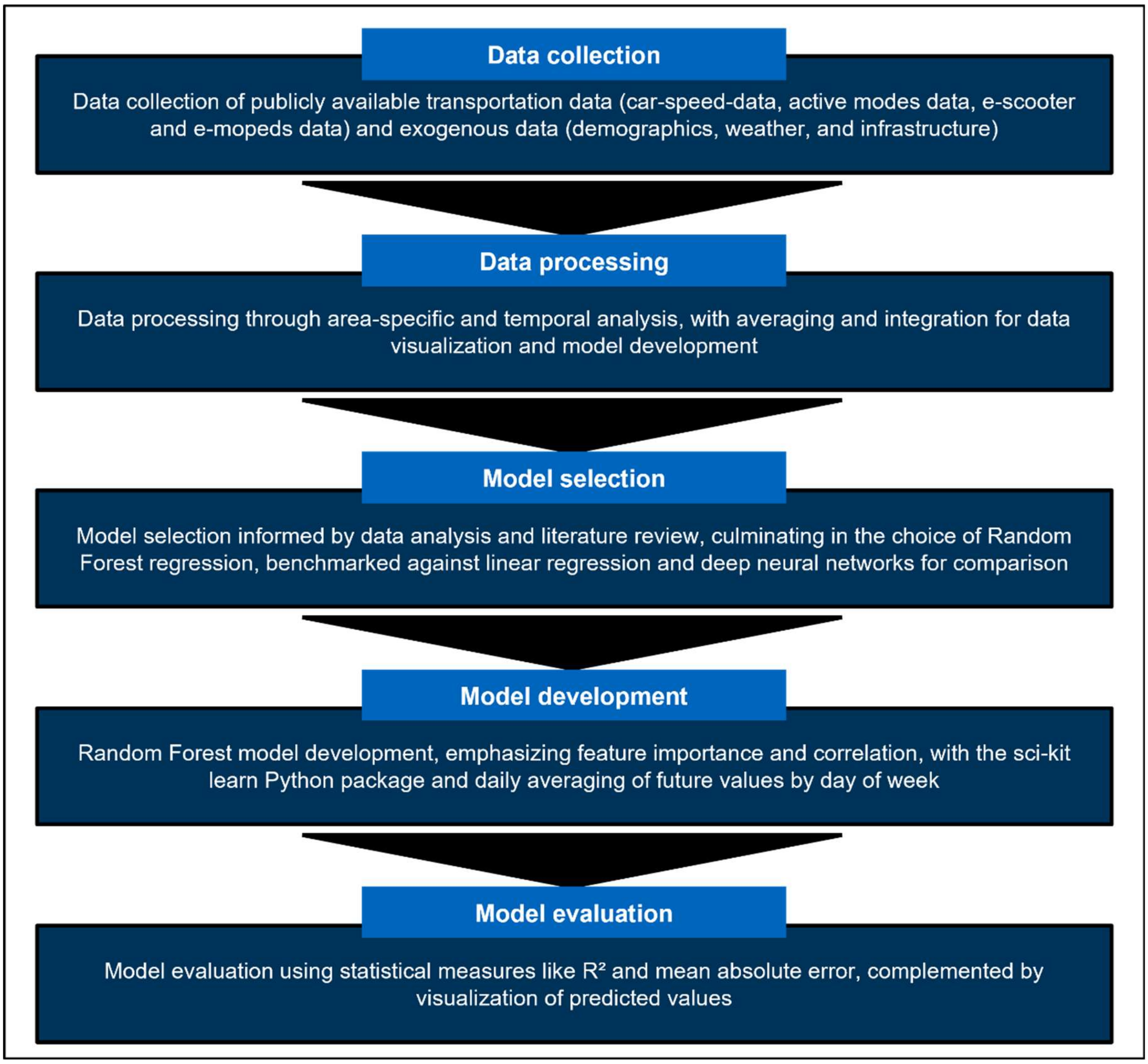

Figure 1: Overview of methodology

3.1. Data collection

The study exclusively utilized open-source data, collecting from various sources like TomTom, Strava, Tier, Emmy, and others to collect publicly available transportation data for model development. Figure 2 illustrates an overview of the time frame of the data collection and the projects duration.

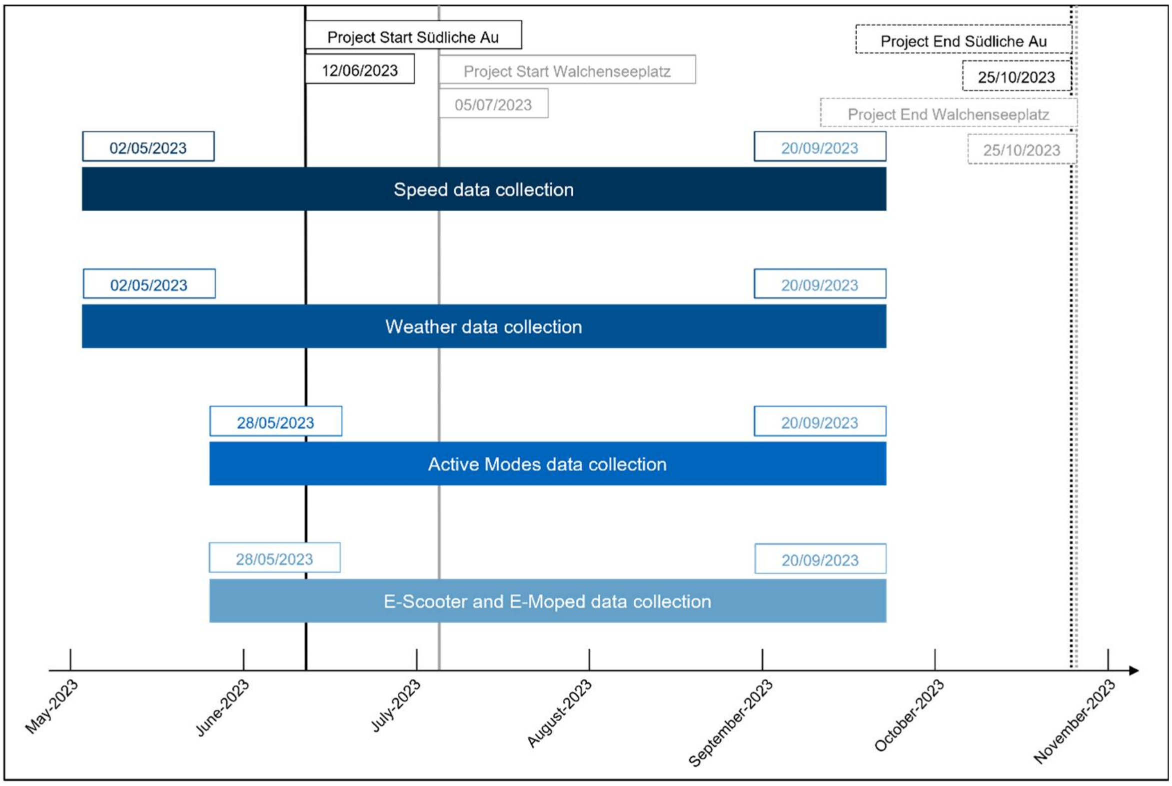

Figure 2: Timeline of data collection and project duration

3.1.1. Project area, demographics, infrastructure and weather data

The study area was defined using two circles, each with a 1.5 km radius centered around the two areas. This area, comprising the overlap of these circles, encompassed seven districts, notably Obergiesing-Fasangarten and Au-Haidhausen, linked to the Landlstraße and Kolumbusstraße/Entenbachplatz/Schlotthauer Platz project sites, respectively. Data collection focused on this region, with occasional inclusion of points outside due to technical factors. The MCube aqt project defined two neighborhoods, 'Südliche Au' and 'Walchenseeplatz', as the project areas within the study area's boundaries. The 'inner area' encompasses these parking license districts, while the remaining study area is considered the 'outer area'. Figure 3 visually depicts these areas along with relevant project streets, including Schlotthauer Platz, Entenbachplatz, Kolumbusstraße, and Landlstraße. In Appendix A1, the Figure 23 illustrates the two designated areas within the Munich cityscape.

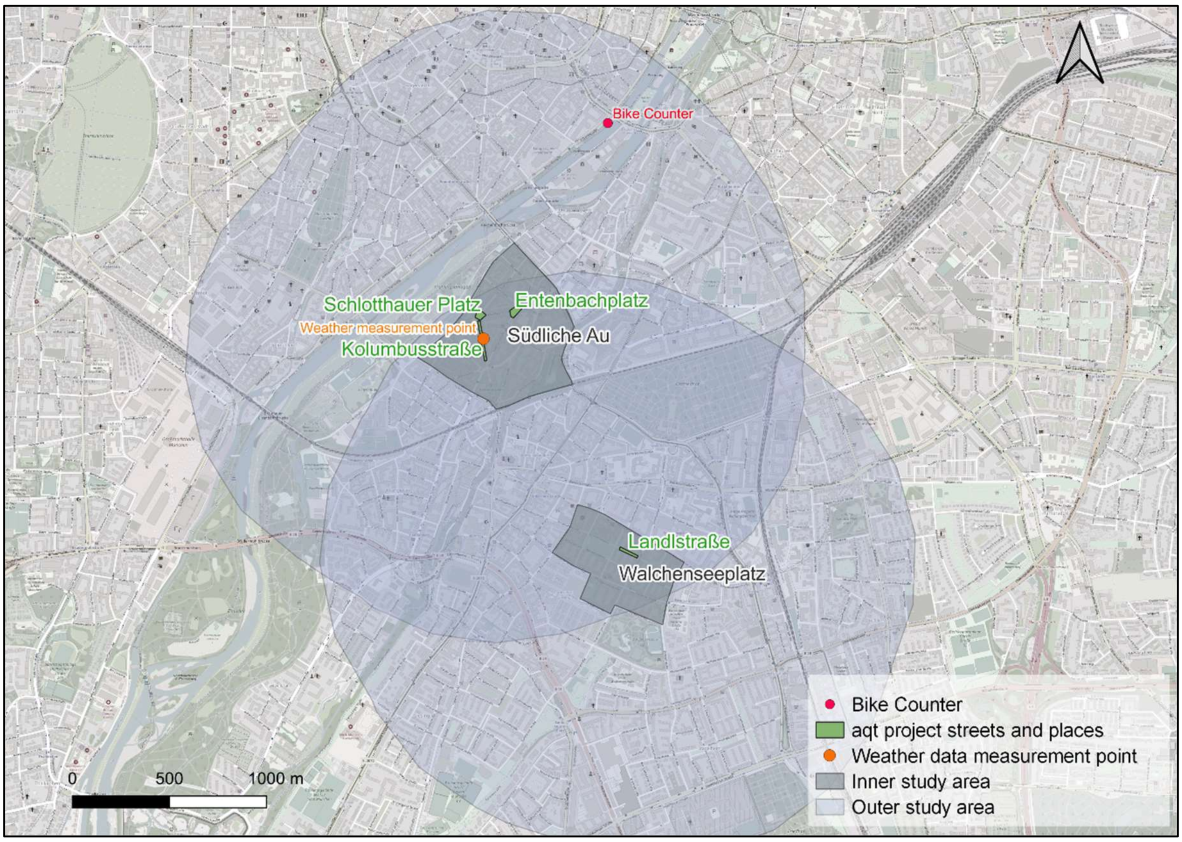

Figure 3: Project and measurement area of aqt project

The data collection spanned from 2 May to 20 September 2023, totalling 142 days. This period was selected to align with the initiation of the Südliche Au and Walchenseeplatz projects, which began on 12 June and 5 July 2023, respectively, and concluded on 25 October 2023. A notable limitation during this period was the API usage restriction from TomTom, which allowed only 2500 calls per day, equating to approximately 100 data points per hour. Consequently, due to these constraints and the need for testing and validation, specific data points were excluded at the beginning and end of the timeframe.

This study's developed model benefited from integrating exogenous variables like weather, demographics, and infrastructure data. These variables, external to the primary focus of relative car speed, are instrumental in understanding traffic dynamics in car-free districts. Weather data including temperature, precipitation, and wind conditions, allowed for the consideration of environmental impacts on traffic flow. Demographics data provided insight into socio-economic factors influencing transportation choices, while infrastructure data, covering amenities, bicycle stands, and project specific changes, shed light on the influence of urban development and the project initiatives on traffic patterns. The combination of these exogenous factors with primary time series data enabled a comprehensive analysis of how external influences interplay with traffic dynamics (Hyndman & Athanasopoulos, 2021; Shafik & Tutz, 2009).

The study's demographic analysis utilized 2011 census data from Germany, mapped to 100 m grid cells, and compared it with 2022 Munich population statistics disaggregated by district and nine age groups (Stadtverwaltung Landeshauptstadt München, 2023; Zensus, 2011), Factors for nine age groups were calculated, enabling the extrapolation of 2011 census data to reflect 2022 population compositions in the study areas.

Infrastructure data was primarily focused on amenities within the measurement area, utilizing OpenStreetMap for geographic coordinates and details. This included data on various amenities, removed parking lots, closed street percentages, and new mobility hubs, crucial for analysing transportation behavior and infrastructure changes due to road closures (García et al., 2019; OpenStreetMap contributors, 2017). Weather data, gathered daily over the study period from Meteostat (n.d.), provided detailed information on temperature, wind conditions, and precipitation. Data collection was centered around Kolumbusstraße, as shown in Figure 3, to capture environmental conditions relevant to the studies area.

3.1.2. Traffic, alternative and active mobility data

Traffic data, essential for analysing vehicular movement, was collected using the TomTom API within the defined aqt project area from 2 May to 20 September 2023. A comprehensive dataset was amassed from 92 strategically placed measurement points across the project area, with data captured hourly. This dataset encompassed vital traffic attributes, including free-flow and current travel times and speeds, along with a reliability metric expressed as a confidence ratio. The effective gathering of this data was enabled by the collecting the data of TomTom Navigation systems in vehicles, providing a continuous stream of real-time traffic information to augment the dataset.

To efficiently utilize the TomTom API, which is limited to 2500 daily calls, the study utilized a network of 92 spatially distinct measurement points, as shown in Figure 4. These points were strategically placed with an inter-measurement distance of approximately 326 meters to ensure comprehensive coverage of the project area and address data scarcity issues. In proximity to specific project sites, distances were adjusted based on available speed data for more detailed analysis. A calibration process determined level 9 as the optimal zoom level for data acquisition with TomTom, striking a balance between the need for detailed spatial resolution and computational limitations. This strategic configuration yielded a dataset rich in both depth and diversity, facilitating an in-depth analysis of vehicular traffic's temporal variations within the project area (TomTom, 2023). To compensate for missing data at certain points and times, historical data was obtained from NGis Geo GmbH through TomTom's Move Portal. Given the discrepancies between collected and NGis-provided data, the model development primarily focused on current speed and free-flow speed as predictive variables for traffic conditions.

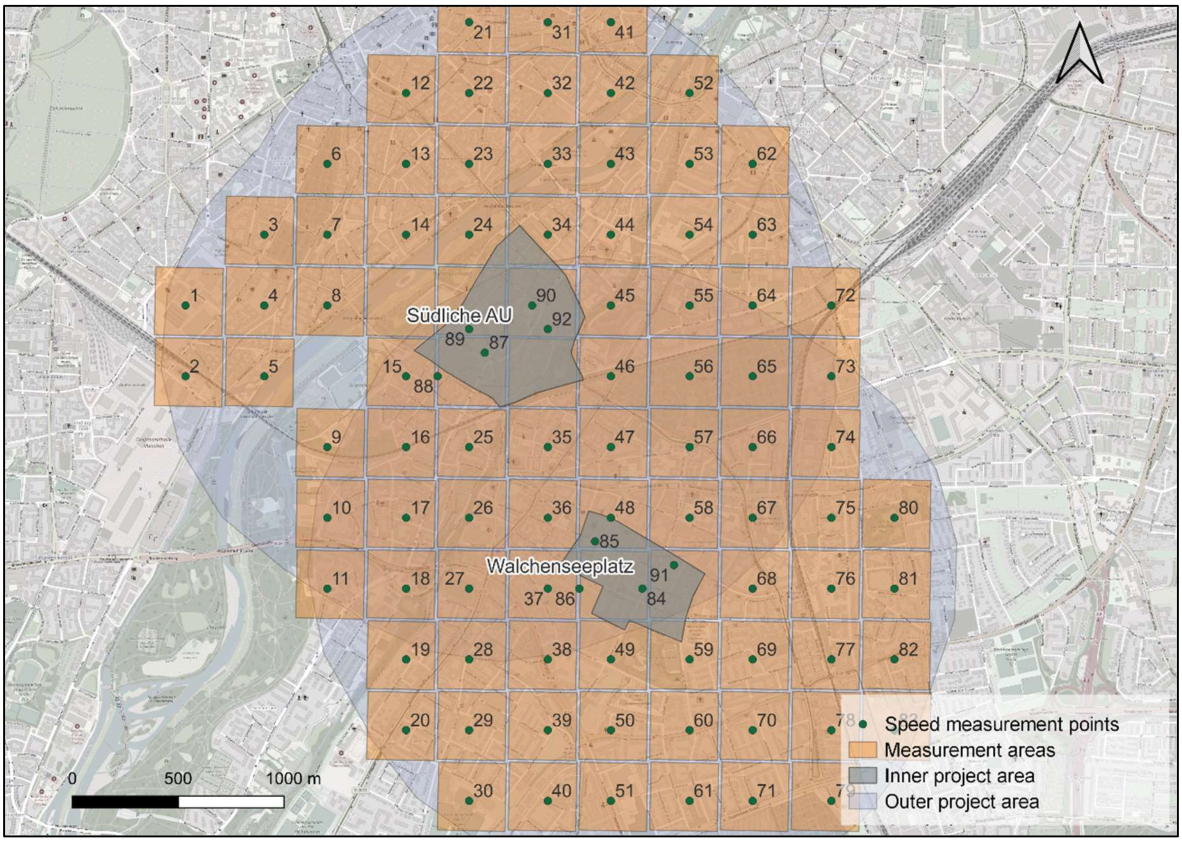

Figure 4: Speed measurement data points

This study identified various alternative transportation providers to investigate different modes of individual transportation, focusing on e-scooters and e-mopeds. These modes have gained prominence in urban settings for their potential to address challenges of traditional commuting and align with the shift towards eco-friendly and shared mobility solutions (Fishman et al., 2013). Data collection from a rental e-scooter and e-bike company, as well as a rental electric motorbike provider, began in late May 2023. It involved hourly tracking of operational vehicles' geographical coordinates in Munich, aiming to provide insights into the dynamics of these alternative mobility modes. Figure 4 displays 90 orange measurement areas for scooter and demographics data. These areas, delineated by 320-meter side orange rectangles, total 90 in number and were strategically chosen, particularly for their relevance in capturing detailed speed measurements for traffic variables in the inner project area.

