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ENHANCING URBAN LIVABILITY: EXPLORING THE IMPACT OF ON-DEMAND SHARED CCAM SHUTTLE BUSES ON CITY LIFE

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Livable cities involve such quality-of-life factors as transportation, convenience of daily life, education, and a safe and stable built and natural environment. The livability of a city also has social and psychological dimensions, such as emotion and perception. This paper explores how the advantages of new transportation technology can be realized under mixed-traffic conditions, while meeting the requirements for safety, convenience, and high educational standards. One of the key challenges to realizing the advantages of a new technology, such as autonomous shuttle buses, under mixed-traffic conditions and under adverse weather conditions is how to strike a balance between innovation and adherence to essential urban demands. Ensuring that the introduction of advanced technologies like autonomous shuttle buses does not compromise safety is of the utmost importance. Under mixed-traffic conditions, autonomous shuttle buses must negotiate interactions with human-driven vehicles, pedestrians, and bicyclists. Predictable and safe driving behavior is vital to gaining the confidence and acceptance of all road users. Additionally, adopting vehicle-to-everything (V2X) communication enables real-time information exchange with other vehicles and infrastructure, which enhance safety. Autonomous shuttle buses also face crucial challenges in adverse weather conditions. Robust sensor systems are required to accurately perceive the environment despite rain, snow, fog, and other weather-related constraints. Continual learning and software updates ensure the system's ability to adapt to changing weather conditions. To overcome these challenges, collaboration with regulatory bodies and traffic management authorities is essential. Furthermore, public awareness campaigns and educational initiatives can inform the public about the safety measures and benefits of autonomous shuttle buses, fostering acceptance and reducing concerns during the transition.

Keywords: Autonomous shuttle bus, road congestion, public transportation of people and goods, livable cities

1. Introduction

Thinking about shared connected cooperative autonomous mobility (CCAM) recognizes several levels of autonomy, and these apply to autonomous shuttle (AS) buses. AS bus with a low degree of autonomy (SAE level 3) is required to travel in a special lane (a.k.a. a segregated lane). A fully automated shuttle bus (SAE level 4) has full control over all functions and can travel in mixed traffic, sharing the road with other road users (motorized and vulnerable ones. ASs can communicate with each other and share information about the surrounding environment. Such communication is not limited to communication between cars, nor between cars and infrastructure (Bucchiarone *et al.*, 2020; Ainsalu, 2018) but can involve communication among all traffic participants to reach the highest level of service as well as of safety. Our motivational idea to introduce an AS bus (TH-AS) at the Technical Hochschule was inspired by a preliminary survey on citizen participation in city life, which solicited opinions from students at the University of Applied Sciences, Aschaffenburg. The preliminary results showed that a shuttle bus connecting all three campuses would lead to safer roads, less congestion, less time in search of parking spaces, and less stress for students trying to get to classrooms on time. The challenges to operating the TH-AS fall into categories: social and research.

As for the social challenges, the TH-AS will travel through the city and share the same roads with public transportation and taxis, in effect competing with them. Also, some people will trust AS less than the alternatives and will have anxious and skeptical attitudes toward the new technology (Salonen & Haavisto, 2019). On the other hand, our experience from open campus days, and various exchanges with citizen groups, shows, that children of kindergarten age and their parents, are open to new opportunities and are ready to engage in discussions about on how to realize an acceptable and convenient AS service. To collect citizens' opinions on this subject, a questionnaire will be distributed, and interviews will be performed to gauge attitudes toward these new technologies. The research challenges to the TH-AS involve its response times to anomalies in real-time (Raiyn, 2022; Inlodean, 2017). An anomaly detection must be able to discover patterns which do not conform to normal expected behavior in the data. Anomalies disrupt both the TH-AS and its users and thus have a negative impact on traffic efficiency. When traffic accidents occur or there is congestion, the traffic flow is abnormal. Anomalies can consist of traffic accidents, bad weather, construction work, special events, rush hours congestions, traffic light phase, and drivers' searching for parking space and charging stations. Other challenges faced by the TH-AS are noise and interference, which are further sources of anomalies in traffic flow. A deep learning approach is proposed for finding these patterns, which can be applied to all roads with usually normal traffic (Ghasedi *et al*., 2021; Bijelic *et al*., 2020). Since the TH-AS is expected to travel in mixed traffic, maneuver recognition, which considers the behavior of all surrounding vehicles, will be needed. Adaptive decision support is proposed to resolve changes arising from identified abnormalities (Raiyn, 2017) and to ensure the safe driving of the TH-AS. Moreover, adverse weather conditions impose significant constraints on AS buses, some of which are related to visibility. Adverse weather such as heavy rain, snow, or fog, can obstruct sensors and reduced sensor performance can lead to decreased accuracy in detecting and identifying objects on the road. Furthermore, poor visibility due to weather conditions can impair the AS's evaluation of its environment, making it hard for the vehicle to navigate safely. Snow-covered or rain-soaked road markings and traffic signs, as well as wet, glossy road surfaces can be difficult for the AS to interpret. This can lead to mishaps from a faulty understanding of road lanes, speed limits, and traffic rules. Adverse weather conditions can also impact data calibration, so that weather-related anomalies in sensor data may require advanced calibration techniques to maintain accuracy.

1.1. Challenges to the operation autonomous vehicles in smart cities

Operating an AS bus in a smart city presents several significant challenges, which must be carefully addressed to ensure the successful integration of this innovative technology into urban environments. Some of the key challenges include:

- Public acceptance: Convincing the public to trust and embrace AS buses is a formidable challenge. Many individuals may have doubts and fear toward the technology, especially during its initial stages of deployment. Public awareness campaigns and educational initiatives will be essential to foster understanding, trust, and acceptance among city residents.
- Weather Conditions: Adverse weather conditions pose a significant challenge for autonomous vehicles. Heavy rain, snow, fog, and other meteorological factors can impair sensor performance and affect the overall operation of the vehicles. Ensuring the reliability and safety of the performance of autonomous systems under various weather conditions is of paramount concern. Robust sensor systems, predictive algorithms, and continuous learning mechanisms are essential components for adapting to changing weather conditions and ensuring safe navigation.

1.2. Motivation and objective

The deployment of an AS in Aschaffenburg city is divided into two phases. The first phase is aimed as deploying the bus to transport students and staff among the university's three campuses. The second phase extends the range of coverage to involve a large portion of the city. This research aims to study the deployment of the shuttle bus in both segregated-lane and mixed traffic, which depends on various factors, including specific use, infrastructure, regulations, and safety. We will analyze the advantages and challenges of both options for deployment of the shuttle bus. A dedicated segregated lane is advantage that can reduce the risk of accidents and collisions with other vehicles and with vulnerable road users (VRUs) (bicycles, pedestrians, etc.) as it enables the shuttle to operate without interaction with other road users. Furthermore, the shuttle can move at a consistent speed without being affected by congestion or traffic lights, leading to faster travel times. On the other hand, the creation of a dedicated lane requires additional infrastructure, which can be costly and may not be feasible in all areas. In contrast, operating a shuttle bus in mixed traffic enables the vehicles to accumulate valuable real-world experience by interacting with other road users (vehicles, VRUs), and operating under everyday traffic conditions. The shuttle has to navigate on different road types and adapt to various traffic conditions, increasing its usability and flexibility. The advantage of this option is that there is no need for additional infrastructure investment, as the shuttle uses existing roadways and infrastructure. However, mixed traffic poses greater risks, as the shuttle bus must interact with unpredictable human drivers and VRUs and handle complex traffic situations. In addition, the shuttle's speed might be affected by traffic congestion or the need to adhere to traffic rules, possibly leading to longer travel times. The application of machine learning (ML) to optimize traffic patterns for ASs is illustrated in Figure 1. This could include studying and prediction traffic conditions, learning from historical data, and adapting to changing transportation dynamics.

This paper is organized as follows: Section 2 gives an overview of research related to smart cities. Section 3 describes the methodology of the ML schemes for TH-AS. Section 4 discusses the results. Section 5 concludes the discussion and points out directions for future research.

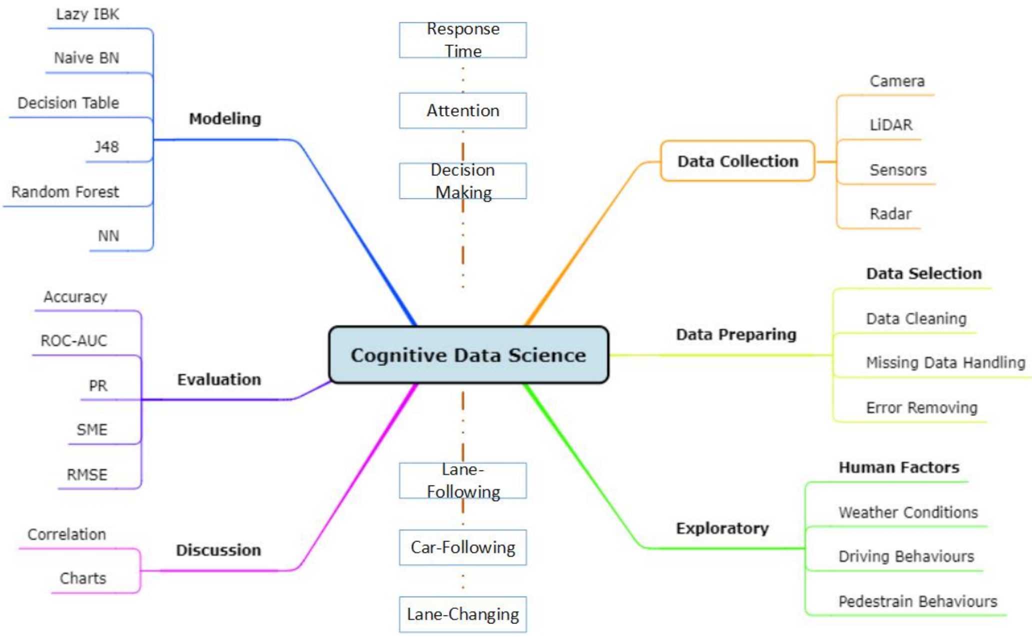

Figure 1. Design of cognitive data science

2. Related work

The increasing deployment of AS systems calls for advanced strategies for efficient traffic management. This paper aims to explore the role of data science and AI in addressing the challenges of traffic congestion, with an emphasis on predicting traffic conditions, leveraging historical data, and adapting to continuously changing transportation dynamics. In smart cities, AS buses are becoming a part of everyday life with the goal of improving public transportation. Esterwood *et al*. (2021) conducted a survey on how individual differences can influence trust, attitude, and the intention to ride AV buses. Tsigdinos *et al.* (2022) identified five areas for developing the urban road of the future: efficiency, safety, liveability, accessibility, and smart technology.

To understand driving behaviour, Flötteröd *et al.* (2021) and Liu *et al.* (2022) analysed real AS bus data. In mixed-road traffic, operating of AS bus is fraught with major challenges, stemming from human factors, road structure, and adverse weather conditions. According to Wang *et al.* (2013), drivers who are young and inexperienced tend to be involved more frequently in accidents. They are disproportionately represented in overall traffic accidents and fatalities, and they are more prone than older and more experienced drivers to be at fault in the accidents in which they are involved.

Additionally, it is acknowledged that there are distinctions in driving behaviour between men and women. For instance, numerous studies indicate that male drivers have higher crash rates compared to female drivers. These gender-based differences in driving behaviour are more often attributed to natural psychological factors than to variations in experience, capabilities, or driving skills.

Laapotti *et al.* (2003) discovered that the divergence in driving behaviour between males and females persisted, and in some respects, even intensified. On average, men demonstrated higher driving tendencies. Raimond *et al.* (2016) observed a correlation between age and gender in relation to speeding behaviour. They found that young and male drivers, on average, maintained higher speeds both before entering and upon exiting roundabouts compared to older and female drivers. Allouch *et al.* (2020) investigated road accidents, focusing on severity levels of accidents at intersections. They employed a multinomial logit model to analyze the relationship between road accidents and traffic flows, particularly in rural intersections. Their research reveals that several factors, including the driver's age, the vehicle type, alcohol consumption, and gender, exert a significant influence on the likelihood of being involved in accidents. The findings show that young male drivers in the age range of 17-19 faced a higher risk of being involved in more severe crashes than drivers aged 23-25.