Due to the unavailability of public transport data from municipal sources, the study initially employed Google Maps' 'popular times' feature as an alternative source, using queries through the Google Maps API. However, this method faced inherent inaccuracies and gaps. A thorough assessment within the project area included all locations near public transit stops corresponding to popular times, while areas beyond were assessed only at transit stops, aligning with the study's scope. Despite these efforts, the data from Google Popular Times proved challenging due to inconsistencies and lack of clarity, compounded by missing information at transportation network stops. Two months into data collection, starting mid-May 2023, Google imposed restrictions on the use of Popular Times data, complicating data acquisition and analysis. Consequently, this paper does not utilize Google Popular Times data in its analysis (Google, n.d.).

To assess active mobility modes like walking and cycling, two primary data sources were utilized. Firstly, Munich's four bicycle measurement stations, with one located in the project area, provided data every 15 minutes, accessible via the Munich open-data portal (Munich, n.d.). Secondly, the Strava heatmap was employed to analyze street utilization patterns related to running and cycling, offering insights into areas of heightened active mobility. However, this dataset predominantly reflects sports activities and may not precisely represent everyday walking and cycling transportation modes. Despite this limitation, increased sports activities could suggest suitability for pedestrian and cycling activities. The heatmap utilizes a cumulative distribution function for contrast enhancement, effectively minimizing quantization artifacts in areas with low heat values. (Strava Inc., n.d.). Due to the unavailability of an open API for the Strava heatmap, a method was developed to capture the heatmap images within the project area and analyze pixel luminance. Figure 5 illustrates the dimensions of these Strava heatmap tiles and the collected images used in this analysis.

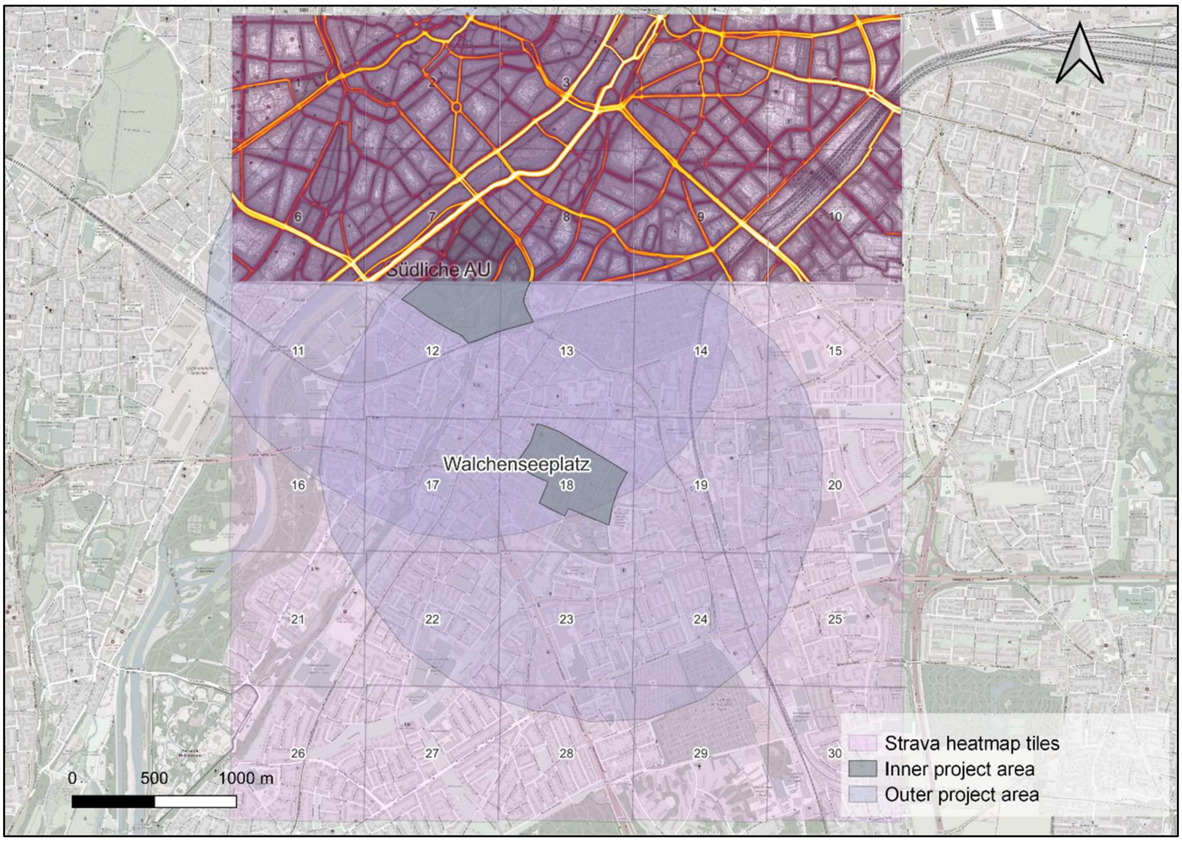

Figure 5: Sports-activity related heatmap tiles and brightness pictures

Initiated in late May 2023, the Strava heatmap was updated irregularly, approximately every 3 to 4 weeks. This initiative involved tracking changes in pixel luminance across 30 images covering the study area. Each new data collection phase yielded about 7.8 million data points.

Over the span of 117 days, beginning on 28 May 2023, six distinct changes in brightness were recorded from the Strava heatmap. This resulted in a total of approximately 43 million data points that required processing.

3.2. Data processing

Time-dependent variables, crucial for modeling infrastructure changes, contrast with time-independent variables, which require specific processing for effective integration into the model. In this study, time-independent variables include demographics and infrastructure data. Conversely, traffic, alternative transportation, sports-related activity, and weather data are categorized as time-dependent variables, reflecting their dynamic nature and influence on model outcomes.

3.2.1. Demographics, infrastructure and weather data processing

To integrate demographic data into the statistical model, it was initially segmented into 90 measurement points, as illustrated in Figure 4. The complexity of incorporating nine age groups per point led to a significant increase in variables. Therefore, age groups were not differentiated for these points. Additionally, an alternative approach was tested, where age groups were aggregated for the four measurement areas, rather than individually for each of the 90 IDs. Both methodologies were evaluated and employed in model development.

Regarding infrastructure-related data, the study adopted the classifications of amenities as outlined by Mulligan & Carruthers (2011) which include:

- Public services and education: Kindergartens, schools, and universities.
- Private consumption goods: Restaurants and bars catering to private consumption.
- Transportation: Public transportation stops, stations, and bicycle stands.
- Cultural institutions: Museums and other cultural entities.

This study's framework for assessing amenity-related infrastructure in the study area involved categorizing the area into four distinct zones, as described in Chapter 3.1.1: the inner areas of two project sites and the outer areas of the measurement zone. Sixteen variables were identified, representing the count of each amenity type within these zones, including bicycle stands. Notably, parking lots removed, mobility options added and road closures due to project-related implementations were classified as time-dependent infrastructure variables, given their removal on specific dates. Weather data, comprising parameters like average, minimum, and maximum temperature, precipitation, sunshine hours, and wind data (speed, direction, gusts), was also considered time dependent.

3.2.2. Traffic, alternative and active mobility data processing

Traffic data was collected over 142 days at 92 measurement points, yielding approximately 287,000 data points. To standardize data from various providers, a variable calculating the ratio of speed to free-flow speed at each point was used. Daily averaging of measurements was necessary due to constraints in hourly data collection, presenting a challenge with more missing data points during the day than at night. To mitigate this, each day was divided into three segments: 12 a.m. to 6 a.m., 6 a.m. to 6 p.m., and 6 p.m. to 12 a.m., with averages calculated for each. These part-averages were then combined for a daily average, assigning double weight to the 6 a.m. to 6 p.m. period due to its longer duration. Ultimately, 11,960 data points from these 92 points over 142 days were utilized for model development.

The data collection for e-scooters and electric mopeds, commencing on 25 May and 28 May 2023 respectively, paralleled the challenges encountered with TomTom speed data. E-scooter data comprised around 100,000 location data points daily over 116 days, a high volume attributed to the absence of spatial restrictions in the API, enabling extensive coverage. Electric moped data involved collecting approximately 1,000 location data points daily throughout the same period.

Data collection was confined to the designated measurement areas for efficiency. 90 measurement points formed 320-meter side rectangular buffers, depicted in Figure 4. Daily vehicle counts within these areas were compared against total vehicle counts in Munich, attributing missing values to an overall decrease in vehicle data. This method highlighted variations in vehicle usage, identifying areas of higher utilization. It was noted that only about 15% of the measurement area was covered by scooter rental services, limiting usable data to 11 measurement points near the Südliche Au project area. Post-processing, e-scooters and electric mopeds contributed to 22 variables over 116 days, resulting in 2,552 data points for the model.

The Strava heatmap data consisted of 30 tiles, each approximately 822 meters per side, containing 512 x 512-pixel images. Each pixel was color-coded with Red (R), Green (G), and Blue (B) values, forming the basis of the color composition. To derive a standardized perceptual brightness index from these pixel values, a formula proposed by Finley (2006) was applied:

$$Brightness = \sqrt{0.299 * R^2 + 0.587 * G^2 + 0.114 * B^2}$$

The study utilized Strava heatmap data, updated every three to four weeks, recording brightness values for each tile and pixel. These values were overlaid onto 90 measurement points from the other data collections. To facilitate daily analysis, the brightness value for a given day was extended to subsequent days until a new update. The average brightness value per day and tile was calculated, with higher values indicating increased sports activity. The processed

Strava heatmap data comprised 90 variables over 117 days, amounting to 10,764 data points. However, the data exhibited low variance and infrequent updates, posing challenges in capturing dynamic activity changes. Ultimately, 341 variables were overall generated for the period from 2 May to 20 September 2023, with the final dataset consisting of 40,298 data points.

A key methodological aspect was the innovative treatment of time-dependent features. In light of the road closure's impact, we developed feature variants representing historical patterns prior to the closure. These were calculated as weekly mean values and extended post-closure, ensuring the continuity of historical trends. This strategy enabled the model to train on a dataset reflecting temporal nuances, aligning pre-closure patterns with post-closure predictions. This approach ensures the model is informed by temporally consistent data, crucial for accurately predicting urban traffic dynamics.

3.3. Model selection, development and evaluation

This chapter details the comprehensive process of model selection, development, testing, and evaluation. It describes the parameterization and adjustments of the model, detailing the specific modifications implemented. Furthermore, the chapter delves into the approach adopted for feature selection and provides an in-depth analysis of the model's performance evaluation, highlighting the resultant findings.

3.3.1. Model selection

The selection of RF regression for this study is based on its distinct advantages in handling complex data scenarios, as compared to linear regression, support vector machines (SVM), and neural networks.

- Non-Linearity Handling: RF is proficient at capturing non-linear relationships within datasets, a common characteristic in real-world data, unlike linear regression models that are limited to linear correlations (Breiman, 2001; Hastie et al., 2017)
- Robustness to Outliers: SVMs are often sensitive to outliers, which can adversely affect model performance. RF, leveraging multiple decision trees, mitigates this issue, enhancing its robustness (Kanamori et al., 2014)
- Feature Importance: RF inherently provides feature importance rankings, offering insights into the variables driving model predictions, aiding in interpretability (Pedregosa et al., 2011; Strobl et al., 2007)
- Ensemble Learning: The ensemble learning technique in RF, which aggregates predictions from numerous trees, reduces the risk of overfitting and improves generalization (Hastie et al., 2017; Rokach, 2010).

- High-Dimensional Data: RF maintains model interpretability even in high-dimensional data scenarios, where neural networks may falter (Bishop, 2006).
- Model Flexibility: RF is user-friendly and less dependent on hyperparameter tuning compared to neural networks, which require extensive data and tuning (Schmidhuber, 2015).

As Hastie et al. (2017) highlight, RF is effective in capturing intricate data interactions with low bias. The literature review in chapter 2.3.2 emphasized RF's suitability for transportation behavior analysis. Considering the extensive time-series data and multiple variables with complex interrelationships, RF was deemed the optimal choice for forecasting traffic patterns post-road closure in this study. Deep Neural Networks were also considered for this study; however, their "black box" nature and challenges in result interpretation led to the selection of RF due to its greater interpretability.

3.3.2. Model development

RF regression combines decision tree regression with ensemble learning, making it suitable for predicting continuous variables in large datasets. Key components include (Breiman, 2001):

- Ensemble Learning: RF integrates multiple decision trees, each built independently. Their aggregated predictions enhance accuracy.
- Decision Trees: These trees segment data into subsets using feature attributes, with leaf nodes in regression trees holding numerical predictions.
- Randomization: RF employs randomization through bootstrap sampling for each tree and random feature selection at splits, reducing overfitting and improving generalization.
- Aggregation: Final predictions are averaged from individual tree outputs.

Developed in Python using Scikit-learn, this study's RF model processed data in pandas data frames, merging based on timestamps (Pedregosa et al., 2011). Post-road closure data was isolated to create target variables, focusing on predicting traffic patterns, particularly relative speed variables, in the project area. These variables, eight per area, reflect traffic performance and congestion.

The longer data collection period resulted in dataset size discrepancies. To address this, the larger dataset underwent random undersampling to match the smaller dataset's length, ensuring balanced representation (Kraiem et al., 2021). The dataset was partitioned into training and testing sets, with 80% for training and 20% for testing. A random state of 42 ensured reproducible splits (Pedregosa et al., 2011).

The study employed a multioutput model to estimate multiple dependent variables simultaneously, capturing the complex interactions among them and offering a comprehensive view of the traffic dynamics (Pedregosa et al., 2011).

3.3.3. Model testing and evaluation

Evaluating the predictive model and the target variables is a critical phase in assessing the model's performance and reliability. Two commonly employed evaluation metrics are the coefficient of determination, R^2, and the mean absolute error MAE. R^2, a widely recognized statistical measure, assesses the model's goodness of fit to the observed data, providing insights into the proportion of variance in the target variable explained by the model:

$$R^2 = 1 - (\frac{RSS}{TSS})$$

Where RSS (Residual Sum of Squares) represents the sum of the squared differences between the predicted values and the actual values in the dataset and TSS (Total Sum of Squares) the sum of the squared differences between each data point and the mean of the dependent variable. It indicates the model's predictive capability, where higher R^2 values indicate better predictive accuracy. The mean absolute error, on the other hand, quantifies the absolute deviation between the model's predictions and the actual values, providing a measure of the model's accuracy:

$$MAE = \left(\frac{1}{n}\right) * \sum |y_i - \hat{y}_i|$$

Where n is the number of data points, y_i is the actual observed value for data point i and $\hat{y}_i$ is the predicted value for data point i.The evaluation process leverages these metrics to gauge the model's ability to faithfully capture and predict the target variables (Breiman, 2001; Chicco et al., 2021; Pedregosa et al., 2011).

Hyperparameter tuning is pivotal for optimizing model performance. This study utilized GridSearchCV from the scikit-learn library for identifying the most effective hyperparameter set for the RF Regression model (Pedregosa et al., 2011). This method comprehensively evaluates different hyperparameter combinations, focusing on ‘max_depth’ and ‘n_estimators’. ‘Max_depth’, which limits the maximum splits in each tree, is crucial for controlling model complexity. A low ‘max_depth’ can cause underfitting, failing to capture complex data patterns, while an excessively high ‘max_depth’ might lead to overfitting and poor generalization. A ‘max_depth’ of 'None' allows trees to expand until they have fewer than ‘min_samples_split’ samples (James et al., 2023; Liaw & Wiener, 2002). ‘N_estimators’ defines the count of decision trees in the ensemble, influencing the ensemble's size and diversity. Increasing ‘n_estimators’ enhances the model's capacity to discern intricate data relationships, improving predictive accuracy. However, beyond a certain point, additional estimators yield minimal benefit and increase computational load (Breiman, 2001; Cutler et al., 2007).

Key hyperparameters in this study also include ‘min_samples_leaf’ and ‘min_samples_split’. ‘Min_samples_leaf’, the minimum number of samples required at a leaf node, balances overfitting and underfitting. A low value may lead to overfitting by making decisions based on minimal data, capturing noise, whereas a high value might result in underfitting by oversimplifying the model. ‘Min_samples_split’, the minimum number of samples needed to split an internal node, also addresses overfitting by avoiding splits in nodes with few samples. However, if set too high, it may cause underfitting by impeding the tree's ability to discern detailed patterns, while a very low value might lead to overfitting by creating overly complex trees (James et al., 2023; Probst et al., 2019). These hyperparameters are data-dependent, and their optimal values, identified through grid search with three-fold cross-validation, are specific to the dataset under study.

Furthermore, the study leveraged the RF model's inherent feature importance attribute for understanding each input's contribution to the model's predictive accuracy. Feature importances were determined based on the reduction in impurity, such as mean squared error, offered by each feature. This approach not only clarifies the model's functionality but also aids in effective feature selection, prioritizing attributes most important to the analysis. Additionally, a correlation matrix using the Pearson coefficient will be presented to facilitate a clearer understanding of the linear interdependencies among the selected feature set (Breiman, 2001; Mei et al., 2022; Shaikh, 2018).

4. Results

This chapter outlines the initial data analysis, model development and evaluation findings. Results are organized according to the four primary measurement zones: inner and outer study area of Südliche Au, and inner and outer study area of Walchenseeplatz. The analysis predominantly contrasts data from periods before and after the respective project starts, highlighting changes due to road closures.

4.1. Data Analysis

4.1.1. Demographics, infrastructure and weather data

Demographic data, segmented into four main project areas was further categorized into nine age groups. Figure 6 shows this data through a heatmap, with dark blue indicating higher resident concentrations and light blue showing lower concentrations in each area and age group. Analysis reveals that the predominant age group in both inner study areas is 30-40 years. In Südliche Au, the 40-50 year age group follows closely, whereas in Walchenseeplatz, it is the 20-30 year age group.