Additionally, in comparisons between the driving behaviours of men and women, it has been shown that men pose a higher risk due to their tendencies toward aggressive driving, impatience, and impulsiveness, factors that often contribute to accidents. Liu *et al.* (2022) conducted research investigating the impacts of age, driving experience, and various covariates on aggressive driving behaviour. They utilized regression analysis to examine the influence of age and driving experience on aggressive driving behaviour. as well as their interactions with other covariates.

The analysis revealed a negative correlation between age and aggressive driving behaviour, while in the multiple regression analysis a positive correlation was found between neuroticism and aggressive driving behaviour. Significant associations were also observed with age, driving experience, depression, and neuroticism. Simple slope tests indicated that depressive symptoms could elevate aggressive behaviour among elderly and experienced drivers.

Shahverdy *et al.* (2020) developed a deep learning approach to analyse driver behaviour focusing on various driving signals, including acceleration, gravity, throttle use speed, and Revolutions Per Minute (RPM). Their method aimed to distinguish among five types of driving styles: normal, aggressive, distracted, drowsy, and drunk driving. A study by Lee *et al.* (2023) based on correlation analysis, a process that examines the degree of correlation between two or more related variables, utilized correlation coefficients to evaluate the relationship between weather data and traffic flow data. The goal was to understand how various weather conditions influenced traffic flow on an expressway, with a focus on assessing the level of weather-related impact on traffic volume.

In a separate study, Kar *et al.* (2023) utilized Random Forest and Support Vector Machine techniques to predict both traffic congestion rates and the speed of traffic flow. This predictive approach can help drivers in actively avoid congested road sections, promoting the efficient utilization of resources and aligning with the goals of timesaving, energy conservation, and environmental protection. Furthermore, negotiating unsignalized intersections poses a constant challenge for autonomous vehicles (AVs) in urban settings. Unlike signalled intersections where traffic lights regulate priorities, unsignalized intersections required AVs to make decisions about when and how to cross safely. This is a more intricate task with no traffic light to guide the way, and the intersections maybe congested, making the vehicle's decision-making process more complex.

On the other hand, roundabouts are gaining popularity in many parts of the world as a way to facilitate traffic flow and alleviate congestion. Governments have increasingly implemented roundabouts as a proven measure to prevent the severe accidents that commonly occur at or near intersections. Roundabouts possess inherent characteristics that contribute to traffic safety, which distinguish them from other types of crossings. Ghasedi *et al.* (2021) explored and identified factors that significantly influence both vehicle and pedestrian accidents and created a highly accurate prediction model.

Machine learning (ML) methods not only facilitate the development of comprehensive and efficient models for pinpointing the major factors that contribute to accidents but also offer valuable insights to authorities, enabling them to implement more precise measures to mitigate the impacts of accidents and enhance overall road safety (Raiyn and Weidl, 2023). The study emphasizes the pivotal role of environmental factors, particularly rainy weather, and lighting conditions, as the primary contributors to the severity of pedestrian accidents.

Fluctuating patterns in weather conditions can have numerous adverse effects on traffic and transportation. Unfavourable weather phenomena include rain, snow, fog, wind, extreme heat, and cold. Given the impact of such conditions on the perceptual systems of AVs, many studies, such as those referenced in Kar and Feng (2023), (Valanarasu *et al.*, 2022), focus on enhancing sensor fusion algorithms. These algorithms amalgamate data from various sensors, such as radar, LiDAR, RGB, event-based cameras, and so forth, with the aim of achieving the greatest possible accuracy in localizing and identifying surrounding objects. Surveys of adverse weather conditions primarily concentrate on rectifying deficiencies in the perception stack and the relevant hardware and addressing weaknesses in various sensors. While identifying weather conditions is crucial, there is also a wealth of research in the area of perception.

It is equally important for AV controllers to take these considerations into account, as they influence the road's friction coefficient and impact the behaviour of surrounding vehicles, shaping the overall environmental dynamics. Adverse weather conditions are one of the most important factors that influence critical-safety events. Various studies have shown that human drivers have a reduced desire to travel under foggy and snowy conditions. On the other hand, conditions, such as heavy fog, rain, snow, and sandstorms can lead to dangerous restrictions of the functionality of the devices used by autonomous vehicles, which impacts the performance of the detection algorithm and can cause massive detection errors (Bejelic *et al*., 2020). Uncertainty and invisibility present challenges for autonomous vehicles. Most of published detection approaches are concerned with distinguishing between clear and foggy weather situations during day and night driving (Valanarasu *et al*., 2022).

3. Methodology

The technical university of applied sciences (TH) Aschaffenburg plans to introduce the TH-AS bus to serve the students who travel among the three university campuses as illustrated by Figure 2. The TH-AS will also serve on demand, outside of the daily lecture breaks, as an alternative means of transportation for both people and goods. It will offer stops on demand for residents and especially the elderly to simplify their daily life. An additional benefit of the TH-AS will be a reduction in urban road congestion in Aschaffenburg, where the traffic demand exceeds the road capacity during rush hour, which is often characterized by slower speeds, longer trip times, delays and increased queuing. Reducing will have a strong impact on noise reduction and on climate change, producing better air quality by reducing carbon dioxide emissions. The smart intersection at TH is already equipped and has been recently upgraded with internet-of-thing devices, such as smart cameras, Lidar, GPS, and sensors to sense the environment (Hetzel *et al*., 2021). The road segments between the two roundabouts (2.1 km in each direction) will be equipped with road site units (RSU) for continuous monitoring of the traffic flow. The data received will be analyzed by a monitoring and control unit (MCU), which can process data in various formats based on a deep learning (DL) scheme. Complementing the RSUs, an unmanned aerial vehicle (UAV), namely, a drone will play a significant role in the deployment of the TH-AS by providing redundant data to ensure traffic safety. Moreover, drones have been used to map and measure the TH-smart intersection. Drone technologies can help to reduce the risks of weather errors and guarantee the safety of the operation. Besides the safety monitoring of the road by drones from a designated air corridor and the TH-AS's designated optimal lane for VRU. i.e., pedestrians, bicycles, and scooters), drones are considered a major step in smart cities' movement toward sustained growth.

3.1. Data collection

The TH-AS performs tasks under its own power on an operations platform. Some capabilities of the TH-AS are sensing the surrounding environment, collecting information, and managing communication with other traffic participants. It uses a combination of cameras, sensors, GPS, radar, LiDAR, and an on-board computer, working together to map the vehicle's position and its proximity to its surroundings. Furthermore, the TH-AS supports various modes of communication, such as, vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle–to-mobile device communication. The overall system intelligence utilizes an advanced DL model of machine learning for classification and visibility detection under foggy weather conditions. DL provides better accuracy in terms of an image dataset and performs multiple iterations of layers on the images, such as convolution, max pooling, and flattening, to classify them correctly for the purposes of recognition, maneuvering, and navigating a safe route.

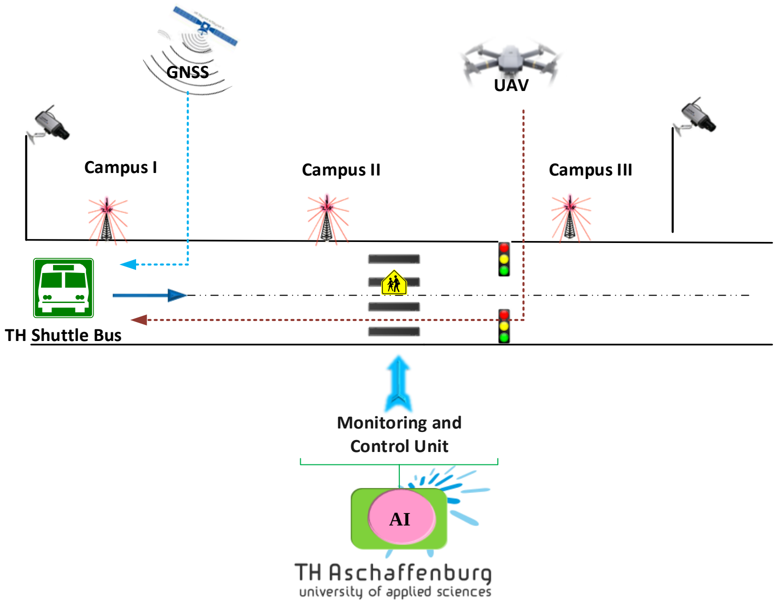

Figure 2. The TH-AS concept

3.2. Data preparation

Historical data analysis is a fundamental component in the congestion management strategy for ASs. Machine learning algorithms analyze past traffic patterns and identify trends and recurrent congestion scenarios. This historical insight enables the system to make informed decisions, optimizing routes and schedules based on observed patterns, and ultimately improving the overall flow of ASs within the transportation network. The TH-AS receives data from various devices in different formats, which could lead to problems with data quality. To deal with this, in the preparation phase on the cloud operation platform, data is converted to a desired format, then the dataset is cleaned, and inconsistent, invalid, and corrupt data are removed. Our algorithms can deal robustly with up to 10% of missing data.

3.3. Feature extraction

Feature extraction is the process of identifying, and filtering raw data, and transforming it into meaningful features that encapsulate essential aspects of driving behavior. These features serve as the foundation for predictive models that empower traffic managers and urban planners to make informed decisions. The variables and parameters selected through feature extraction encompass a wide range of critical information, including vehicle positions, speeds, accelerations, relative speeds, time, and space headway, and more. By extracting features like these, these models enable traffic managers to predict and manage congestion, optimize traffic signal timings, and enhance overall traffic flow. The precise measurement and analysis of time headway facilitate safe and efficient traffic management. Feature extraction techniques allow for the identification and analysis of acceleration patterns, contributing to anticipatory traffic management strategies. These strategies help reduce sudden braking events, minimize fuel consumption, and improve overall traffic flow efficiency. Machine learning and artificial intelligence techniques play an increasingly integral role in feature extraction, enabling models to adapt and learn from real-world driving scenarios. The variables used in the driving models (e.g., position, speed, and the acceleration of various vehicles; relative speed; time and space headway) were selected based on those used in the EU's L3Pilot Project. This open-source data made it possible to prepare the models that will perform the data analysis of traffic flow among the three TH-university campuses.

Table 1. L3Pilot open data characteristics

Notation	Description	Symbol
Min_ax	Minimum longitudinal acceleration	min(a_x)
Max_ax	Maximum longitudinal acceleration	max(a_x)
SD_ax	StDEV of longitudinal acceleration	sd(a_x)
SD_ay	StDEV of lateral acceleration	sd(a_y)
Mean_v	Mean speed	m(v)
SD_v	Standard deviation of speed	sd(v)
Max_abs_ay	Maximum absolute lateral acceleration	max($\|a_y\|$)
Max_v	Max speed	max(v)
Mean_pos_in_line	Mean position in lane	sd(Pos in lane)
Mean_THW	Mean time headway	m(THW)

3.4. Exploratory data analysis

The data analysis results show that the data collected was influenced by various factors, such as human factors (e.g. age, gender, experience), traffic flow characteristics (speed, acceleration, headways, and vehicle position, and orientation inside the lane and in relation to the lane markings) and adverse weather conditions (fog, heavy rain, snow). Correlation analysis, as it is generally used, has two aspects, qualitative and quantitative. Quantitative analysis mainly calculates the correlation coefficient between two variables based on the size of their values, in order to judge the degree of correlation between them. This study used quantitative correlation analysis to assess the relationship between the two variables of weather data and traffic flow and to determine how various weather conditions affect the flow of traffic in the city, as illustrated in Figure 3. We first determined the linear relationship between the two variables as the primary goal of a simple correlation analysis before looking at the correlation coefficients. To provide a mathematical description of the correlations, we used statistical techniques such as regression analysis, which enabled us to model the relationship between the dependent variable (e.g., driving behavior) and one or more independent variables (e.g., fog, heavy rain, snow, daytime, and road surface). Mathematically, the multiple linear regression model can be written as:

$$Speed^S = \beta_0^S + \beta_1^S \times V \times \beta_2^S \times Day\_T + \beta_3^S \times Road\_S + \varepsilon^S , \quad (1)$$

where
V is the variable Visibility,
Day_T is Day_Time,
$Road\_S$ is Road_Surface,
β_0^S is the intercept specific to summer.
β_1^S, β_2^S, β_3^S are coefficients specific to summer; and
ε^S is the error term for Summer and as

$$Speed^W = \beta_0^W + \beta_1^W \times V + \beta_2^W \times Day\_T + \beta_3^W \times Road\_S + \varepsilon^W, \quad (2)$$

where
β_0^W is the intercept specific to winter;
β_1^W, β_2^W, β_3^W are coefficients specific to winter; and
ε^W is the error term for winter.