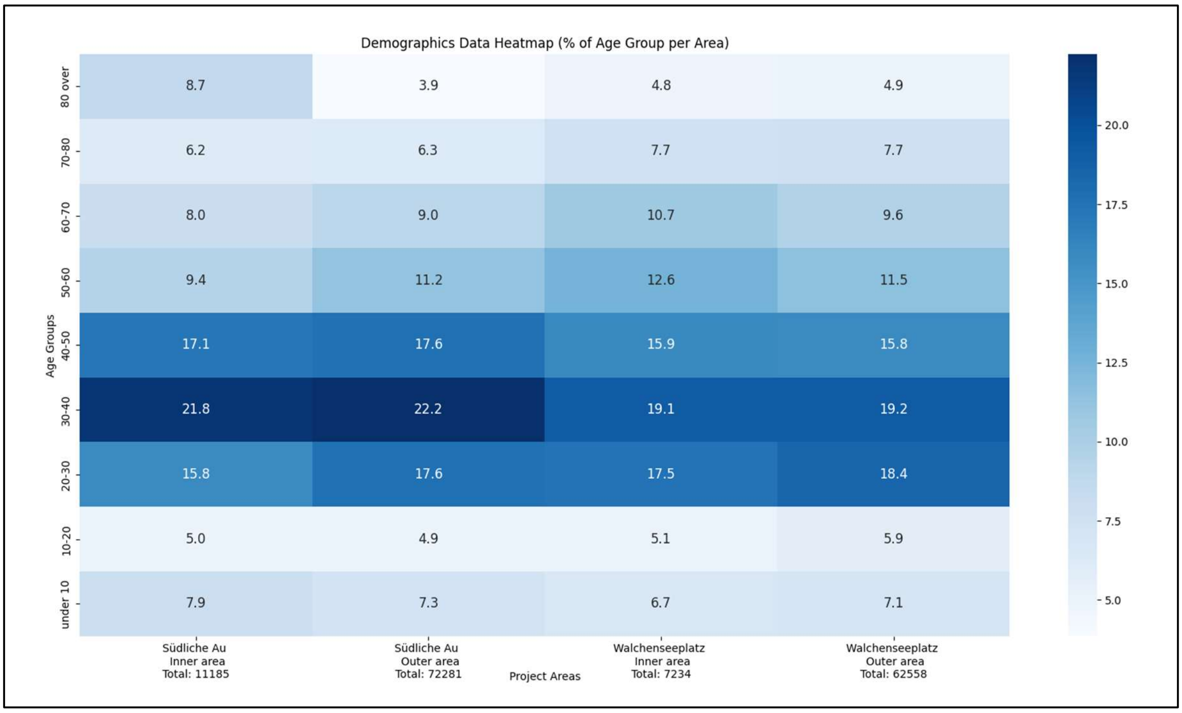

Figure 6: Demographics in percentage of age group per study area (Munich, n.d.; Zensus, 2011)

The combined population across all study areas totals 128,741, though this figure includes some double counting in the outer project areas, as indicated by the heatmap data.

Details regarding infrastructure data will be presented in Table 3.

Table 3: Number of amenities in the study areas

	Südliche Au Inner	Südliche Au Outer	Walchenseeplatz Inner	Walchenseeplatz Outer
Kindergarten, schools	3	61	0	36
Restaurants, cafes	20	436	6	114
Transportation	15	193	4	154
Museums	0	6	0	0
Bicycle stands	11	256	6	176
Removed parking lots[1]	129	0	41	0
Percentage of closed road[1]	0.09	0	0.04	0
New mobility hubs[1]	3	0	2	0

In terms of amenities, the outer Südliche Au area, partially intersecting with Munich's city center, displays the highest count, particularly in restaurants and cafes, as shown in Table 3. This contrasts with the fewer amenities in Walchenseeplatz, emphasizing its more residential nature. Spatial distribution details of these amenities are provided in the Appendix A2.

The project's implementation influenced infrastructure in the Südliche Au region, with 9% (480 meters) of its total street length of 5,200 meters closed to motorized vehicles. The Walchenseeplatz area saw 4% (190 meters) of its 4,600 meters of streets similarly restricted. Those roads in both inner areas are mainly residential and secondary streets, with not heavy traffic. The projects initiative also led to the creation of new mobility hubs—three in Südliche Au and two in Walchenseeplatz—enhancing vehicle sharing and repair services.

Weather data, sourced solely from Südliche Au, offers a comprehensive view for the entire study area. Figure 7 illustrates this data, displaying average temperature and precipitation from 02 May to 20 September 2023 on the left, and sunshine duration and wind speed over the same time frame on the right. Post-projects implementation, a rise in average temperature and more frequent precipitation days were observed, while sunshine duration peaked just before the project and remained stable afterward.

[1] From the respective project start

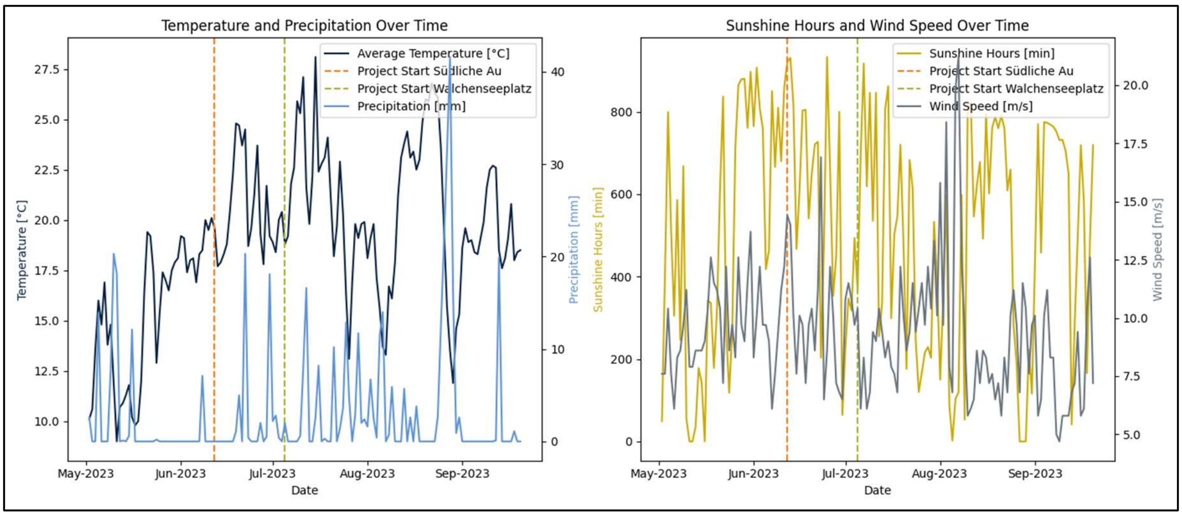

Figure 7: Temperature, precipation, sunshine hours and wind speeds

Prior to 12.06.2023 (Südliche Au project start), the average temperature in the study area was 15 °C, which increased to an average of 20 °C after the 12th June, 2023. Precipitation levels also rose, from 2 mm to 4 mm, and average daily sunshine duration extended from 494 to 508 minutes. Wind speeds, however, remained constant, fluctuating between 9 and 10 m/s both before and after the project's start. Similar trends were observed in Walchenseeplatz post-project commencement on 05.07.2023, with pre-project data closely aligning with post-project figures. A comprehensive table detailing these statistics is included in the Appendix A3.

4.1.2. Traffic, alternative and active modes

The traffic data results are presented as the ratio of current speed to free flow speed. A higher ratio signifies a more favorable traffic condition, as the current speed approaches the optimal free flow speed. Figure 8 displays speed metrics for both project zones: the inner and outer areas. The congruence in data between these two zones suggests comparable traffic conditions across both areas.

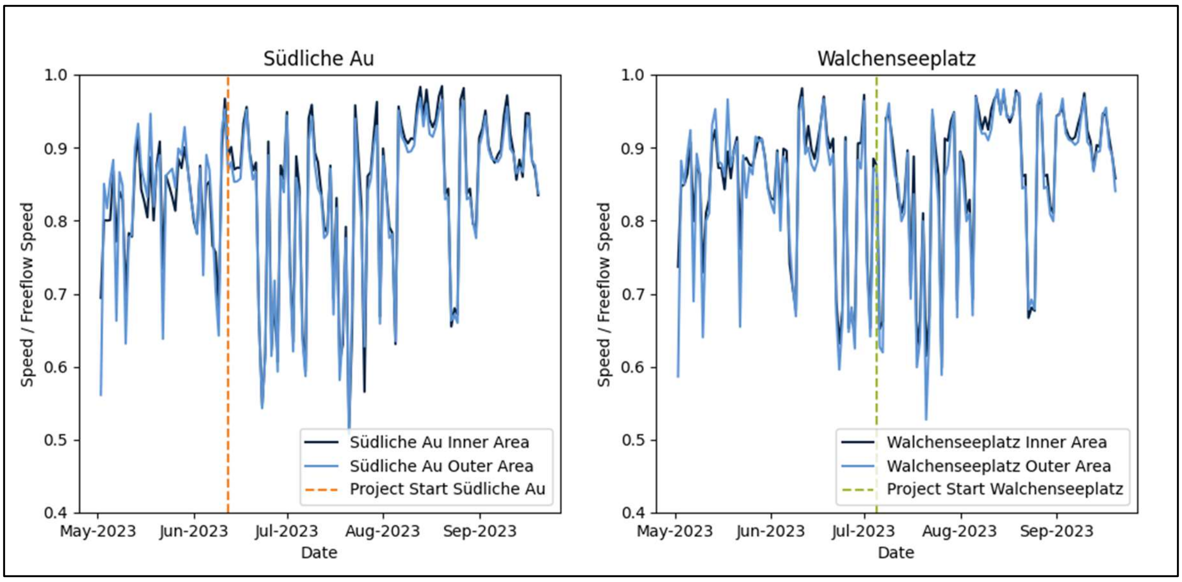

Figure 8: Speed data in project areas

Table 4 provides descriptive statistics for each area, comparing conditions pre- and post-project implementation. The outer areas exhibited no change in the average speed's mean. However, the inner zones experienced an increase in relative speed, with a notable four percentage point rise in the median speed for the inner Südliche Au zone post-implementation.

Table 4: Descriptive statistics relative speed data

	Südliche Au				**Walchenseeplatz**			
	Before 12.06.23		After 12.06.2023		Before 05.07.2023		After 05.07.2023	
	Inner	Outer	Inner	Outer	Inner	Outer	Inner	Outer
Mean	0.82	0.83	0.84	0.83	0.85	0.84	0.87	0.86
Median	0.84	0.85	0.88	0.88	0.89	0.88	0.89	0.90
Variance	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Range	0.54	0.64	0.61	0.82	0.48	0.64	0.48	0.82
25th percentile	0.76	0.76	0.79	0.74	0.80	0.76	0.80	0.78
75th percentile	0.90	0.93	0.94	0.96	0.93	0.94	0.97	0.97
Skewness	-0.60	-1.10	-1.00	-1.05	-1.00	-0.94	-1.20	-1.22
Kurtosis	2.22	0.80	0.09	0.37	0.08	-0.15	0.46	0.86

A significant shift in kurtosis in the inner Südliche Au zone was also observed. Higher kurtosis pre-implementation indicated a predominance of extreme speed measurements, which went towards zero post-implementation, reflecting more consistent speed readings. Across all datasets, negative skewness indicates a predominance of speed measurements above the mean, punctuated by occasional lower-speed outliers.

Figure 9 presents a side-by-side comparison of e-scooter and e-moped usage trends in the Südliche Au area, with e-scooter data on the left and e-moped data on the right. No data was available for the Walchenseeplatz study area due to restricted rental areas of the companies. The e-scooter data, at first observation, shows fewer extreme values, a phenomenon that can be attributed to their higher usage frequency in complete Munich compared to e-mopeds.

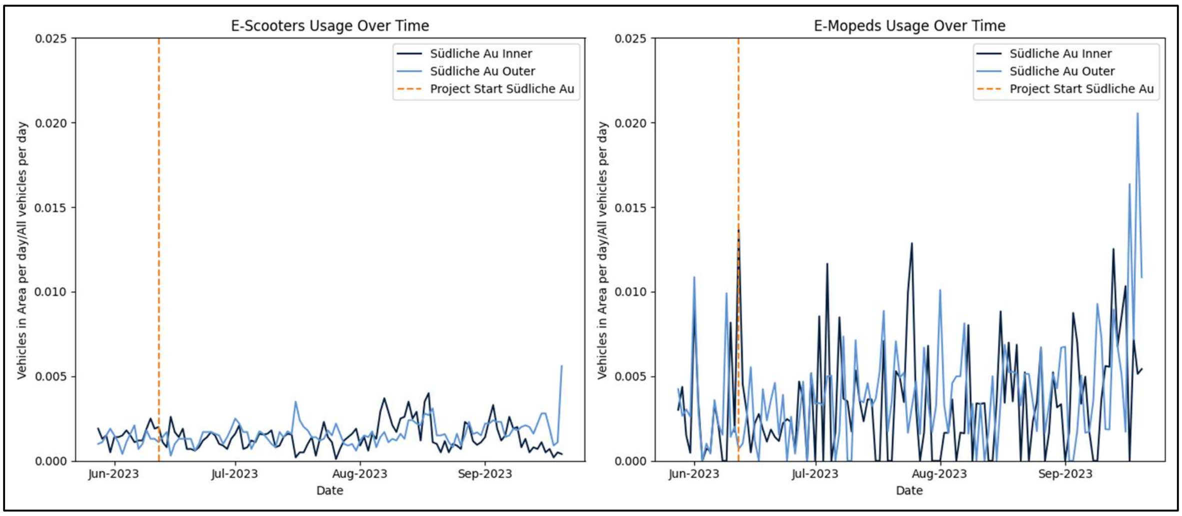

Figure 9: E-scooter and e-moped usage in study area

Table 5 provides a comparative analysis of e-scooter and e-moped usage in Südliche Au, before and after the project's initiation. The data indicates a post-project decrease in e-scooter usage in the inner study area, with e-mopeds showing an increase in both areas of Südliche Au. The median for e-moped usage remained zero in all areas, both pre- and post-project, suggesting that at least half of the data values were zero. Both transport modes exhibited a variance of zero in the data, due to dividing the number of vehicles to all vehicles, which led to small values and therefore very small variance. Post-project, the 25th percentile (Q1) for e-scooters was zero in both regions, denoting that 25% of speeds were zero, with a notable shift in the outer region from a non-zero value pre-project to zero post-project. Skewness analysis revealed a significant positive skew in all regions, particularly for e-mopeds, indicating frequent occurrences of speeds above the mean. Additionally, both e-scooters and e-mopeds displayed increased kurtosis post-project, reflecting the longer pre-project duration compared to the post-project period.

Table 5: Descriptive statistics e-scooter and e-moped data

	E-Scooter data				E-Moped data			
	Before 12.06.23		After 12.06.2023		Before 12.06.2023		After 12.06.2023	
	Inner	Outer	Inner	Outer	Inner	Outer	Inner	Outer
Mean	0.00025	0.00026	0.00024	0.00033	0.00043	0.00065	0.00059	0.00081
Median	0.00025	0.00020	0.00015	0.00020	0.00000	0.00027	0.00000	0.00000
Variance	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Range	0.00080	0.00100	0.00160	0.00410	0.00817	000817	0.00743	0.01273
25thpercentile	0.00010	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
75thpercentile	0.00040	0.00065	0.00038	0.00070	0.00057	0.00137	0.00169	0.00176
Skewness	0.69	0.61	1.67	2.03	2.43	1.48	2.72	2.33
Kurtosis	2.11	1.11	4.40	8.34	6.32	2.34	10.21	6.47

Figure 10 illustrates the heatmap brightness values, correlating with the intensity of sports activities like running and cycling from the Strava activity heatmap. Analysis of the timeline indicates an overall reduction in activity levels across all areas during the data collection period. An exception is observed in the inner area of Südliche Au, where a noticeable increase in activities occurs shortly after the project's initiation. Comparative analysis between the two regions shows that Südliche Au consistently exhibits higher luminosity on the heatmap, indicating a higher level of sports activity engagement compared to the Walchenseeplatz area.

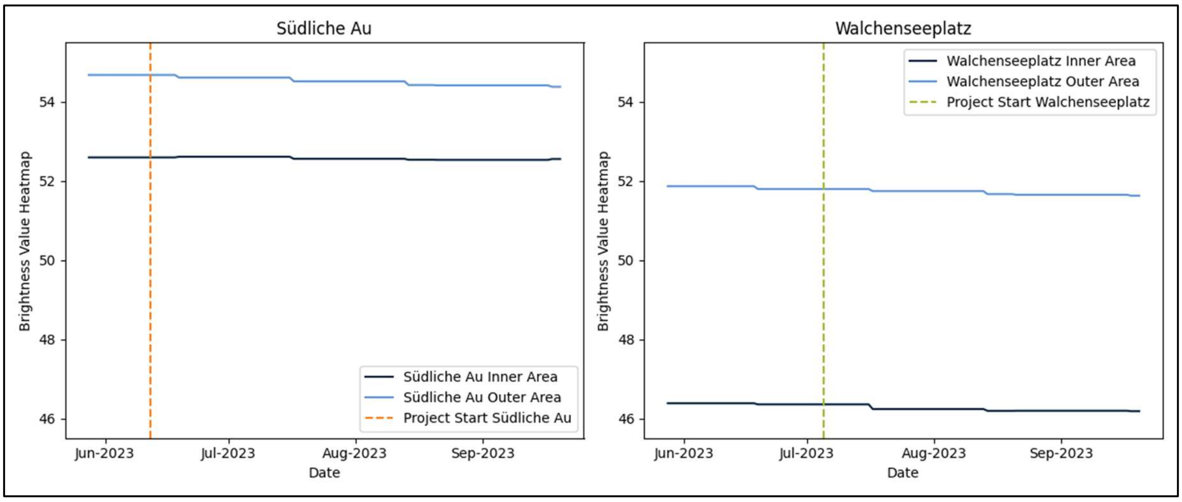

Figure 10: Brightness values of sports activity heatmap

Table 6 summarizes the brightness values from the sports activity heatmap data. A key observation is the presence of only a single recorded value before the project's start in Südliche Au due to irregular data updates, leading to zero variance, skewness, and kurtosis. Overall, a decrease in brightness values was observed across all regions as the project advanced. The broader range of values in the outer areas is notably influenced by the inclusion of the Isar area, a location known for its high level of sports activity.

Table 6: Descriptive statistics brightness values of sports activity heatmap

	Südliche Au				Walchenseeplatz			
	Before 12.06.23		After 12.06.2023		Before 05.07.2023		After 05.07.2023	
	Inner	Outer	Inner	Outer	Inner	Outer	Inner	Outer
Mean	52.60	54.64	52.57	54.48	46.37	51.36	46.23	51.23
Median	52.69	52.69	52.62	52.69	44.93	52.53	44.83	52.19
Variance	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01
Range	0.29	20.22	0.49	20.56	11.13	19.02	11.32	19.15
25th percentile	52.56	52.40	52.60	52.22	43.32	44.93	43.17	44.75
75th percentile	52.69	61.54	52.70	61.38	44.95	54.55	44.83	54.42
Skewness	0.00	0.00	0.25	0.12	0.11	-0.09	1.07	0.21
Kurtosis	0.00	0.00	-1.32	-0.61	-2.00	-2.00	0.21	-0.07

4.1.3. Key findings

This chapter presents a detailed analysis of the inner and outer Südliche Au and Walchenseeplatz areas, highlighting key findings of the data analysis:

- Demographics: Both inner areas predominantly house residents aged 30-40 years, with a total population of 128,741 across all regions, accounting for potential overlaps in the outer areas.
- Infrastructure: The outer Südliche Au area, being closer to Munich's city center, is characterized by a higher density of amenities like restaurants, cafes, and transportation facilities, contrasting with Walchenseeplatz's more residential nature.
- Weather Data: Data from Südliche Au shows an increase in average temperature and precipitation days after the project's start. Sunshine duration was at its peak just before the project and stabilized thereafter.
- Traffic Data: Speed metrics comparison pre- and post-project in both areas indicates stable traffic conditions, with a minor increase in relative speed in the inner regions post-implementation.
- Alternative Modes: Post-project, there was a slight increase in e-scooter usage in Südliche Au outer area, while e-moped usage increased in both study areas.

- Sports Activities: Heatmap brightness values revealed a general decline in sports activities, such as running and cycling, with the exception of a temporary increase in the inner Südliche Au region following the project's initiation.