Equation 1 describes the average speed during summer which is influenced by visibility, daytime, and road surface metrics. However, their effects are weak. Equation 2 describes the average speed during winter, which likewise is influenced by visibility, daytime, and road surface metrics.

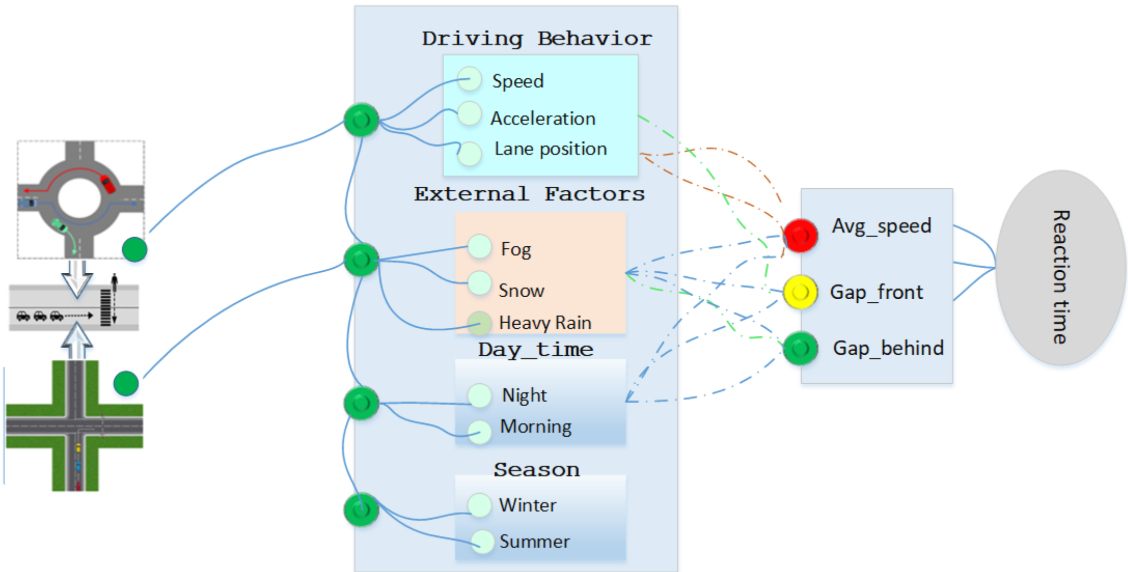

Figure 3. Driving behavior analysis

3.5. Data processing

These raw data were processed using various techniques to extract relevant features, as illustrated in Figure 4, ML algorithms were applied to identify road anomalies and cognitive models were developed to track the maneuvers the surrounding objects, that could have an impact on collision risk, hazard avoidance and safety. Moreover, for trustworthy systems, explanations will be provided, which are feasible due to the qualitative structure of the cognitive hierarchical models. The DL model was designed to deal with the quality of the raw data as illustrated in Figure 5. The quality of raw GNSS measurements (also called observables) is affected by satellite communications, signal propagation and receivers. The signals transmitted by satellites propagate through the atmosphere, they can be subject to delays caused by ionospheric and tropospheric media. At ground level, a multipath effect, namely, the multiple reception of signals that are reflected from obstacles such as buildings surrounding the receiver, can cause some of the largest errors. Furthermore, weather conditions, such as fog, clouds, rain and snow reduce the quality of raw data that is received by cameras or a GNSS.

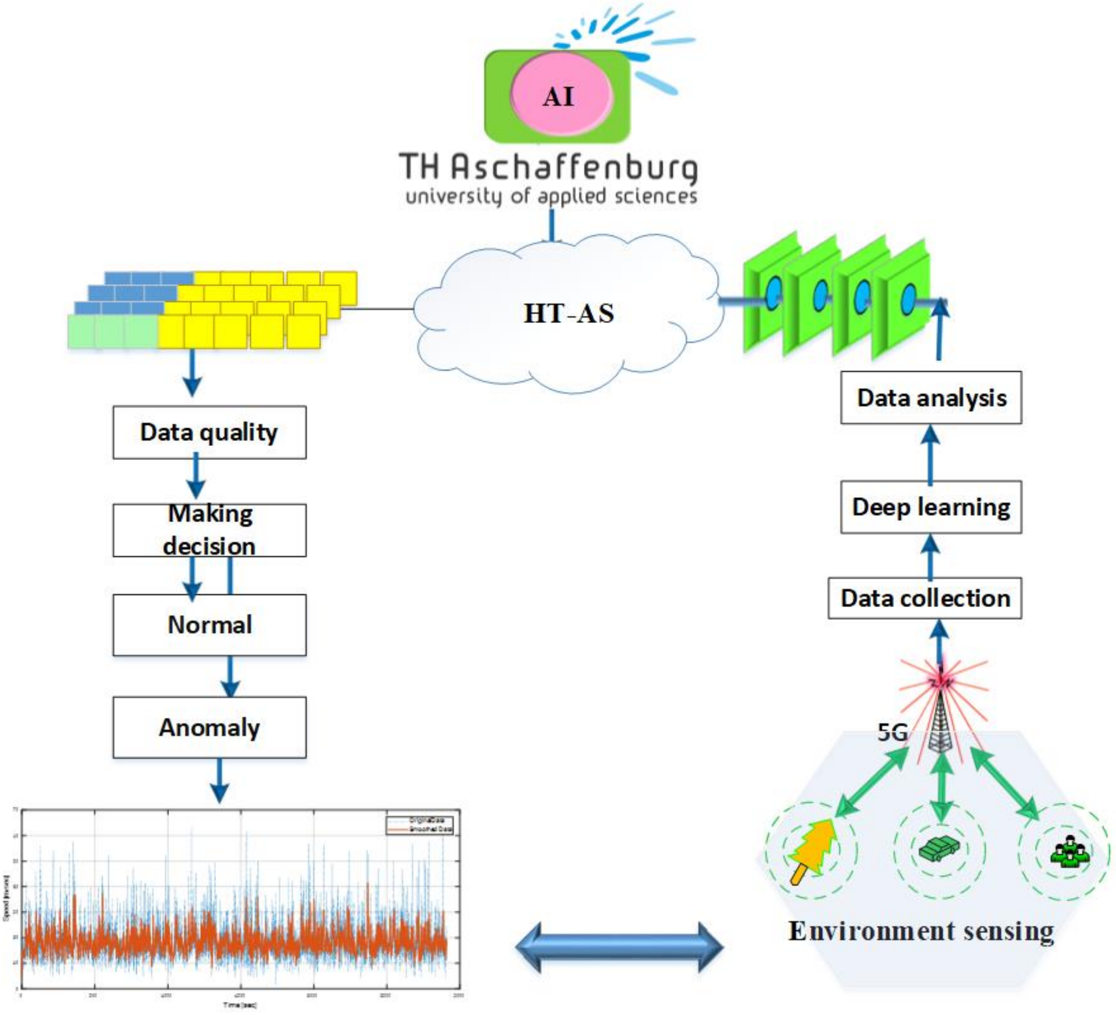

Figure 4. TH-AS sensing strategy

3.6. Performance metrics and correlation analysis

The provided statistics were common metrics used to evaluate the performance of a predictive model, particularly in the context of regression analysis. The correlation coefficient measures the strength and direction of a linear relationship between a predicted value and an actual value. In this case, as Table 2 shows, a value of 0.4258 indicates a moderate positive correlation. The closer the coefficient is to 1, the stronger the positive correlation, while the closer it is to -1, the stronger the negative correlation. The mean absolute error (MAE) is a measure of the average absolute differences between the predicted and actual values. In this context, a MAE of 5.7911 means that, on average, the model's predictions deviate by approximately 5.79 units from the actual values. The root mean squared error (RMSE) is another measure of the average differences between predicted and actual values, but it gives more weight to large errors. The RMSE of 9.4326 suggests that the typical prediction error (presented in the same units as the target variable) is around 9.43. The relative absolute error (RAE) is the MAE relative to the mean absolute error of the target variable. A value of 85.477% indicates that the model's average absolute prediction error is approximately 85.48% of the mean absolute error of the target variable. The root relative squared error (RRSE) is similar to the RMSE but is relative to the squared differences between the predicted and actual values. A value of 90.4803% indicates that the model's typical prediction error is approximately 90.48% of the squared differences between the predicted and actual values. While the correlation coefficient indicates a moderate positive linear relationship, the error metrics (the MAE, RMSE, RAE, and RRSE) provide insights into the accuracy and precision of the model's predictions. Low MAE and RMSE value are desirable, indicating small prediction errors, while low RAE and RRSE percentages bet a more accurate model relative to the mean absolute error and squared differences, respectively. Table 3 describes the correlation analysis and highlights various connections between average speed and some other factors.

There is a positive correlation between average speed and daytime, suggesting that higher speeds are linked to specific times of the day. A positive correlation between higher speed and the gap behind the vehicle in lane 1 signifies a mild positive relationship, indicating that as the gap behind the vehicle increases, the average speed tends to rise. Similarly, the gap in front of the vehicle in lane 1 exhibits a positive correlation with average speed, indicating that larger front gaps are associated with higher speeds. The season (see Equation 1, which uses different variables for summer and winter) has a positive correlation with average speed, indicating that certain seasons may be connected to elevated average speeds. On the other hand, the correlation with road surface is weak, indicating that specific road conditions are associated with slightly lower average speeds. Additionally, the negative correlation with visibility is slight, suggesting that lower visibility may be linked to slightly lower average speeds. The most significant negative correlation, a moderate one, is rainy conditions, which are associated with lower average speeds, suggesting that adverse weather conditions have a noticeable impact on driving speed. It is essential to interpret these correlations carefully, bearing in mind that correlation does not imply causation. Further investigation is necessary to comprehend the underlying dynamics that influence these relationships.

Table 2. Correlation analysis

Statistical Measurements	Values
Correlation coefficient	0.4258
Mean absolute error	5.7911
Root mean squared error	9.4326
Relative absolute error	85.477 %
Root relative squared error	90.4803 %

Table 3. Multiple statistical measures

Attribute	Average speed	Visibility	Gap_front	Gap_behind
Season	0.074	0.185	0.015	0.021
Daytime	0.294	0.205	0.130	0.190
Rain_state	-0.134	-0.093	0.005	0.008
Road_surface	-0.024	-0.303	0.050	0.074
Visibility	-0.050	-	-0.038	-0.057
Gap_front	0.088	-0.038	-	0.185
Gap_ behind	0.133	-0.057	0.185	-
Average speed	-	-0.051	0.088	0.133

3.7. Machine learning schemes

Machine learning algorithms play a pivotal role in predicting future traffic conditions, enabling AS systems to plan routes and schedules. Various models have been employed to forecast traffic congestion based on real-time data from sensors, cameras, and other sources as illustrated Figure 5. The utilization of predictive modeling enhances the ability of ASs to navigate traffic more efficiently. ML methods are the most useful tools in artificial intelligence (Aradi *et al.,* 2022). The ML process inputs information in a hierarchical way, where each successive level of processing involves more abstract global and invariant features (Ensafi *et al.*, 2022). A ML system learns the features of a dataset and then combines them to achieve a specific goal. The ML method is used to find solutions to complex problems, in this case, problems with intelligent transportation systems. In this paper, a ML method is proposed to overcome the limitations of the AS bus and improve its performance under severe weather conditions. It is composed of two main phases: training and testing. The system here is composed of four phases: (1) preparation of the dataset, (2) a training phase, (3) a testing phase, and (4) a performance metrics phase. Figure 2 illustrates the knowledge flow of the WEKA platform based on ML schemes.