4.2. Random Forest regression model

A RF regression model was developed to analyze traffic patterns in car-free zones. The model's configuration, key influencing variables, and performance will be discussed in the following chapters.

4.2.1. Model design and feature set

In this study, the variable set was streamlined from 343 to a smaller, more manageable number to enhance the model's universality and interpretability. This simplification process was carefully managed to avoid diminishing the model's effectiveness. Measurement variables were categorized into two spatial groups: inner and outer study areas. In each category, data from various locations were consolidated into single, mode-specific variables. Notably, the e-scooter and e-moped data were exclusive to the Südliche Au area and thus not applicable to Walchenseeplatz. Table 7 is providing outlining key features and their definitions, omitting those with minimal impact on later model stages. For prediction, historical averages of time-sensitive variables based on the day of week, including target variables, were used, differentiating them in the model by appending an underscore "_" to each feature name. Day of week was chosen due to its highest feature importance next to the other time-dependent features which could not be predicted.

Table 7: Feature names and definitions

Feature name	Definition
inner_speed_	1-8, equal speed measurement points within the study area
outer_speed_	Averaged all outer speed measurements for each outer study area
tavg_, tmin_, tmax_, prcp_, wspd_	Weather data such as average temperature, precipitation
Removedparking, newmobility, closedroads	Number of removed parking spots for each inner study area, number of new mobility hubs and percentage of closed roads
inner/outer-amenities	Number of amenities differentiated by classification and area
biketotal_	Number of bikes passing through the biking measurement station
inner/outer_actmode_	Sports activity related heatmap data for inner and outer area
inner/outer_escooter_ / emoped_	Number of escooter and emoped in the study area relative to all vehicles
inner/outer_age	Number of residents in the inner and outer study area

Variables with their original future value were added in the model development to see which influence it would have when adding the prediction for variables like weather to the model training. The target variables were identified within the internal areas of the study. The selection of these eight variables was determined by pre-established data collection points, as indicated in Figure 11, meaning the numbers of the variables are merely a spatial indicator. The choice of these locations was also based on the information provided by the external company.

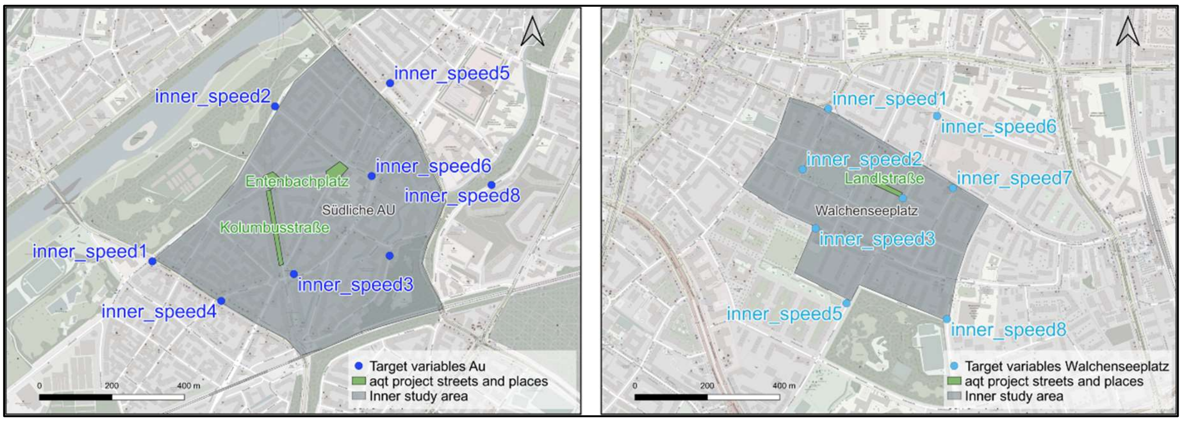

Figure 11: Target variables for Südliche Au (left) and Walchenseeplatz (right)

4.2.2. Random Forest model analysis - Südliche Au

In addressing missing values within the feature dataset, mean imputation was applied, utilizing the column-wise and weekday-specific averages. Although alternative methods were considered, mean imputation demonstrated higher model performance. The optimal hyperparameters for the Südliche Au model were determined through the technique of GridSearchCV. The finalized parameters, chosen based on minimizing mean squared error, are as follows: 1120 trees (estimators), no limit on tree depth, a minimum of 5 sample per leaf, at least 12 samples required to split, and a test size of 20%.

The selection of target variables was influenced by the geographical scope of the Südliche Au study. Predictor variables were evaluated using performance metrics like mean squared error, contributing to the efficacy of the multi-output model. Model accuracy was assessed using mean absolute error (MAE) and coefficient of determination (R^2), along with visual evaluations.

For a comprehensive understanding of feature interdependencies, Figure 12 presents a correlation matrix for the Südliche Au study, utilizing the Pearson coefficient. A notable observation from this matrix is the high correlation between relative speed values, both within and across the inner and outer areas. The relative speed features, despite their correlation, are retained in the RF model, as this approach can effectively handle correlated predictors. In fact, these correlated features contribute positively to the model's overall accuracy. Additionally, the average temperature ('tavg') displayed a significant correlation, scoring 0.73, with both biking data ('biketotal') and inner e-scooter data. This suggests a strong relationship between temperature and mobility patterns in these modes of transport. Interestingly, the infrastructure changes related to the project, represented by the addition of new mobility hubs ('newmobility'), exhibited almost negligible correlations with all other features, indicating a limited direct impact on the studied variables.

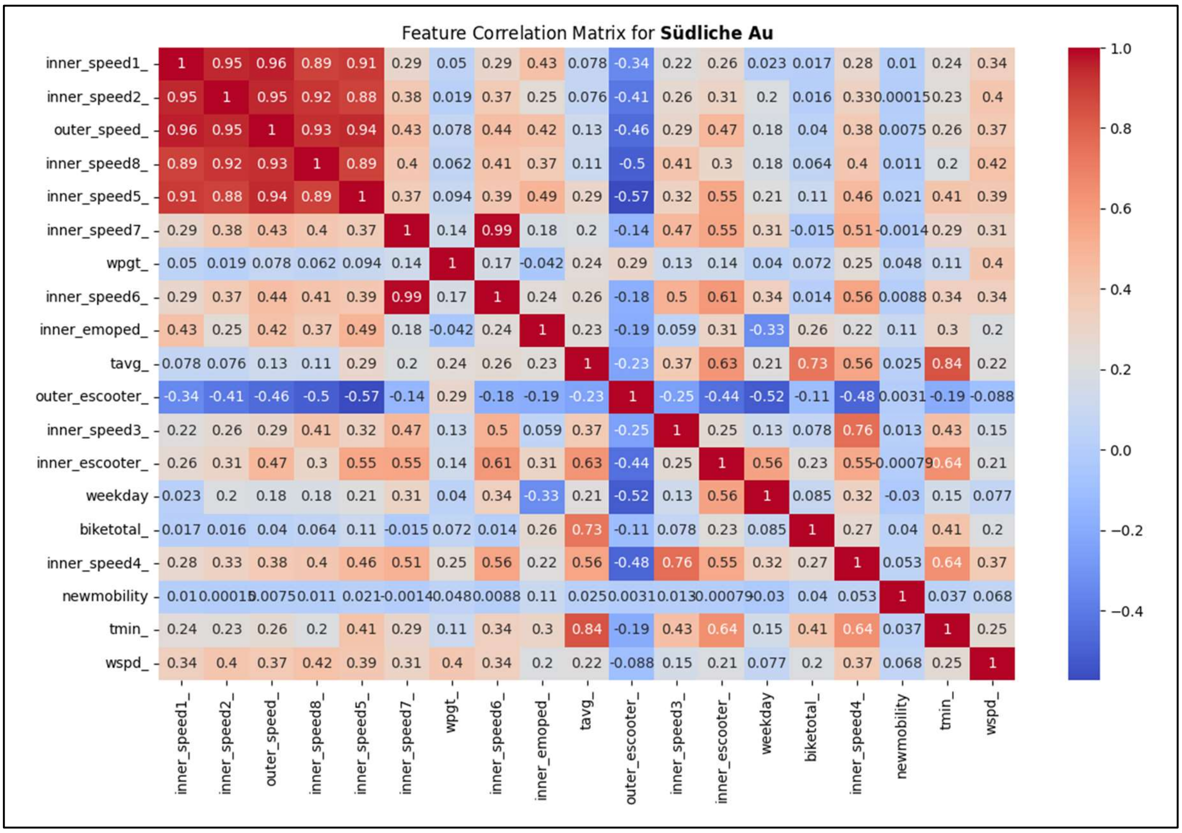

Figure 12: Feature correlation matrix for Südliche Au

A comprehensive feature set was found to support model robustness, leading to R^2 of around 0.2, although not all the features used could be logically justified. Time-independent variables, such as age and amenity data, showed no high impact on model performance and were excluded. Despite minimal influence, heatmap data related to activity levels were kept due to their negligible computational overhead.

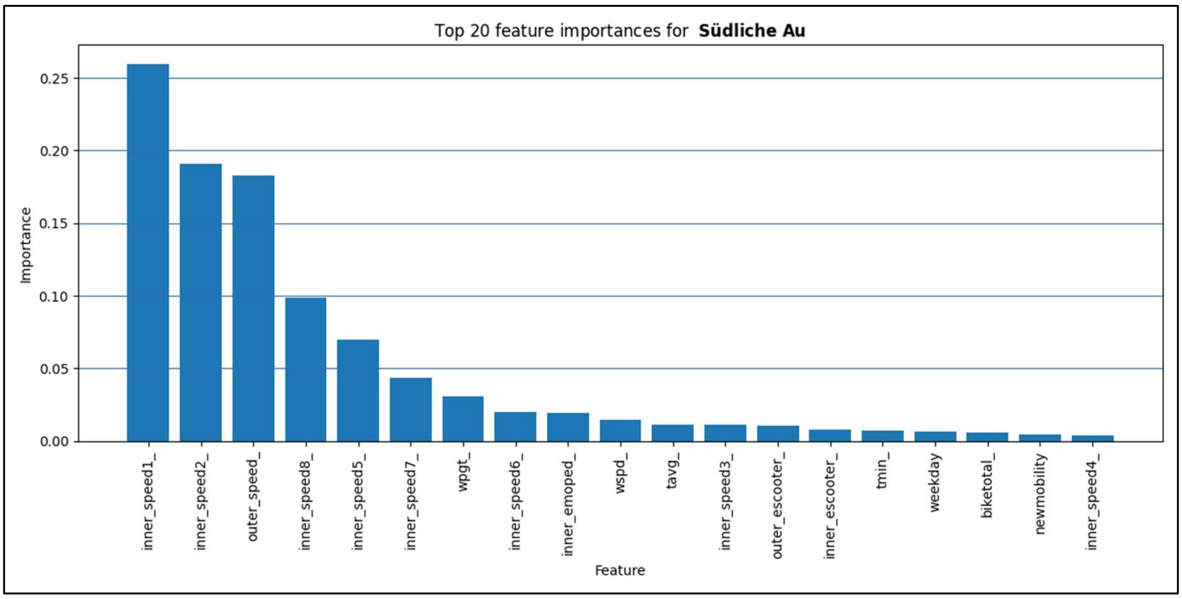

Figure 13: Top 20 feature importances at Südliche Au

Figure 13 delineates the top 20 features importance for the prediction of speed variables within the Südliche Au study area. Mainly speed variables, e-moped, e-scooter and weather variables such as wind peak gust ('wpgt') and wind speed ('wspd') have a higher influence, but the number of mobility hubs as a project related features made it into the top 20, while developing the model with over 30 variables. Table 8 presents a detailed overview of the eight most influential features in the model, along with their corresponding importance values. Additionally, it includes the target variables, each accompanied by its respective R^2 (coefficient of determination) and MAE (mean absolute error) values, providing a clear picture of the model's predictive accuracy for each target. The overall model demonstrates a modest aggregated R^2 of 0.17 and an MAE of 0.102, indicating its general predictive performance. It is important to note that the presence of an underscore '_' following a feature name signifies that the feature has been averaged by weekday for future values, similar for the Walchenseeplatz model. This distinction is important as it means these averaged features are not identical to their corresponding target variables, representing a different aspect of the data.

Table 8: Feature importances and target variables with their statistical measures

Input	**Feature**	**inner_speed1_**	**inner_speed2_**	**outer_speed_**	**inner_speed8_**
	Importance	0.26	0.19	0.18	0.10
	Feature	**inner_speed5_**	**inner_speed7_**	**wpgt_**	**inner_emoped_**
	Importance	0.07	0.04	0.03	0.02
Output	**Target variable**	**inner_speed1**	**inner_speed2**	**inner_speed3**	**inner_speed4**
	R^2	0.21	0.20	0.21	0.12
	MAE	0.093	0.086	0.105	0.110

	Target variable	inner_speed5	inner_speed6	inner_speed7	inner_speed8
Output	R^2	0.20	0.11	0.12	0.21
	MAE	0.103	0.108	0.112	0.107

The model's predictive accuracy was assessed by averaging the forecast values of each target variable to derive a relative speed metric, which was then compared against the averaged actual mean speed. Figure 14 illustrates these findings, depicting a scatterplot on the left that highlights the variance between true and predicted values, and on the right, a graphical representation of these values across the predicted time series.

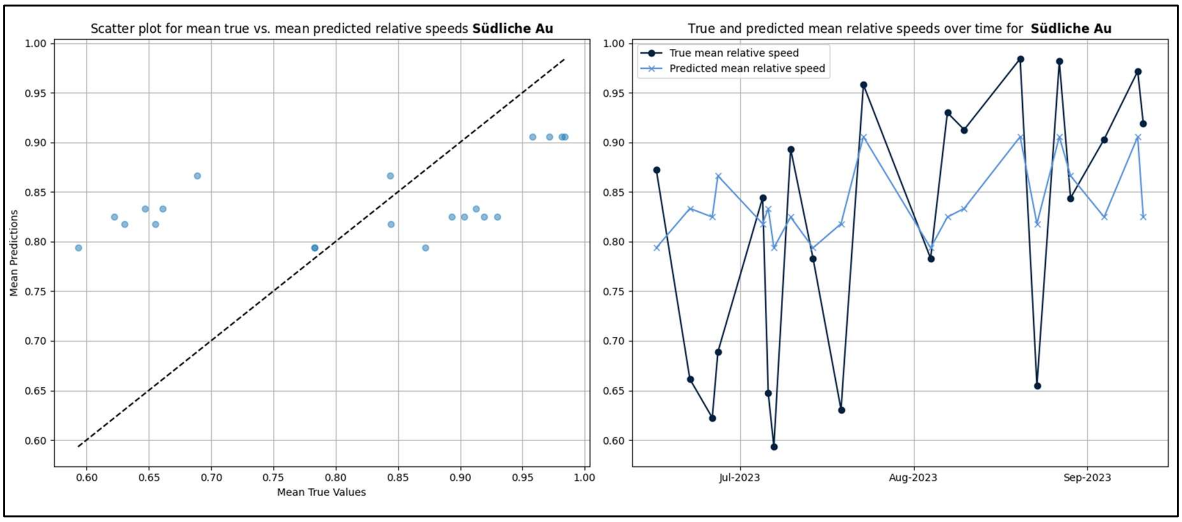

Figure 14: True vs. predicted relative speed values of Südliche Au model

The scatterplot analysis indicates that predicted values predominantly are located within the 0.75 to 0.95 range, in contrast to the mean true values which span from 0.55 to 1.00. This discrepancy is further illustrated in the right diagram, where the predicted values show a lower range of outliers compared to the mean true values.

Enhancements to the model involved incorporating actual post-road closure feature values, specifically sports-activity heatmap data, which resulted in an increased overall R^2 of 0.26. Interestingly, the addition of future weather data, despite being identified as significant features, paradoxically reduced the model's R^2 to -0.06. Similar with e-scooter and e-moped data which had a higher influence but reduced the overall R^2. Sole reliance on weather data for predictions aligned the predicted values more closely with true values, yet further decreased the R^2. When only using speed variables, the overall R^2 decreased a small amount in performance reducing it to a R^2 of 0.16. The models developed as part of this research are detailed in Appendix A5.

To compare the RF model accuracy, a linear regression model was developed and its results are showed in Figure 15. This figure includes a time-series showing the mean true vs. mean predicted relative speed values indicating the pattern of the relative speed feature, averaged per weekday, and a scatter plot that underscores the model's limitations, particularly in predicting lower relative speed values. The model required training on the complete dataset and was subsequently tested on post-project data to avoid yielding a negative R^2 value, a situation that arose when employing the same methodology (20% test size post project) as used in the RF approach. Consequently, the linear regression demonstrates an inadequate fit, with an R^2 value of only 0.11. This low R^2 value signifies the model's inability to accurately represent the data's trends, a challenge stemming from the non-linear nature of the dataset which linear regression—a statistical method for modeling the relationship between a dependent variable and one or more independent variables—cannot adequately address. The analysis reveals 'outer_speed' and 'inner_speed3' as the only significant features (p-value < 0.005), along with 'weekday', indicating their substantial influence on the model despite its overall poor performance.

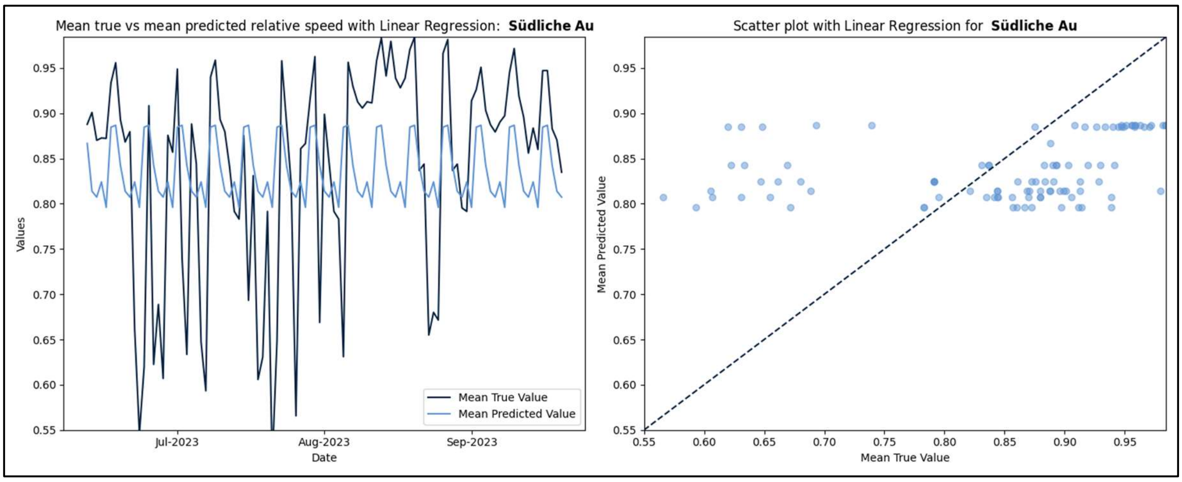

Figure 15: Linear Regression model for Südliche Au

4.2.3. Random Forest model analysis - Walchenseeplatz

The methodological approach applied in the Südliche Au study was replicated for the Walchenseeplatz area. The finalized hyperparameters parameters chosen based on minimizing mean squared error, are as follows: 1120 trees (estimators), no limit on tree depth, a minimum of 5 samples per leaf, at least 2 samples required to split, and a test size of 0.2. The model development strategy and feature importance assessment were consistent, with the top 20 features displayed in Figure 16. Notable differences from the Südliche Au included decreased impact of weather data and a slight increase in the significance of activity-related data. Time-independent features continued to show minimal to no importance for the model's performance in Walchenseeplatz. However, the variable representing removed parking lots in the project area exhibited a higher influence on the model's performance.