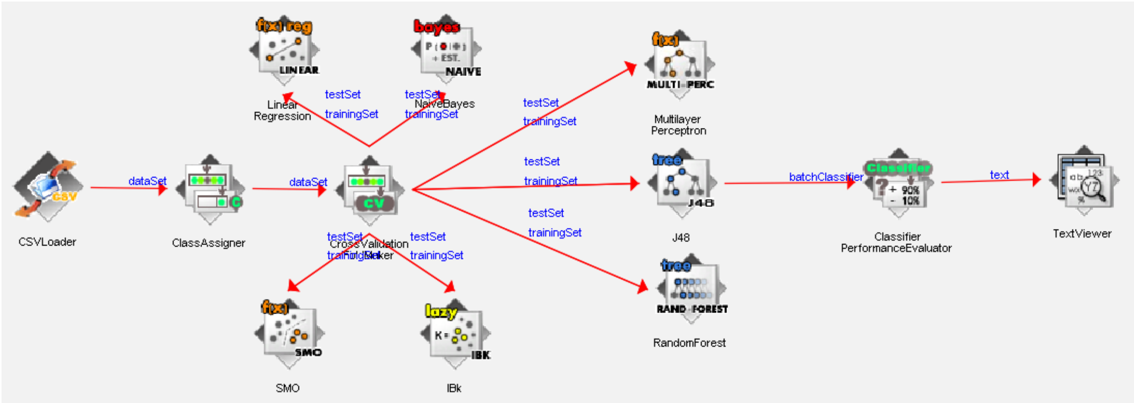

Figure 5. Machine learning schemes

4. Result and discussion

The *time headway* is the interval of time between the front of one vehicle and the front of the following vehicle passing a given point. Judging headways is essential for safe and efficient operations, for avoiding collisions and for ensuring the safety of passengers and other road users. Proper time headway management contributes to smooth traffic flow, as it reduces the likelihood of sudden braking and accelerations. The AS bus's reaction time and capability to adjust to time headways are more precise than those of human drivers, which means it can respond more quickly to changes in traffic conditions and adapt its speed to ensure that it maintains a safe distance from the vehicle ahead. However, in some scenarios, in order to manage time headway AS buses need to communicate with each other and cooperate. A partial correlation analysis was performed on features of the vehicle's kinematic data; the results are shown in Figure 6. The correlation coefficients between mean time headway and mean_v_leadVeh (which represents the mean velocity of the lead vehicle), Max_ax (which represents the maximum acceleration of a vehicle) and mean_Long_Dist_LeadVeh (which represents the mean longitudinal (front-to-back) distance between the ego vehicle and the lead vehicle) show strong positive correlations. Under conditions of clear visibility, like good weather, the gap_front (refers to the distance or gap between the front ego vehicle and the vehicle in front of it) between vehicles appears larger. This could be because vehicles are more easily discernible from a greater distance, which sharpens the perception of a larger gap. Conversely, when visibility is low due to environmental conditions like fog, heavy rain, and low-light situations, the gap_front between vehicles seems smaller. The observed gap_front size is influenced by the level of visibility, with clear conditions making gaps appear larger and unclear conditions making them appear smaller as illustrated in Figure 7.