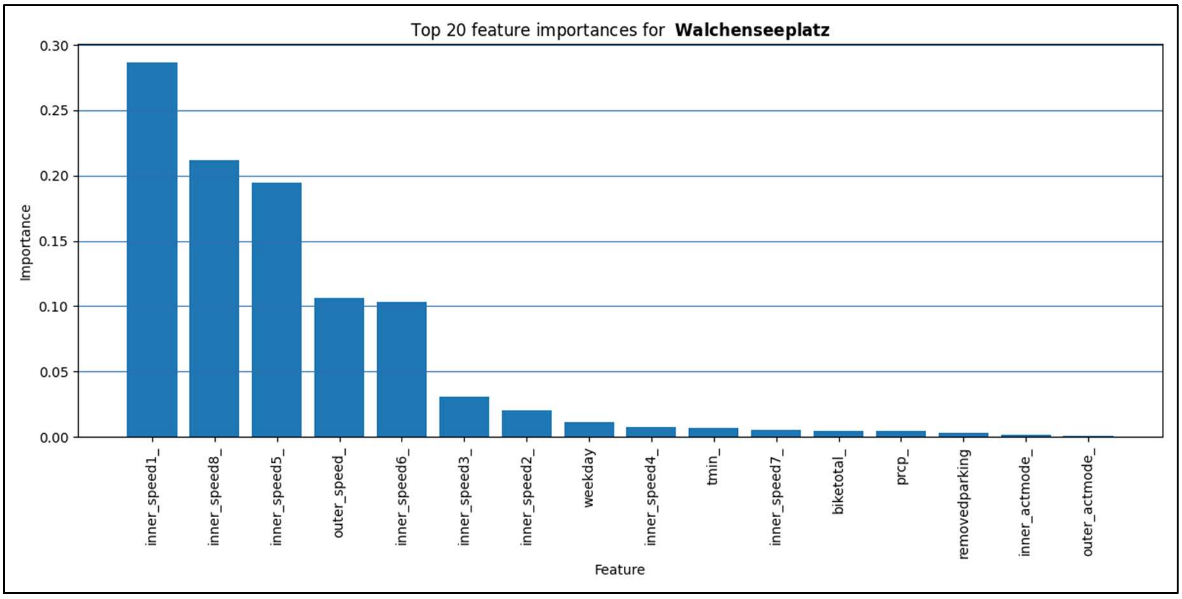

Figure 16: Top 20 feature importances at Walchenseeplatz

Similar to the Südliche Au study, a correlation matrix was also developed for Walchenseeplatz, detailed in Appendix A4. This matrix revealed similar interdependencies between the inner and outer relative speed variables as observed in the Südliche Au study. In the context of Walchenseeplatz, the project-related infrastructure change was quantified by the number of removed parking lots. Like the Südliche Au findings, this particular feature—removal of parking lots—demonstrated almost no correlation with other variables. An interesting aspect of the Walchenseeplatz study is the negative correlation observed between the minimum temperature and both inner and outer activity-related data. This relationship implies that higher minimum temperatures could lead to decreased activity, which is a counterintuitive finding.

Table 9 highlights eight out of the ten most dominant features in the Walchenseeplatz study, including their importance scores, and the R^2 and MAE for each target variable. These features exhibit similarities to those in the Südliche Au study, with the notable exception of the omission of e-moped data and the inclusion of ‘weekday’ as a feature in this analysis. In contrast to the Südliche Au model, the Walchenseeplatz model demonstrates lower MAE values across all variables, indicating more precise predictions. Additionally, the range of R^2 values in the Walchenseeplatz study is broader, with more pronounced outliers in both higher and lower spectrums. This suggests a variation in the model's predictive accuracy across different variables. Overall, the Walchenseeplatz model exhibits an R^2 of 0.19 and an MAE of 0.085, signifying a notable improvement in performance compared to the Südliche Au model.

Table 9: Feature importances and target variables with their statistical measures

Input	**Feature**	**inner_speed1_**	**inner_speed8_**	**inner_speed5_**	**outer_speed_**
	Importance	0.29	0.21	0.19	0.11
	Feature	**inner_speed6_**	**inner_speed3_**	**weekday**	**tmin_**
	Importance	0.10	0.03	0.01	0.01
Output	**Target variable**	**inner_speed1**	**inner_speed2**	**inner_speed3**	**inner_speed4**
	R^2	0.20	0.09	0.25	0.17
	MAE	0.086	0.088	0.090	0.085
	Target variable	**inner_speed5**	**inner_speed6**	**inner_speed7**	**inner_speed8**
	R^2	0.28	0.13	0.11	0.27
	MAE	0.085	0.078	0.079	0.085

Figure 17 illustrates the predictive and true values for the Walchenseeplatz area. The predicted values ranged between 0.80 and 0.95, while the true values spanned from 0.65 to 1.00. The time-series diagram in the Figure 17 further demonstrates that while the predictive values follow the true values, they do not capture the outliers to the lower values observed in the mean true values.

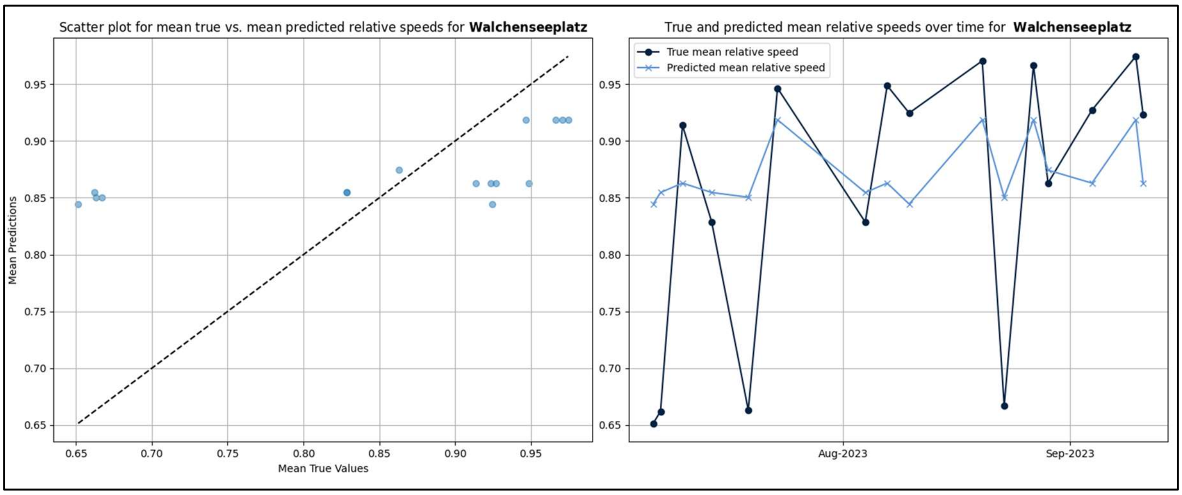

Figure 17: True vs. predicted relative speed values of Walchenseeplatz model

Alternate modeling strategies, such as the incorporation of weather data and the gradual introduction of future feature values, mirrored the effects observed in the Südliche Au model. Particularly, the addition of inner and outer activity-related heatmap data notably enhanced slightly the model performance. Incorporating all future feature values including the outer speed, as opposed to averaging based on historical data, significantly increased the feature importance of the outer speed value to nearly 1, resulting in an overall R^2 of 0.94 and a MAE of 0.02. However, this approach assumes the availability of future values of the outer relative speed value for prediction, which may not be practical. Speed-related variables showed high correlation within the area-defined zones. Eliminating the speed variable entirely shifted the dominant predictor to wind direction, followed by other weather variables, similar to the Südliche Au model, leading to a negative R^2 of -0.10 and an increased MAE of 0.10.

4.2.4. Cross-model validation

In this chapter, the applicability of the developed models to future car-free area projects will be evaluated by testing their performance across different settings. Specifically, the model trained on the Walchenseeplatz dataset, which exhibited higher performance, was applied to the Südliche Au dataset. This required aligning the feature variables and target variables in length. The relative speed prediction locations at Südliche Au and Walchenseeplatz varied, so the values of the eight target variables were averaged to simplify them into a single measure. Initially, only 20% of post-road closure data from Südliche Au was used for testing the Walchenseeplatz model. The results, displayed in Figure 18, show a scatterplot of the predictions against actual values. The model yielded a negative R^2 value of -0.04 and a Mean Absolute Error (MAE) of 0.092, indicating a poor fit between the predicted values (ranging between 0.75 and 0.90) and the actual mean values.

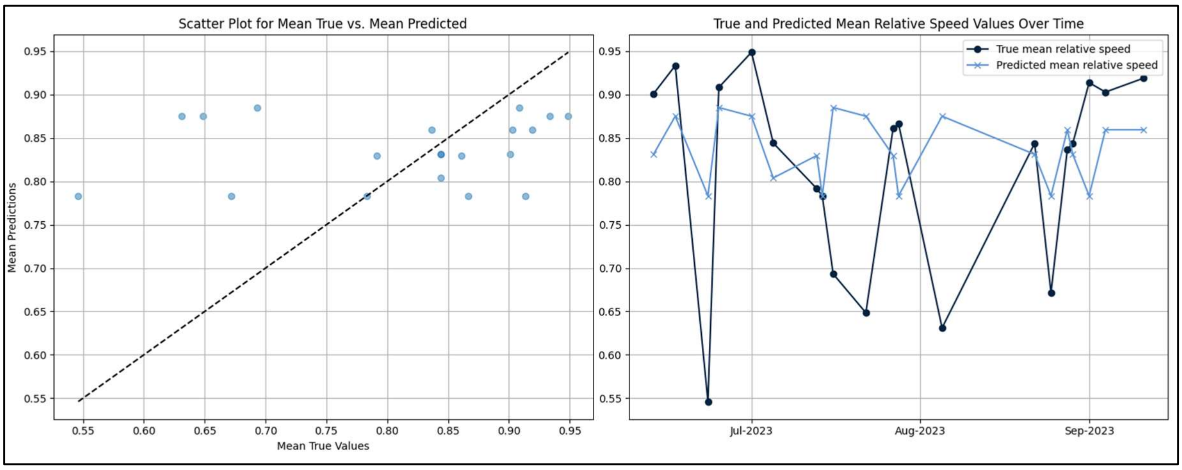

Figure 18: True vs. predicted relative speed values of Südliche Au with Walchenseeplatz model

In an alternative approach, 20% of the entire data collection period from Südliche Au was utilized for testing, resulting in improved R^2 and MAE values. However, it is important to note that the values prior to the road closure were accurately predicted due to their inclusion in the training data of the Walchenseeplatz model. As shown in Figure 19, the model accurately predicts values up to June 2023, after which it begins to deviate. The overall R^2 achieved was 0.23 with an MAE of 0.086. While this includes pre-closure values predicted with high accuracy, the post-closure predictions also exhibited reasonable higher accuracy than the first approach, when inspecting the shown diagrams.

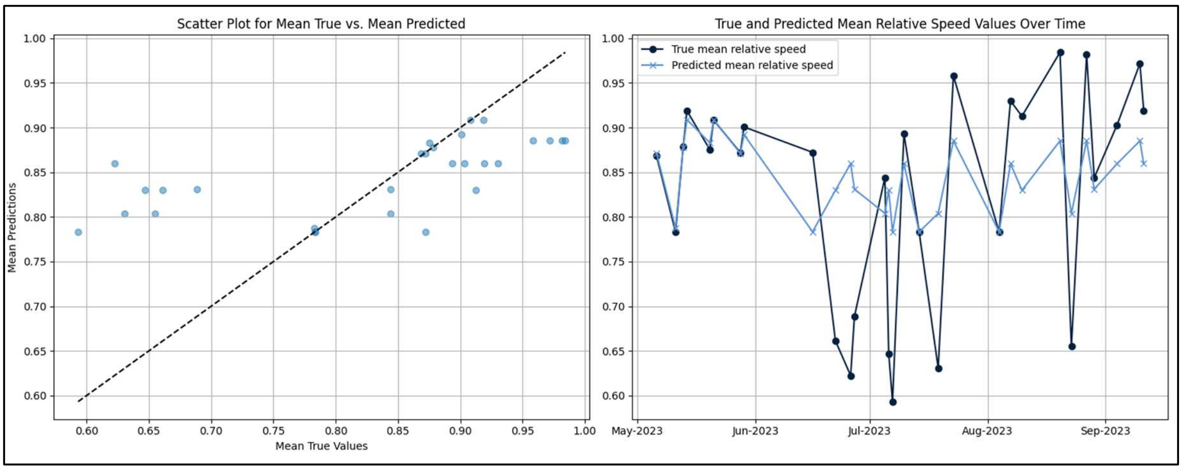

Figure 19: True vs. predicted relative speed values of Südliche Au tested on Walchenseeplatz model on complete project duration

5. Discussion

This chapter delves into interpreting the findings, beginning with a discussion on the specific outcomes of the projects. It integrates insights from literature reviews, contrasting them with the data results. Additionally, this chapter addresses the constraints encountered in data collection and processing. In evaluating the models' efficacy, the focus is on analyzing the predictive capabilities of the developed models, along with a comprehensive assessment of the RF regression model's overall performance. The chapter also includes a critical reflection on the methodological approaches employed in the study.

5.1. Interpretation of data related findings

5.1.1. Analysis of project-specific impacts

In the demographic analysis, the predominant age groups in the study areas were identified as 20-40 years, suggesting a prevalence of younger residents. Regarding infrastructure, Südliche Au exhibits a commercial character with a higher presence of cultural amenities and consumer services, whereas Walchenseeplatz is predominantly residential. The results indicating almost no change in relative speeds suggest that the age groups within the specified city area and their amenities do not heavily rely on individual motorized traffic for their transportation needs. The availability of extensive public transport options in both areas further implies a reduced reliance on automobiles among residents. The data collection spanned from May to September 2023, starting with typical spring weather that progressed to higher temperatures and precipitation levels over time. Notably, an unusual increase in precipitation was observed, attributed to a dry period at the end of May and beginning of June. However, wind speeds and sunshine duration showed no significant variation before and after the project commencements.

Analyzing traffic data, a marginal increase of 0.02 percentage points in average relative speed in Südliche Au was observed, which is not significant. The minimal change observed also suggests that road closures affecting between 4% and 9% of a specific area do not significantly impact traffic conditions. This change in relative speed could be influenced by various external factors, such as school holidays, weather conditions, and the number of construction sites, all potentially impacting traffic flow. Figure 20 illustrates the relationship between temperature, precipitation, and relative speed in the inner Südliche Au area. While no direct correlation between these variables is evident, a pattern emerged in August, suggesting improved traffic conditions with higher temperatures. Conversely, increased precipitation towards the end of August resulted in a reduction in relative speed. Further analysis of these relationships is explored in the section discussing the model's efficacy. Similar it was seen at Walchenseeplatz, which can be looked at in Appendix A6.

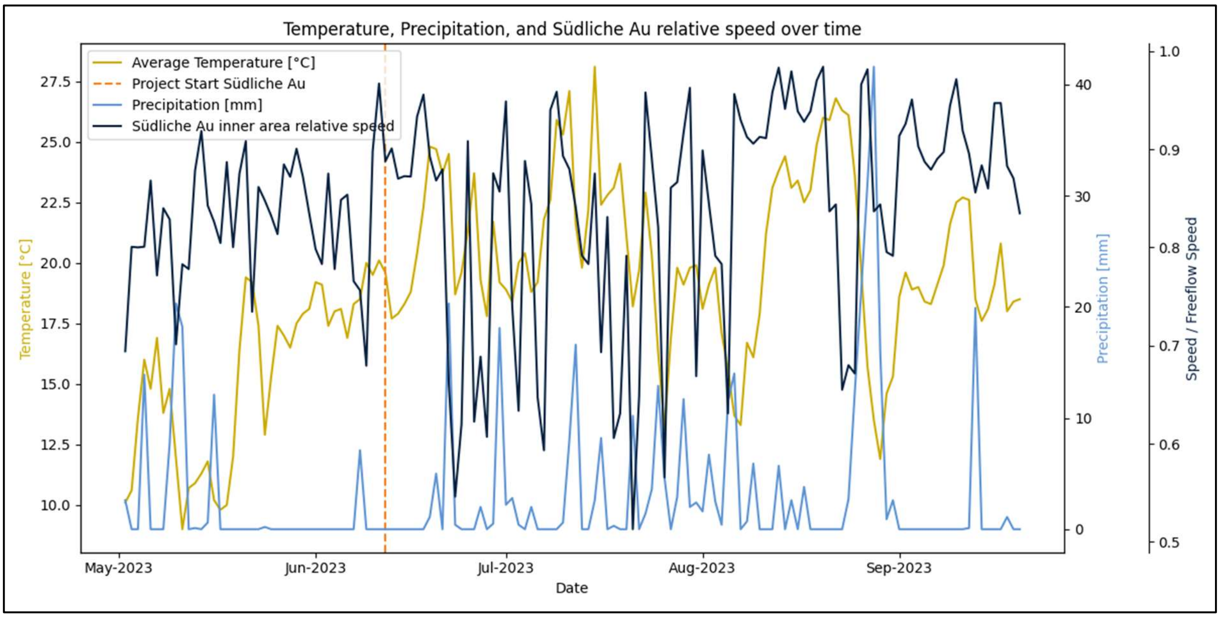

Figure 20: Relative speed, temperature and precipitation changes over time in Südliche Au

A key observation from the study is the negligible difference in average relative speeds between the outer and inner study areas of both project locations. While the outer areas exhibited slightly higher speeds, this can be attributed to the greater number of measurement points with better traffic conditions. Notably, a change was observed in Südliche Au immediately following the project's initiation on June 12, 2023. For approximately 10-12 days, there was a marked increase in relative speed, which subsequently reverted to normal levels. This temporary spike was also mirrored, though not identically, in the outer area speeds, suggesting that factors other than the road closures might have influenced the slightly improved traffic conditions. Another interesting finding is the correlation between reduced precipitation, a two-week school holiday period and improved traffic conditions. This trend suggests that during school holidays, possibly due to residents being on vacation, the overall traffic flow improved noticeably.