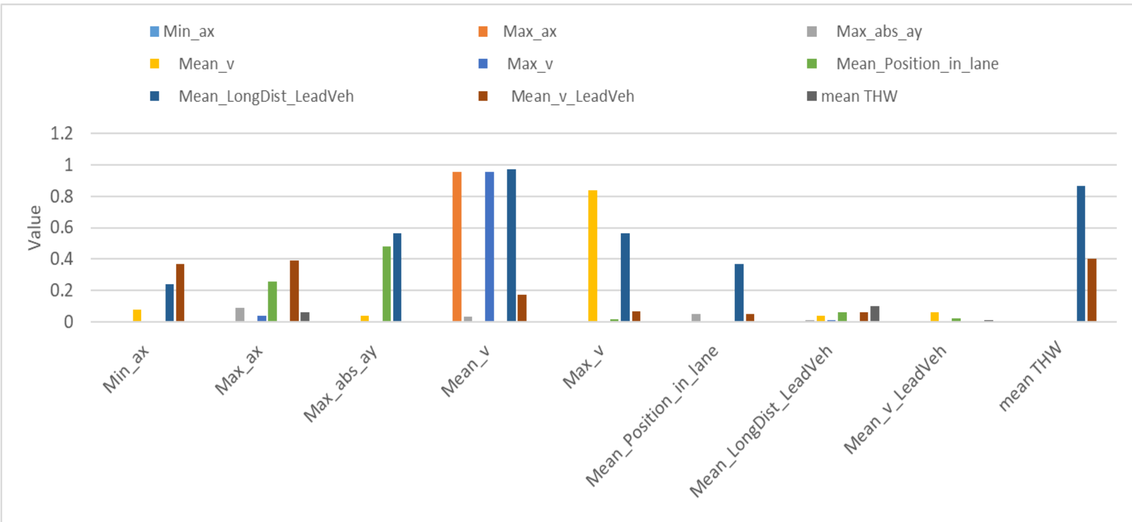

Figure 6. Vehicle behavior

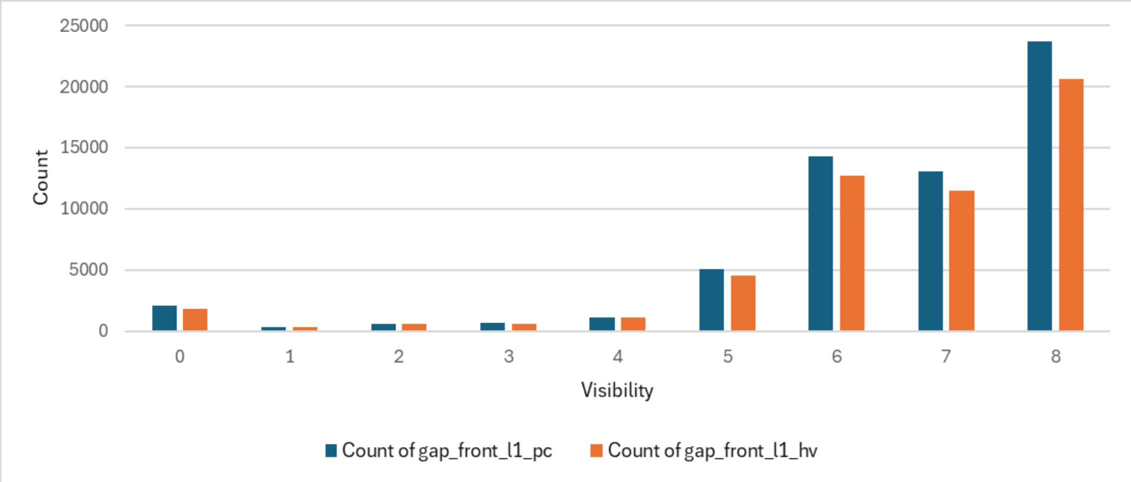

Figure 7. Visibility under adverse weather conditions

4.1. Data evaluation

Multiple statistical measures, such as the mean and the standard deviation of a variable, variance, the mean absolute error (MAE), root mean squared error (RMSE), and the relative absolute error (RAE) and their interactions with other features are used to discriminate between normal and abnormal traffic flow and to explain the reasons for any differences. The main contributions of the model described in this article are as follows: First, it is capable of detecting anomalies in traffic data. Second, it can extract the features of traffic data and identify the sources of anomalous data. Third, it can make short-term travel forecasts by applying CNNs, and fourth, it makes it possible to compare the accuracy of results through measurement methods such as the RMSE and the MAE.The data were collected at a public intelligent intersection (i.e., equipped with sensors) at TH Aschaffenburg, Germany, which is situated amidst the university's three campuses (Goldhammer *et al*., 2012). The dataset describes the transitions between the waiting and starting movements of cyclists (see Figure 8). To reduce the waiting time, in the simulation, the intersection can be managed by programming the traffic light to changes to green based on demand and traffic flow density. As alternative, the traffic light could be removed from the intersection to prioritize the performance of the TH-AB bus. We want to explore the potential of using reinforcement learning for traffic flow optimization in scenario with traffic lights that are based on the information exchange between vehicles and infrastructure (C2X). It is important to note that any changes made to the intersection's management should be carefully planned and executed to ensure the safety of all road users. We will design and conduct further studies and analyses before implementing any changes to the actual intersection. Furthermore, it may be beneficial to consider the potential impacts of these changes on the surrounding area and its residents. Table 5 describes the performance of ML schemes based on true positive detection.

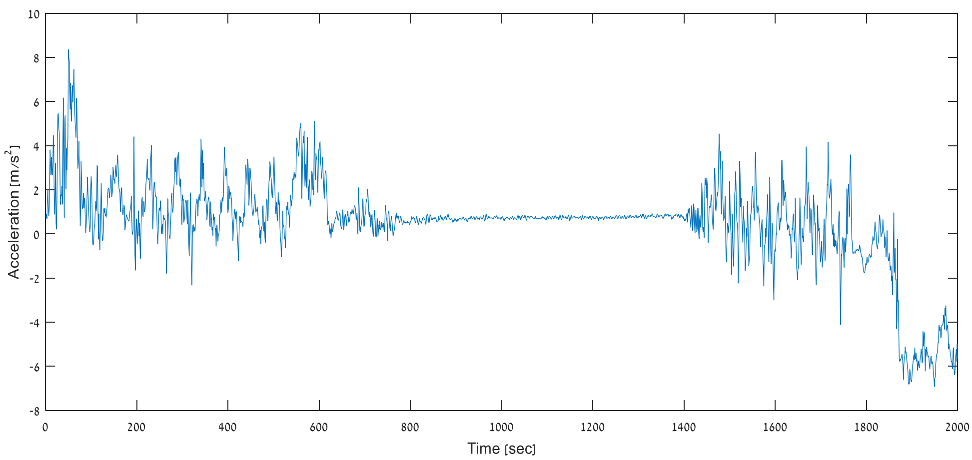

Figure 8. Transition between waiting time and start movement

Table 4. ML schemes compared based on accuracy

ML schemes	TP	FP	Precision	Recall	F-measure	MCC	ROC	PRC
lazy IBK	0.993	0.007	0.993	0.993	0.993	0.986	0.993	0.99
naïve BN	0.928	0.08	0.927	0.928	0.927	0.849	0.98	0.981
decision table	0.971	0.031	0.971	0.971	0.971	0.94	0.997	0.997
J48	0.992	0.009	0.992	0.992	0.992	0.982	0.996	0.995
Ramdom Forest	0.995	0.005	0.995	0.995	0.995	0.991	1	1
NN	0.999	0.001	0.999	0.999	0.999	0.999	1	1

5. Conclusion

In the rapidly evolving landscape of AS buses within smart cities, several challenges and deployment strategies have come to the forefront. The degree of autonomy, ranging from SAE level 3 to level 4, significantly impacts how ASs operate within urban environments. A level 3 AS relies primarily on segregated lanes, while a level 4 AS has full control in mixed traffic, consisting of various types of road users. Effective communication between an AS and all traffic participants is pivotal for achieving optimal service levels and ensuring safety.

In this paper, we have described a plan for an AS bus (as TH-AS) at Technical Hochschule of Applied Sciences in Aschaffenburg, Germany, which was inspired by a preliminary survey that unveiled the potential benefits of this technology, particularly for students, which include safer roads, reduced congestion, time savings, and decreased student stress. However, the TH-AS faces social and research challenges. Skepticism and anxiety regarding emerging technologies, as well as perceived competition with existing transportation services, are notable hurdles.

On the research front, the real-time detection of anomalies has emerged as a critical aspect of TH-AS operations. Anomalies, comprising traffic accidents, adverse weather, construction activities, and rush hours, disrupt regular traffic flow and can lead to discomfort for TH-AS users. The proposed ML schemes for anomaly detection and maneuver recognition seek to enhance the TH-AS's adaptability and responsiveness to such challenges. Adverse weather conditions, particularly visibility-related issues, have been identified as significant constraints on ASs. Rain, snow, fog, and other meteorological factors can obstruct sensors, leading to reduced accuracy in detecting objects on the road. Furthermore, poor visibility affects environmental perception and the interpretation of critical road markings and signs. Effective data calibration under adverse weather conditions necessitates the implementation of advanced techniques to ensure operational accuracy.

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Conflict of interest

The authors declare that they have no conflict of interest.

Data availability

Most of the datasets used in this paper are publicly available. Private datasets can be furnished upon request.

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