The data from Walchenseeplatz did also not indicate any significant changes post-project commencement. This outcome is likely due to the smaller size of the area and a lower proportion of road closures, resulting in minimal impact on traffic. A notable observation from the Walchenseeplatz study area was the higher skewness in speed data, reflecting a predominance of values above the mean and a presence of a few lower-speed outliers. This pattern might be influenced by occasional severe traffic conditions on the Mittlerer Ring, Munich's primary circumferential road, which is a small part of the outer Walchenseeplatz study area. Additionally, the generally higher mean speed in the inner study area could be attributed to its more residential character, which typically experiences fewer and less intense traffic disruptions compared to more commercial or busy areas. In conclusion, the relative speed data did not show any significant changes attributable to the projects in either the inner or outer study areas. This is consistent with expectations given the primarily residential nature of these areas and therefore a limited effect on the overall traffic state. Table 10 below shows the average changes and their t-test of the data prior and after the project implementations.

Table 10: Overview of value changes and t-tests of data in the study areas after the projects implementation

Area Variable	t-statistic	p-value	Change in %	Evaluation
Südliche Au inner relative speed	-0.71	0.48	1.68%	Not significant, minimal increase
Südliche outer relative speed	-0.16	0.88	0.38%	Not significant, negligible increase
Südliche Au inner e-scooter	0.41	0.68	-5.90%	Not significant, slight decrease in usage
Südliche Au outer e-scooter	-1.98	0.05	28.40%	Borderline significance, noticeable increase
Südliche Au inner e-moped	-1.11	0.27	38.86%	Not significant, substantial increase in usage
Südliche Au Outer e-moped	-0.91	0.36	25.23%	Not significant, noticeabl increase in usage
Südliche Au inner activity data	3.40	0.00	-0.05%	Statistically significant decrease (slight change)
Südliche Au outer activity data	6.82	0.00	-0.29%	Statistically significant decrease (noticeable)
Walchenseeplatz inner relative speed	-1.37	0.17	2.68%	Not significant, slight increase
Walchenseeplatz relative speed	-1.24	0.22	2.70%	Not significant, slight increase
Walchenseeplatz inner activity data	14.89	0.00	-0.30%	Statistically significant decrease (noticeable)
Walchenseeplatz outer activity data	13.09	0.00	-0.26%	Statistically significant decrease (noticeable)

Post-implementation of the project, e-scooter activity in the inner Südliche Au area witnessed a decrease of around 5%. This observation requires cautious interpretation due to the fact that data collection commenced only two weeks before the project's start. Conversely, a 27% increase in e-scooter usage was also observed in the outer areas which is borderline significant, where data coverage was incomplete due to the rental providers' operational zones. This trend could also be influenced by rising temperatures, encouraging greater use of e-scooters. The inner and outer activity related speed data showed a statistically significant impact of the road closures, but this might be due to only updates of the heatmap four to six weeks. The weather conditions also showed a statistically significant increase in temperature and precipitation, not showed in the Table 10, but these impacts are not project related.

In contrast, e-moped usage in the inner area saw a 38% increase in average, though this change was not statistically significant. In the outer areas, e-moped usage experienced a roughly not significant 25% rise. These shifts suggest a trend that may reflect the pattern observed in outer e-scooter usage, potentially influenced by warmer weather conditions that encourage the use of shared vehicles. This hypothesis is supported by the observed correlation between e-scooter and e-moped usage data and temperature variations. Overall, while road closures seem to have had minimal impact on overall vehicle usage, the distinct trends in the inner and outer areas, as well as between e-scooters and e-mopeds, indicate some level of influence from these changes.

The heatmap data, indicative of sports activity levels, generally showed a decline in both study areas. Not captured in the table, however, is a slight rise in activities within the inner Südliche Au area following the project's initiation. This increase in sports activities likely does not correlate directly with the project implementations, but somehow shows negative correlation with the temperature data. This relationship implies that higher minimum temperatures could lead to decreased activity, which is a counterintuitive finding. Typically, one might expect increased temperatures to encourage outdoor activity, making this negative correlation a point of interest of potential further investigation, as it suggests an inverse relationship that contradicts common assumptions about temperature and outdoor activity levels. The observed decrease may be attributed to the heatmap's methodology, which compares yearly activity levels against global benchmarks. Thus, the negative values in these areas could reflect a global increase in activities, with a comparatively smaller rise in the specific study regions. Consequently, the influence of the projects on sports activities appears to be minimal.

5.1.2. Context within the literature findings

The study areas, primarily consisting of residential roads, were expected to encounter minimal traffic disruption from road closures. This aligns with the literature's characterization of such streets as vibrant living spaces that promote reduced dependency on cars (Davis & Duany, 2018). This concept suggested a negligible impact on traffic from the implementations.

Extensive literature, particularly Cairns et al. (1998, 2002), indicates that traffic is more elastic than previously assumed, with road closures having a limited impact on traffic conditions around the closed areas. This study corroborates this, showing no significant effect on relative speed across the study areas, despite road closures. Although we did not observe a clear reduction in traffic akin to the 11% decrease reported by Cairns et al. (2002), the overall traffic conditions did not worsened due to the project implementations. This minimal change aligns with Melia & Calvert (2023), where traffic reductions on a small-scale road demonstrated no significant impact, mirroring the patterns observed in our study.

Goodwin et al. (1998) found that the long-term elasticity of traffic in response to road closures is typically greater than initially expected. Although our study of a temporary road closure event couldn't extensively analyze long-term effects, initial data from Südliche Au indicated an immediate improvement in traffic conditions post-project commencement. However, after 10-12 days, traffic states reverted to varying levels, often influenced by weekdays.

Examining global road closure and car-free initiatives reveals that closures of heavily used roads typically lead to changes in traffic conditions or alterations in user travel routes and times. However, the roads in our study, Südliche Au and Walchenseeplatz, were less utilized with heavy traffic occupations. Consequently, the impacts observed in major projects like the Parisian Riverbank closure or Cheonggyecheon's lane reduction show limited parallels to our findings. Notably, the long-term analysis of Cheonggyecheon revealed a gradual decline in the road closure's impact and a subsequent decrease in vehicle usage, underscoring the elastic nature of traffic responses to road closures.

Mansoor et al. (2022) highlight that the primary benefits of car-free districts stem from increased non-motorized traffic, leading to more physical activity. In our study, such an increase was initially observed in the inner Südliche Au post-project implementation, but the activity diminished within three weeks, as indicated by declining heatmap brightness values across all measured areas. Consequently, the main anticipated benefits were not substantiated in this study, partly due to the lack of environmental or social impact assessments in the study areas.

5.1.3. Data integrity and limitations

A key element of this study is the use of open-source data, offering significant advantages such as replicability of the data collection process across different areas and public accessibility. This methodology allows for the straightforward application of our data collection procedures in various locations. However, challenges with open-source data include issues with consistency, usage limitations, and the difficulty of obtaining specific data needs. Consequently, our approach to analyzing transportation effects had to adapt to the available data, rather than being driven by our specific data requirements.

The study encountered specific challenges in data collection. Google Maps data, initially selected to measure public transportation impacts, proved inconsistent and unsuitable. Similarly, collecting data on walking and cycling activities was challenging, particularly in cases without active tracking, which limited the utility of heatmap-related data. This data was reliant on users recording their activities, a prerequisite for inclusion in the study. Moreover, the infrequent updates of the heatmap, occurring every four to six weeks, limited the accuracy of observations regarding the project's impacts. Additionally, obtaining data on alternative transport modes like e-scooters, e-mopeds, and e-bikes was problematic due to limited open data access from various other rental companies and the exclusion of the Walchenseeplatz area from the companies' service zones. Furthermore, refining the data processing of counting vehicles in specific areas is needed, as the chosen method may not accurately reflect actual usage frequency. Although overall traffic data showed greater consistency and availability, using only relative speed data provides a limited view of an area's traffic state. Incorporating vehicle counts and lane information could yield more comprehensive results.

Another significant challenge in this study was the disparity in data collection durations for pre- and post-project phases, constrained by the paper's time limitations. Additionally, missing values throughout the datasets hindered effective averaging, which was essential for synthesizing large volumes of data and understanding inter-dataset relationships. While daily averaging provided a general overview, it failed to capture nuances like rush hour trends or time-specific outliers in all variances of data. The strategy of utilizing available data, rather than specifying needs, offers reproducibility benefits. However, challenges such as combining diverse data sources, managing inconsistencies, and navigating usage restrictions can adversely affect the accuracy of the results.

5.2. Evaluation of model efficacy

This chapter examines the features and target variables employed in our model development, evaluating the models' predictive performance, goodness of fit, and cross-model validation across both study areas. It also reflects on the methodological approach in light of these results.

5.2.1. Comparative analysis of feature and target variables in models

In evaluating models for both study areas, the inner and outer speed variables emerged as key predictors, though their time-dependency necessitated averaging by weekday. The prominence of these speed variables in predictions is logical, given their direct relation to the outcomes they forecast. However, a model relying solely on these speed variables underperformed compared to the more comprehensive model in both study areas, evidenced by a lower R^2 and higher MAE. Splitting the inner and outer features across the 92 measurement points improved the model's R^2 by 0.04. However, for clarity and ease of reuse, the model employed summarized features despite this apparent enhancement. In this multioutput model with eight target variables, each averaged counterpart features exhibited distinct feature importances.

While 'inner_speed1' was a dominant feature in both models, the significance of subsequent features varied.

Table 11: Inner mean relative speeds and variance (in brackets) before and after the projects implementation of each target variable

	Südliche Au (12.06.2023)		Walchenseeplatz (05.07.2023)	
	Before	After	Before	After
Inner_speed1	0.86 (0.009)	0.86 (0.014)	0.79 (0.012)	0.83 (0.011)
Inner_speed2	0.86 (0.010)	0.85 (0.013)	0.83 (0.009)	0.85 (0.012)
Inner_speed3	0.87 (0.001)	0.83 (0.015)	0.85 (0.009)	0.86 (0.013)
Inner_speed4	0.71 (0.004)	0.86 (0.014)	0.86 (0.010)	0.90 (0.010)
Inner_speed5	0.83 (0.012)	0.86 (0.015)	0.85 (0.012)	0.86 (0.013)
Inner_speed6	0.84 (0.006)	0.85 (0.015)	0.87 (0.011)	0.90 (0.010)
Inner_speed7	0.83 (0.007)	0.85 (0.016)	0.86 (0.010)	0.90 (0.010)
Inner_speed8	0.81 (0.011)	0.77 (0.017)	0.87 (0.011)	0.86 (0.013)

In the Südliche Au model, 'inner_speed4' exhibited minimal importance, aligning with the findings presented in Table 11. This table details the mean and variance (indicated within brackets) of the target features, highlighting a significant difference in the relative speed of 'inner_speed4' before and after the project implementation. This lack of importance is reflected in the high Mean Absolute Error (MAE) and one of the lowest R^2 values for 'inner_speed4'. Furthermore, variables like 'inner_speed1', 'inner_speed2', 'inner_speed5', and 'inner_speed8' in Südliche Au demonstrated lower MAEs and higher R^2, likely due to their higher variance, approximately 0.01, compared to the around 0.005 variance of 'inner_speed4', 'inner_speed5' and 'inner_speed7' with a resulting R^2 of around 0.11. This difference becomes more pronounced post-road closure, with variances around 0.015.

In contrast, Walchenseeplatz's model identified 'inner_speed8' as having the lowest importance, unique in its decreasing relative speed but on the other hand having one of the higher R^2. Which again can be reasoned by the higher variance before the project start, similar to 'inner_speed1' and 'inner_speed5', which have the highest variances before and also higher R^2 around 0.25. The higher variances and lower R^2 values observed in some prediction variables are likely attributable to their varying locations within the inner study areas. These different locations can lead to distinct traffic patterns, influencing the variability and predictability of these variables. Also, the overall variation in the feature importances of different 'inner_speed' variables can be attributed to their correlations and distinct locations within the inner study areas, resulting in more pronounced differences in relative speeds. Interestingly, the 'outer_speed' feature, like the inner area features, exhibits high importance and predictability in the model. It's noteworthy that this feature represents an average across approximately 50 distinct measurement points. The similarity in mean and variance between 'outer_speed' and the inner area features suggests that it is a reliable predictor, demonstrating comparable behavior across different areas of the study.

Interestingly, in the Südliche Au area, wind peak gust emerged as a significant predictor, initially seeming unrelated. This correlation might be attributed to the impact of stormier weather conditions, indicated by higher wind speeds, on traffic dynamics. Conversely, in the Walchenseeplatz model, wind peak gusts emerged as one of the less significant weather features, with minimum and average temperatures showing greater influence. The role of the weather dataset in this model, especially regarding the importance and accuracy of features like minimum and average temperature, requires additional investigation and research to validate the model's accuracy. Beyond weather factors, the day of the week stood out as a critical feature, with its future values being predictable. This suggests that the day of the week has a substantial influence on relative speed, more so than other variables that could be predicted, offering valuable insights into traffic behavior.

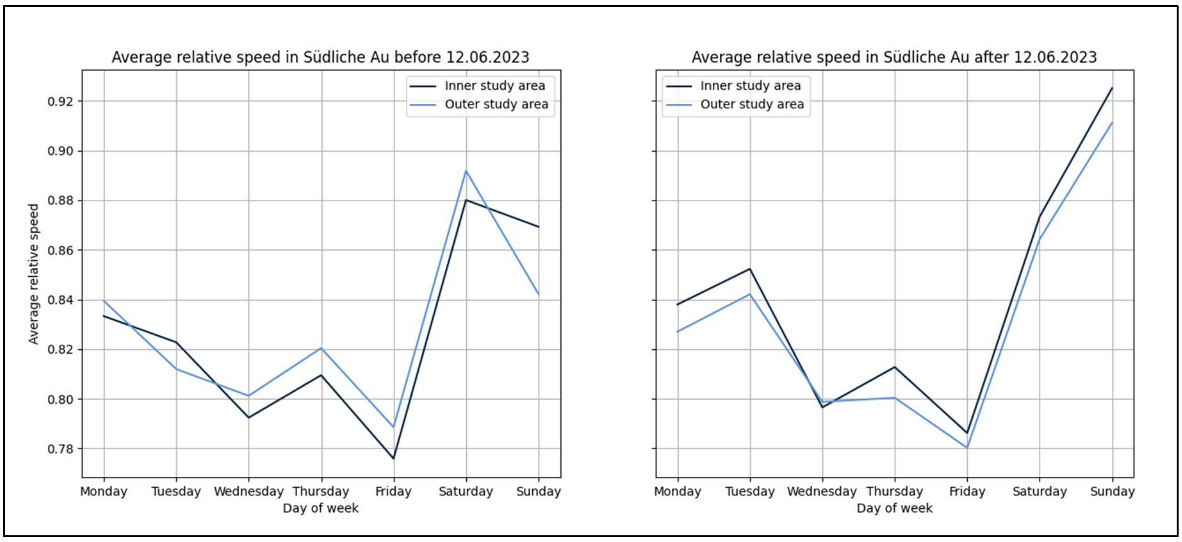

Figure 21: Averaged relative speed per day of week in Südliche Au

Figure 21 displays the average relative speed by day of the week in Südliche Au, highlighting the day's influence on traffic conditions both before and after road closure. This observation aligns with expectations, particularly when considering weekday traffic patterns, which are typically more congested due to work-related commuting, compared to weekends. A similar trend is evident in the Walchenseeplatz data, as shown in the Appendix A7.

The influence of alternative mobility features like e-scooters and e-mopeds on speed prediction is minimal, with inner area features being more impactful than outer area ones. However, their effect is negligible, as excluding these variables only worsens the model's R^2 by 0.001. Adding to this influence is the aspect that the data collection started around three weeks later than the traffic data collection, which led to imputation and shortening parts of the earlier time frame. They were retained in the model due to potential correlations. Notably, attempts to predict inner e-scooter and e-moped usage were inaccurate, suggesting that this data may be challenging to forecast effectively without specialized model training and tuning.

In the Südliche Au model, the inner and outer sports-related activity data had no significant impact on model performance. This outcome is understandable, given the near-zero variance in the heatmap data due to the late start of data collection, which contributes minimal predictive value. In contrast, within the Walchenseeplatz model, this feature ranks in the top 20, likely due to the absence of e-scooter and e-moped data, because the importance is still very low. However, attempts to predict inner and outer heatmap-related data were unsuccessful, primarily because of the extended duration between changes in the data and the negligible variance observed. The bicycle data from Erhardtstraße influenced the model's prediction, with a strong correlation observed among north, south, and total directions, leading to the inclusion of only the total count. Conversely, at Walchenseeplatz, despite the measurement point being farther away than Südliche Au, bike data had a more significant impact.

Features describing the project implementation were also time-dependent, such as the number of removed parking spots, new mobility hubs, and the percentage of road closures. Initially, these values were zero and then increased post-implementation. Notably, at least one of these variables influenced each model, indicating their minimal impact on prediction. The variation in the significance of these features across different models may be attributed to correlations among them and the complexity of the machine learning model. Despite the values remaining constant post-road closure, their slight importance in the model suggests that the road closures had some effect on relative speeds. Overall, using these variables to represent the project's initiatives might not be the most effective approach for future studies.

The negligible impact of non-time-dependent variables such as age and amenities on the model's prediction power can be attributed to several factors. Primarily, their relevance to time-dependent variables, which are characterized by temporal dynamics, is minimal. If there's little or no correlation between these non-time-dependent features and the target variables, their influence on predictions is almost null. This is particularly evident with variables like age, where there may be no direct correlation between the residents' age and the area's overall traffic state, especially considering factors like transit or drive-through traffic. Moreover, other variables in the model might have a greater influence and effectively encompass the information that non-time-dependent features could provide.

5.2.2. Assessment of overall model prediction performance

The performance of the RF model was assessed using R^2 for goodness of fit and MAE for accuracy. For each of the eight target variables and the overall multioutput models, the R^2 did not exceed 0.3, indicating a modest fit. Similarly, the MAE was around 0.1, not optimal considering 50% of predictions were within a range of 0.16. In contrast, J. Wood et al. (2023) reported R^2 values between 0.64 and 0.78 in their RF model, suggesting a significantly better fit due to the inclusion of precise passenger occupancy data with weather information. Meanwhile, Yang et al. (2023) achieved high predictive values in a classification task using RF, as reflected by their F1 scores, although this metric is not directly comparable to R^2. Though, when comparing the RF model to the constructed linear regression, it shows superior performance, suggesting a well-reasoned approach in model selection.

In our study, the hyperparameters for the RF models were optimized using GridSearchCV, revealing similar configurations for both study areas. Each model utilized 1120 trees, striking a balance between complexity and performance. For the Südliche Au model, a 'max_depth' set to None permitted trees to grow until reaching a 'min_samples_split' of 12. This configuration was key in capturing intricate patterns within the data. Additionally, setting 'min_samples_leaf' to 5 helped prevent overfitting by ensuring that each leaf node had enough samples. Conversely, in the Walchenseeplatz model, 'min_samples_split' was reduced to 2, the lowest possible value, with 'max_depth' set to None aiming to discern extremely fine-grained patterns. However, this heightened sensitivity necessitated caution against overfitting. To mitigate this risk, 'min_samples_leaf' was also set to 5, ensuring a balance between capturing detailed data patterns and maintaining the model's ability to generalize effectively.

Predicting future values based solely on historical data yielded a low R^2, close to 0, suggesting that historical data alone were insufficient for accurate predictions of future relative speed. This lack of predictive power can be attributed to the unpredictability of speed using only historical values and possibly the choice of predictors derived from open-source data, which may not significantly influence speed. Other variables, such as school holidays and other potentially influential events, were not included in the data collection, further limiting the model's effectiveness. To improve predictions, future values were estimated by averaging historical data by weekday. This method, selected after testing two imputation strategies (mean and averaging by weekday), proved higher effectiveness. The choice was also influenced by the significant impact of weekdays on the model.

In efforts to enhance the model, incorporating actual future values improved performance selectively. Including real-time future weather conditions paradoxically worsened the model's fit, despite increasing the importance of these features. The outcome, which suggested that weather variables influenced relative speed despite worsening the model fit, presents a paradox that warrants further detailed investigation. This contradiction in the results indicates a need for more focused research to understand the true impact of weather conditions on relative speed and to resolve the apparent discrepancies in the model's performance. Contrarily, integrating future values from activity-related heatmap data raised the overall R^2 to 0.28, a result that was challenging to rationalize given the decline in data values, lack of variance, and minimal importance when averaged. Notably, the inclusion of future outer relative speed values significantly boosted model performance, elevating R^2 from around 0.3 to approximately 0.9. This substantial improvement underscored the strong correlation between outer and inner speed values.

When assessing the predictive capabilities of the models for both areas, the model for Walchenseeplatz exhibited a higher R^2. This can primarily be attributed to the more extensive collection of pre-project data, providing a larger dataset for training. Consequently, the model could better capture and predict the variance in the target variables due to the increased volume of pre-project training data.

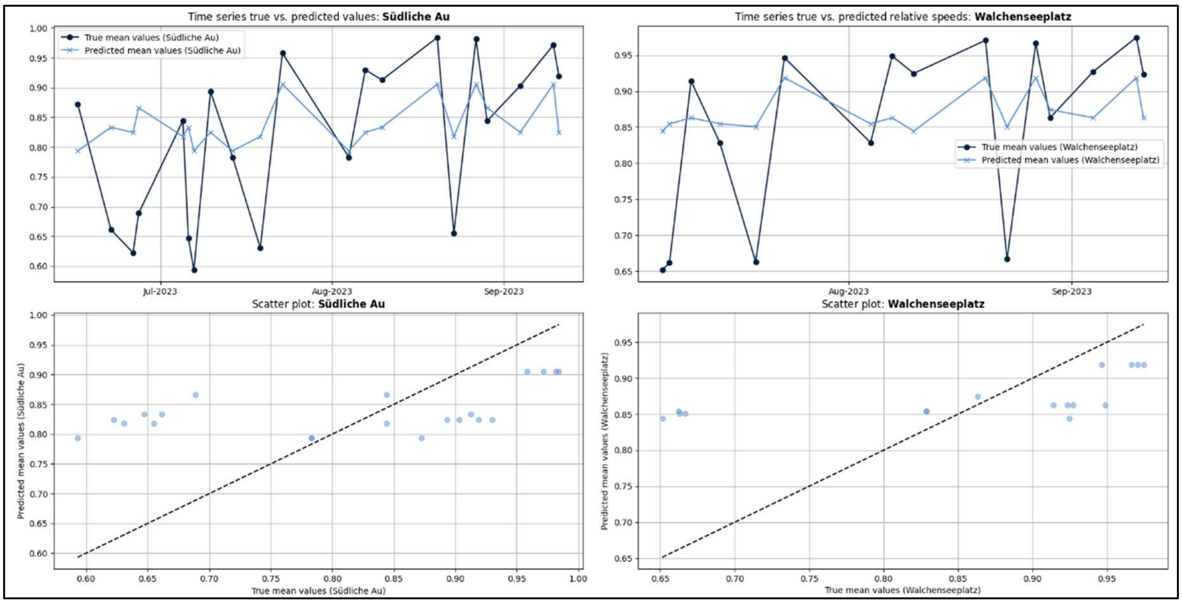

Figure 22: Time-series and scatter plot for Südliche Au (left) and Walchenseeplatz (right)

Figure 22 showcasing time-series and scatter plots for both study areas, reveals another reason for the higher prediction accuracy of the Walchenseeplatz model: its mean true values display less variance, ranging between 0.85 and 0.95. In contrast, the Südliche Au area shows a wider range of 0.75 to 0.95. Additionally, the aspect of extending data collection before the start of the project is a non-negligible factor. For future projects, a prolonged period of data gathering could lead to higher and improved model accuracy. Longer data collection periods provide a more comprehensive dataset, allowing for a deeper understanding of baseline conditions and more precise modeling of potential impacts. Furthermore, the similarity in the prediction time-series of both areas suggests comparable traffic conditions, indicating that the projects' initiatives had a limited impact on the overall traffic state. The plots collectively indicate that the model struggles to accurately predict variance in the data, as evidenced by the low R^2 and higher Mean Absolute Error (MAE). This suggests limitations in the model's ability to capture and replicate the variability present in the underlying data.

For the purpose of evaluating the model's applicability to similar projects, the Walchenseeplatz model was applied to the Südliche Au project. This cross-application revealed significant limitations. When tested solely on post-project initiation data, the model yielded a negative R^2, suggesting that simply using the mean of the data would have been more predictive. Incorporating pre-project data improved the goodness of fit slightly, yet the overall predictive capability remained suboptimal. These results unfortunately indicate that the model, as trained on the Walchenseeplatz data, may not be effective for forecasting traffic conditions following road closures in urban settings. This limitation highlights the challenges in transferring predictive models across different urban contexts and the importance of tailoring models to specific project characteristics and data environments.

5.2.3. Reflection of methodological approaches

This section reflects on the modeling approach chosen for this study, particularly focusing on the use of RF models and their associated challenges. Despite their capabilities, both models in our study did not yield highly accurate results. One key difficulty with RF models is their interpretability; as observed, features such as bike and weather data impacted the model's predictions in ways that were not easily explainable.

Additionally, RF models depend on robust and complete datasets. In our case, computational issues led to some missing values, potentially undermining the model's performance. The overall feature selection for data collection could have been improved regarding the choice of locations and the duration of the collection period. While thoguh the data collection process provided a rich dataset with a high number of variables, which in theory could enhance model training, RF can sometimes struggle with datasets featuring many features. Also, the high number of variables in the model contributed to challenges in interpretation and reproducibility for future projects. Additionally, presence of many variables in the dataset, leading to increased overall data volume, presented challenges during the hyperparameter tuning phase of our RF model, notably in terms of computational demands. This complexity in the dataset, combined with the intensive process of hyperparameter optimization, resulted in computational difficulties, impacting the efficiency and feasibility of the modeling process.

On the positive side, RF is known for its robustness against overfitting and its ability to effectively handle non-linear relationships, making it a potentially strong candidate for complex analytical tasks. However, to comprehensively evaluate the effectiveness of our methodological approach, exploring alternative machine learning techniques, such as Deep Neural Networks, could be beneficial. Due to the scope and limitations of this thesis, such exploration was not feasible at this stage, but it presents a valuable avenue for future research.

6. Conclusion

The conclusion summarizes the thesis's key findings, explaining how the research question was answered and the impact of car-free initiatives on urban mobility. It discusses the practical implications and potential applications of the methodology in urban planning. The conclusion also recognizes the study's limitations and suggests future research directions to expand upon these findings.

6.1. Summary and contribution

This thesis aimed to explore the traffic impacts of road closures within the aqt project in Munich, analyzing historical data including traffic conditions, alternative and active transportation modes, demographics and weather conditions.

The literature review on reducing car infrastructure showing an 11% decrease in traffic volume, which aligns with this thesis, and different results from global case studies. In cities like Seoul, Calgary, and Oslo, initial increases in travel time and public transport use, as well as reductions in vehicle trips, were observed. These changes, however, often diminished over time, reflecting the traffic system's elasticity. Notably, a long-term study in Seoul showed a gradual improvement in speed over three years, with declining car ownership and rising public transport use. In contrast, Paris's road closure study highlighted increased congestion and worsened traffic conditions. These varied findings highlight the complexities of road closures and infrastructure reduction in urban mobility.

In this study, data-driven modeling in transportation research was found effective, with RF Regression achieving R^2 values between 0.6 and 0.8 in different studies. To analyze travel behavior changes in two project areas, data on multiple transportation modes, weather, amenities, and demographics were collected within a 1.5 km radius of the projects. This included measurements of current and free-flow speed at 92 points, e-scooter and e-moped counts, and analysis of heatmap data for foot and cycling mobility. All data, sourced from open platforms, was processed for analysis and visualization. A RF model, adept at handling non-linear data and complex patterns, was developed. Its accuracy, assessed using mean absolute error and R^2, was fine-tuned through hyperparameter optimization.

Before the project, average relative speeds were 0.82 in Südliche Au and 0.85 in Walchenseeplatz, both increasing by 0.2 post-implementation, a change not deemed significant. E-scooter usage in Südliche Au's inner area fell by about 5%, but rose by 28% in outer areas. E-moped usage grew by 25% in outer and 38% in inner areas. Activity heatmap data showed a slight decrease, marking the only features with significant change. Weather data from Südliche

Au indicated higher average temperature and precipitation, but stable wind speeds and air pressure. Demographics revealed a predominant 30-40 year age group in both areas, with Südliche Au being more commercial and Walchenseeplatz more residential. Road closures of the aqt project accounted for 9% of street length in Südliche Au and 4% in Walchenseeplatz. The RF models for Südliche Au and Walchenseeplatz primarily identified speed variables, averaged by weekday from pre-project data, as dominant features. Day of week and weather variables also influenced model accuracy. Despite their insights, both models achieved only moderate fit, with an R^2 of around 0.2 and an MAE of approximately 0.1. This performance, while modest, surpasses the linear regression's R^2 of 0.1 obtained using the complete training dataset. The longer duration of data collection at Walchenseeplatz contributed to a slightly better model accuracy. However, when this model was applied to Südliche Au, it necessitated the inclusion of pre-project data to achieve a reasonable fit. Omitting this pre-project data led to a negative R^2, highlighting the model's dependency on historical context for accuracy.

The findings of this thesis reveal that the car-free initiatives in the study areas had minimal impact on traffic, evidenced by the lack of significant change in data and the low accuracy of the model in predicting traffic post-road closure. A slight increase in relative speed suggests that reducing car infrastructure might improve traffic conditions, echoing literature findings that generally associate traffic volume reduction, particularly when major roads are not affected. The younger demographics and abundant amenities and public transport options in Südliche Au and Walchenseeplatz suggest a lower dependency on cars among residents, possibly contributing to the minimal impact of car-free initiatives on traffic in these areas. Dominant features of the RF like historical relative speed, weather, and day of the week were identified, but the absence of factors like major construction events and school holidays could have limited the model's accuracy. This suggests that such other variables, not included in the project's initiative, might play a more significant role in determining traffic conditions. Interestingly, incorporating future values of e-scooters and e-mopeds enhanced model accuracy slightly, while using the outer area's relative speed to predict the inner area's speed significantly increased R^2 to around 0.95. This high correlation implies a strong dependency between inner and outer area traffic, indicating that the road closures in the inner areas did not substantially affect traffic flow. Furthermore, the enhanced predictive capability of the Walchenseeplatz model underscores the value of detailed and extended data collection in achieving better model accuracy. This observation affirms the overall efficacy of the modeling approach employed, particularly when contrasted with linear regression methods, which yielded less favorable outcomes. The higher success of the Walchenseeplatz model suggests that investing in comprehensive data collection and analysis can significantly improve the precision and reliability of predictive models.

The research presented in this thesis demonstrates that road closures have a negligible impact on travel behavior, considering factors such as relative speed, alternative modes of transportation, weather conditions, amenities, and demographics. The observed minimal improvement, though slight, indicates that the initiatives do not substantially disrupt traffic conditions. Furthermore, they may encourage the adoption of sustainable transportation modes and enhance active mobility. Given the limited predictive power of the models developed, the findings are primarily applicable to the studied areas. This research also underscores the complexity of urban mobility and the nuanced impact of car-free initiatives.

6.2. Practical implications, limitations and future direction

This thesis explores the effects of car-free initiatives on urban mobility, employing open-source data to develop predictive models. While the initial models, lacking future values and an extensive and detailed data collection, showed limited predictive power, integrating forward-looking variables like weather and alternative transport modes may improve their efficacy. For broader application and refinement, the models and datasets are openly accessible (see Appendix A) to facilitate enhancements or adaptations to similar projects. The data collection, rooted in open-source methods, is replicable with the addition of API keys and other cost-free resources detailed in the repository, ensuring wide accessibility and adaptability.

However, the study faces limitations due to its dependence on open-source data chosen for availability rather than specific research needs, leading to challenges in data acquisition and processing. For example, the use of inconsistent crowding data at public transport stations was hindered by data restrictions. Additionally, the large and semi-structured nature of the open-source data required extensive processing, and computational and API constraints led to the averaging of data from hourly to daily measurements, potentially omitting critical contextual details like peak hours. Moreover, the study's scope, focused on Munich, may limit its applicability to other cities or varied urban initiatives. Similarly, the time constraints faced during this thesis limited the extent of detailed data collection both before and after the implementation of the projects' initiatives, potentially restricting the depth of the research conducted.

Despite these challenges, this thesis lays a solid groundwork for future exploration in car-free initiatives, providing valuable insights and methodologies that could significantly influence the creation and management of new car-free zones and events. It underscores the potential of these initiatives to enhance urban sustainability and liveability, all while minimally impacting traffic flow. The findings, demonstrating negligible traffic disruptions in specific urban settings, offer essenital insights for urban planners and policymakers considering similar car-free strategies. These strategies are aimed not only at reducing automobile dependence but also at promoting sustainable and eco-friendly transportation alternatives, which are increasingly vital in today's urban landscapes.

As we look forward, this research sets a course for comprehensive investigations into the multifaceted impacts of car-free environments. The adoption of car-free zones represents a transformative approach to urban development, going beyond merely easing traffic congestion. It's about reshaping urban spaces to prioritize community well-being, environmental responsibility, and enhancing overall quality of life. This thesis suggests that future research should expand its focus to include a wider range of data sources, encompassing varying urban dynamics. Cross-city comparative studies could provide a broader understanding of the efficacy of car-free zones in diverse urban settings. Conducting long-term studies would offer insights into the enduring effects and public reception of these initiatives. Advanced modeling techniques should be employed to capture the complex dynamics of urban mobility and the socio-economic and environmental facets of car-free zones. Moreover, the potential for applying this model to other projects is further enhanced by integrating longer and more extensive data collection. Such an analytical approach is essential to understand the broader implications of these initiatives and to guide effective policy-making. It advocates for building urban spaces that are not only livable but are also resilient and forward-looking, leading the way towards a sustainable, car-free future. This vision for urban development is not just an aspiration but a necessary evolution to create cities that are adaptive, environmentally conscious, and focused on the health and happiness of their residents.

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Appendix

Appendix A: Access to open-source models

The data collection, model development, and testing processes for this study are documented in the referenced GitHub repository 'masterthesis-lin-tim'[2], which contains guidelines for using and further developing the model. However, for data collection, additional efforts are required, such as obtaining API keys and specifying location points. It's important to note that the data processing phase involved the use of multiple tools, which are not included in the repository. Consequently, users may need to independently manage these aspects of the process.

Appendix A1: Study areas in the context of the city of Munich

Figure 23: Study areas within the Munich cityscape

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[2] github.com/tolltim/masterthesis-lin-tim

Appendix A2: Geographical visualization of amenities in the study area

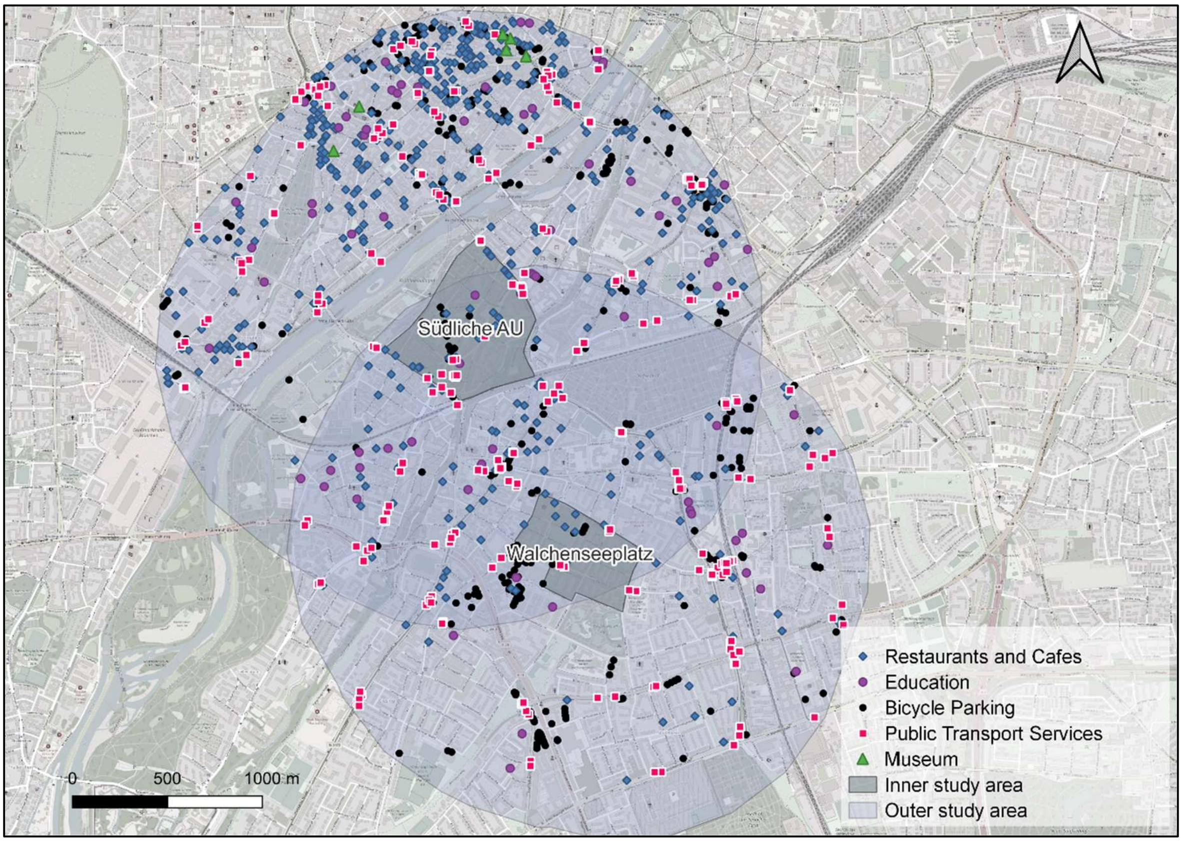

Figure 24: Amenities visualized in the study areas

Appendix A3: Descriptive statistic of weather data for both study areas

Table 12: Descriptive statistics weather data

Südliche Au | **Walchenseeplatz**

	Before 12.06.23				After 12.06.2023				Before 05.07.2023				After 05.07.2023			
	tavg[3]	prcp[4]	tsun[5]	wspd[6]	tavg	prcp	tsun	wspd	tavg	prcp	tsun	wspd	tavg	prcp	tsun	wspd
Mean	15.32	2.02	493.76	9.56	20.36	3.48	507.79	9.22	17.19	2.12	524.41	9.72	20.33	3.81	493.71	9.04
Range	11.10	20.30	907.00	7.60	16.20	41.60	933.00	16.50	15.80	20.30	933.00	10.80	16.20	41.60	917.00	16.50
25th percentile	11.90	0.00	246.00	8.30	18.38	0.00	276.00	7.10	14.80	0.00	296.75	8.30	18.20	0.00	229.00	6.80
75th percentile	18.10	0.00	799.00	11.20	22.82	2.73	737.00	10.40	19.42	0.43	800.75	11.20	22.90	3.60	73.00	10.10
t-statistics					-8.01	-1.18	-0.35	0.56					-4.89	-1.52	0.68	1.47
p-value					0.00	0.24	0.73	0.58					0.00	0.13	0.49	0.14

In Table 12 the t-statistics and p-value is calculated on the change before and after the projects implementations.

[3] tavg = Average temperature [°C]

[4] prcp = Precipitation [mm]

[5] tsun = Sunshine duration [min]

[6] wspd = Wind speed [m/s]

Appendix A4: Correlation matrix for Walchenseeplatz

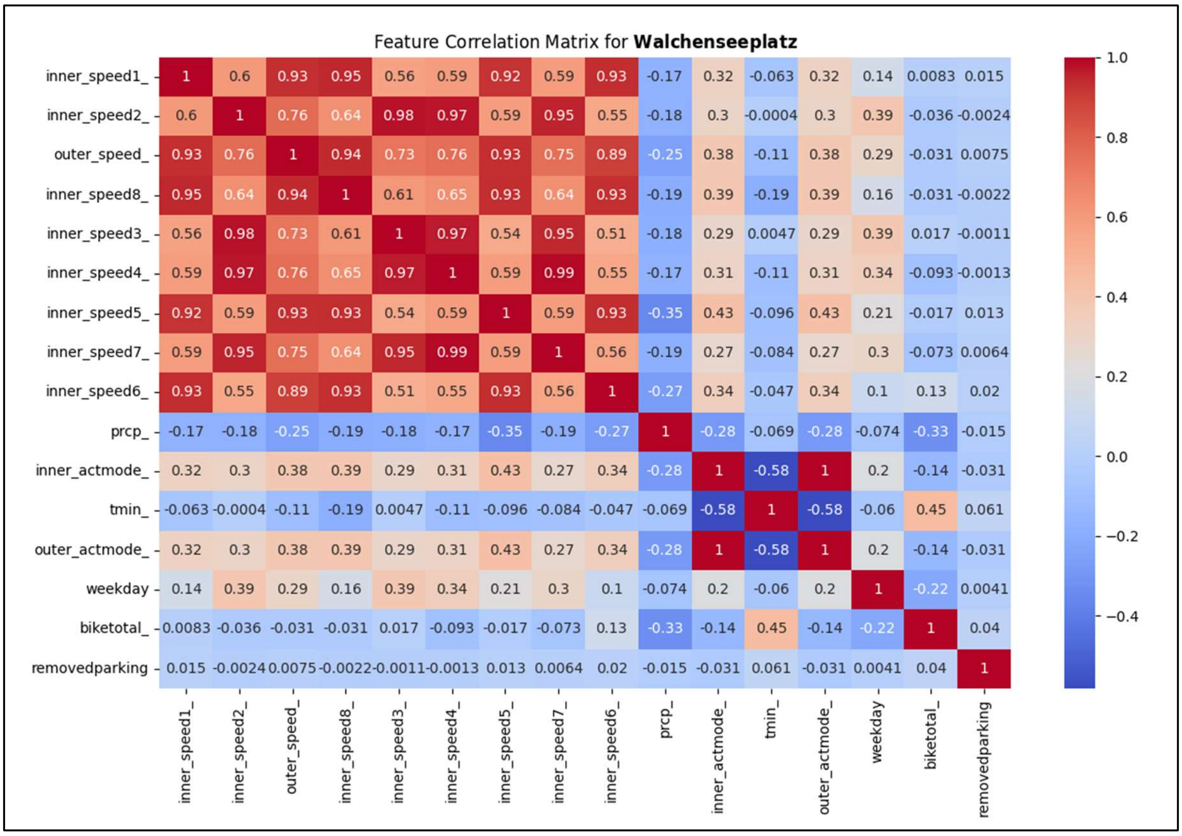

Figure 25: Correlation matrix for Walchenseeplatz

Appendix A5: Further developed models

Building a RF model incorporating future values of e-scooter, e-moped, and activity data raised the overall R^2 to 0.26, with 'inner_escooter' as the dominant feature and others also significantly influencing model accuracy, as shown in Figure 26.

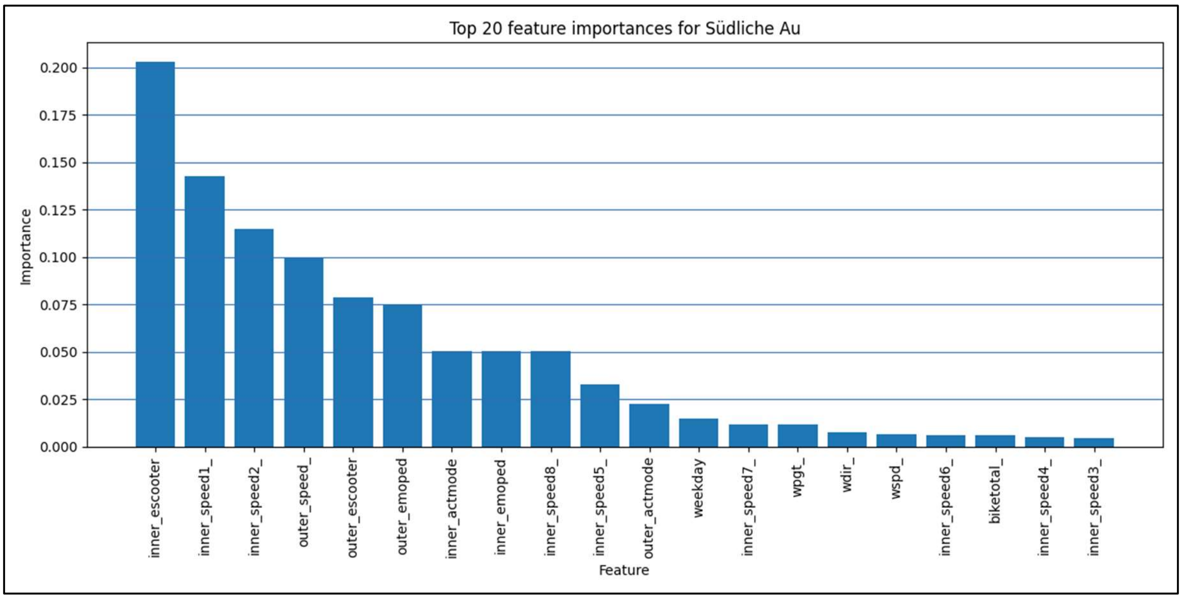

Figure 26: Top 20 feature importances Südliche Au with future values

The scatter plot and the prediction vs. actual values could be predicted better, with the diagrams showing in Figure 27.

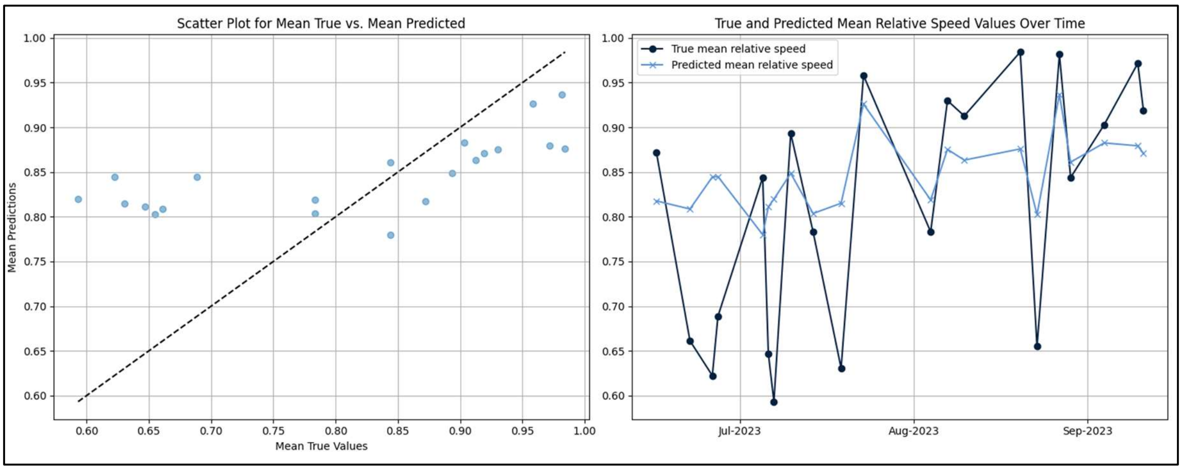

Figure 27: True vs. predicted values for Südliche Au with future values

At Walchenseeplatz, the inclusion of future activity-related data, in the absence of e-scooter and e-moped data, improved the model's R^2 to 0.26. This enhancement is depicted in the scatter plot in Figure 28 Additionally, the feature importances for both inner and outer ‘actmode’ rose to approximately 10%.

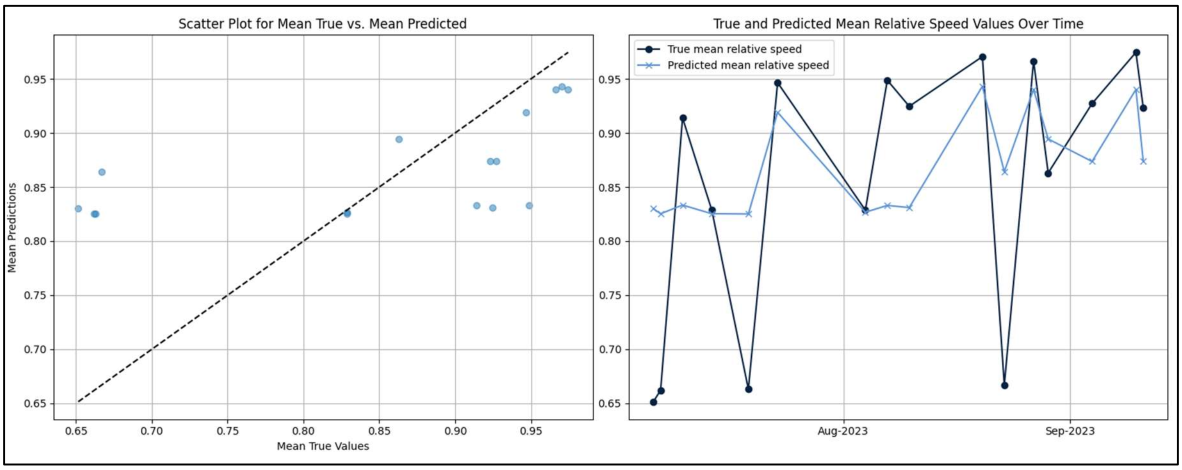

Figure 28: True vs. predicted values of Walchenseeplatz with future activity related data

Introducing the future values of the ‘outer_speed’ variable significantly improved the R^2 of both models, reaching between 0.92 and 0.96. This highlights the similarity in traffic conditions between the inner and outer study areas. Figure 29 Introducing the future values of the ‘outer_speed’ variable significantly improved the R^2 of both models, reaching between 0.92 and 0.96. This highlights the similarity in traffic conditions between the inner and outer study areas.

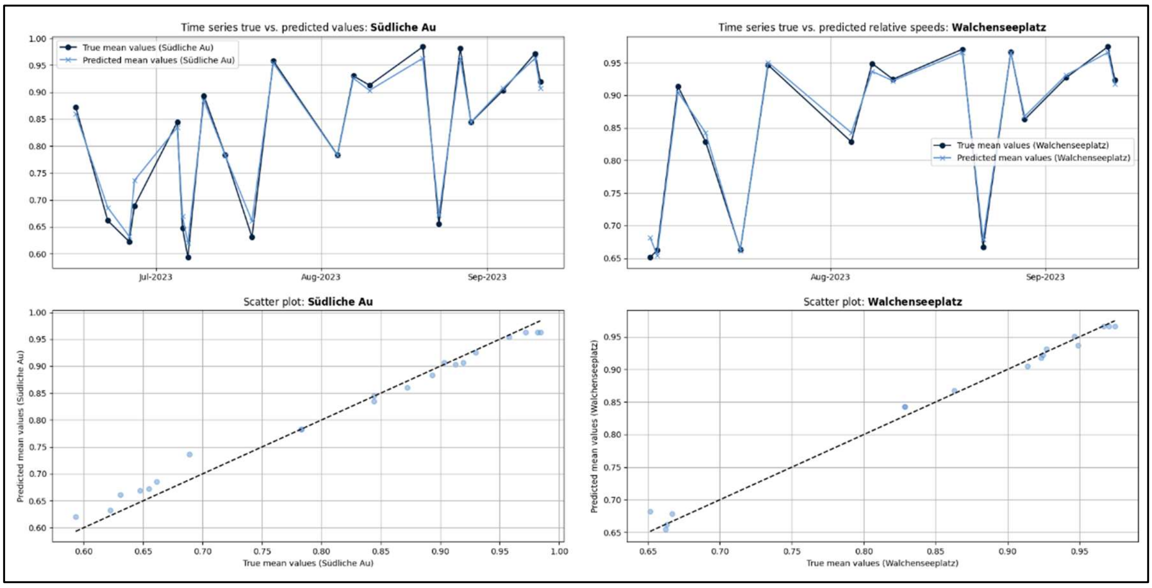

Figure 29: True vs. predicted values for Südliche Au (left) and Walchenseeplatz (right) with future outer relative speed data

Appendix A6: Precipitation, temperature and relative speed over time at Walchenseeplatz

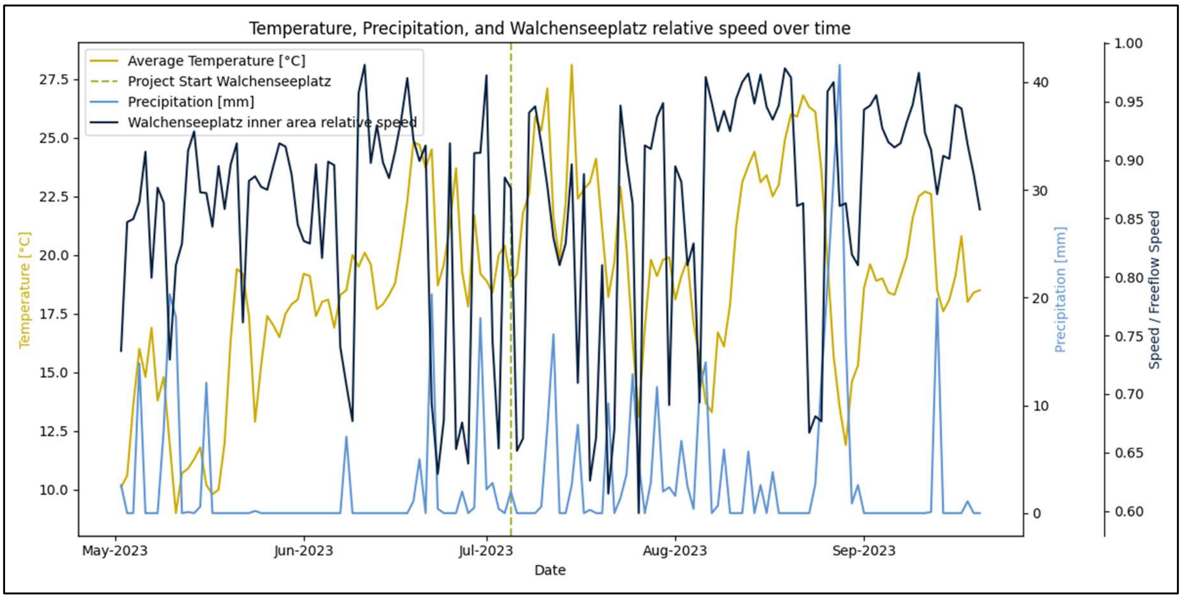

Figure 30: Precipitation, temperature and relative speed over time of Walchenseeplatz

Appendix A7: Relative speed per day of week of Walchenseeplatz before and after project start

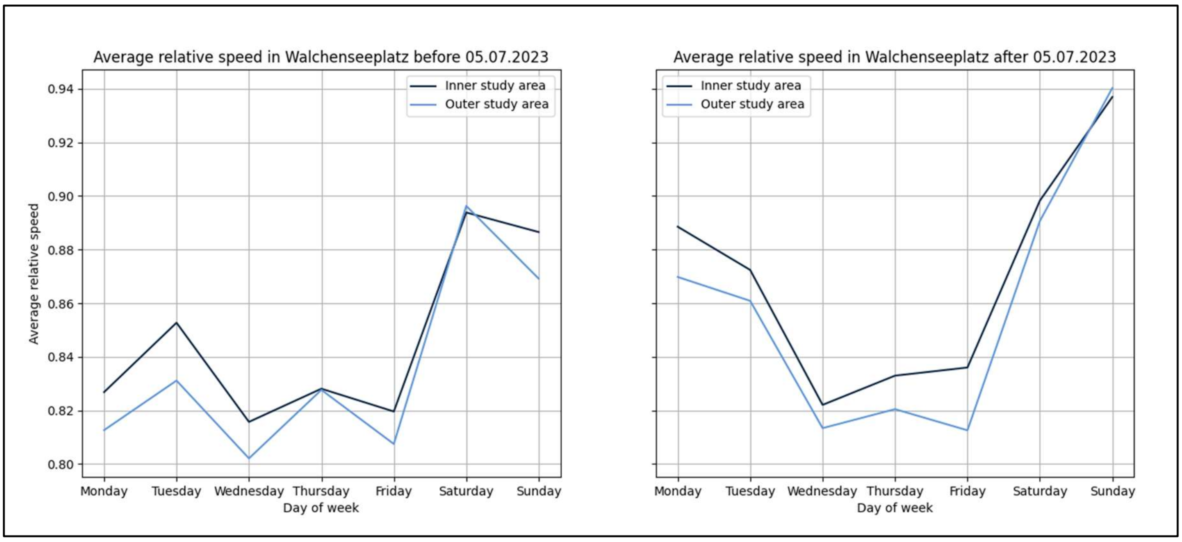

Figure 31: Relative speed per day of week of Walchenseeplatz before and after project start

Declaration

I hereby confirm that the presented thesis work has been done independently and using only the sources and resources as are listed. This thesis has not previously been submitted elsewhere for purposes of assessment.

Munich, 01.12.2023 Lindermaier

Place, Date, Signature