Driver Behavior at Roundabouts in Mixed Traffic: A Case Study Using Machine Learning

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Abstract: Driving behavior is a unique driving habit of each driver, and it has a significant impact on road safety. Classifying driving behavior and introducing policies based on the results can reduce the severity of crashes on the road. Roundabouts are particularly interesting because of the interconnected interaction between different road users at the roundabouts, in which different driving behavior is hypothesized. This study investigated driving behavior at roundabouts in a mixed traffic environment using data-driven unsupervised machine learning to classify driving behavior using a data set from three roundabouts in Germany. We used a data set of vehicle kinematics for a group of different vehicles and vulnerable road users (VRUs) at roundabouts and classified them into three categories (i.e., conservative, normal, and aggressive). The results showed that most drivers proceeding through a roundabout can be classified into two driving styles—conservative, and normal—because traffic speeds in roundabouts are relatively lower than at other signalized and unsignalized intersections. The results also showed that about 77% of drivers who interacted with pedestrians or cyclists were classified as conservative drivers, compared with about 42% of drivers who did not interact with pedestrians or cyclists, and about 51% of all drivers. Drivers tend to behave abnormally when they interact with VRUs at roundabouts, which increases the risk of crashes when an intersection is multimodal. The results of this study could help to improve the safety of roads by allowing policymakers to determine effective and suitable safety countermeasures. The results also will be beneficial for advanced driver-assistance systems (ADAS) as the technology is deployed in a mixed traffic environment. **DOI: 10.1061/JTEPBS.TEENG-8325.** *© 2024 American Society of Civil Engineers.*

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Introduction

Driver behavior describes the actions that drivers take while driving on different road infrastructures. In recent decades, many researchers have invetigated driving behavior due to the dramatic increase of vehicle users and interactions with other road users, specifically pedestrians and bicyclists. Understanding the behaviors of drivers could lead to enhanced applicability of advanced driving assistants (ADS), safer roads by reducing crash severity, and increased effectiveness of intelligent transportation systems (ITS) for traffic operation. In addition, it could lead to better understanding of the relationship between driving behavior and the annual increase in road crashes. Because many factors can affect driving behavior, such as age, gender, emotions, and experience, driving behavior is different for the same driver in different situations, including on different road infrastructures. Various methods have been used to investigate driving behavior. According to Jeihani and Banerjee (2018) and Mohammadnazar et al. (2021), data collection methods include surveys, questionnaires, simulations, roadside camera observations, and naturalistic experiments. Using data that have been extracted from naturalistic experiments is suitable due to the high reliability. Therefore, many data sets of driver behavior have been collected for such uses, such as the HDD (Ramanishka et al. 2018), highD (Krajewski et al. 2018), inD (Bock et al. 2020), and rounD (Krajewski et al. 2020) data sets. Classifying driving behavior also is useful in understanding and mimicking humans' behavior so that it can be used for safety and operation purposes. One of the effective methods is the use of classification algorithms in machine learning, which includes unsupervised algorithms such as *k*-means, and supervised algorithms such as decision trees (DL), naïve Bayes, support vector machines (SVMs), and deep learning (Osisanwo et al. 2017). Machine learning techniques hold significant promise for advancing ADS at roundabouts, offering potential applications to enhance road safety (Garcia Cuenca et al. 2019; Wang et al. 2022; Zubaidi 2021). By leveraging advanced algorithms, ADS can analyze complex driving behaviors, predict driver intentions, and anticipate potential risks in real time. These techniques enable ADS to provide proactive assistance, personalized interventions, and early warnings to drivers, thereby mitigating the likelihood of collisions and improving overall traffic flow efficiency. Additionally, machine learning algorithms facilitate adaptive control systems that dynamically adjust ADS parameters based on changing traffic conditions and driver behavior, ensuring

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optimal performance in diverse scenarios. By harnessing the power of machine learning, ADS can effectively navigate the complexities of roundabout environments, ultimately contributing to safer and more-efficient transportation systems.

Understanding driving behavior at roundabouts is important for several reasons (Alkheder et al. 2020; Al-Saleh and Bendak 2012; Deveaux et al. 2021; Yang et al. 2018; Zhao et al. 2017). First, roundabouts are designed to reduce the severity and frequency of accidents compared with traditional intersections, but the safety benefits depend on drivers behaving in a reasonable and safe manner. Understanding how drivers behave at roundabouts can help identify potential safety hazards and inform improvements to the design and operation of roundabouts. Second, roundabouts can improve traffic flow by reducing delays and minimizing the need for traffic signals or stop signs. However, traffic flow can be affected by driver behavior, such as improper lane use or failure to yield to other vehicles. Understanding driving behavior at roundabouts can help identify areas in which traffic flow can be improved. Third, efficient use of roundabouts depends on drivers using proper behavior, such as entering and exiting the roundabout in the correct lane, yielding to other vehicles already in the roundabout, and signaling their intentions. Fourth, compliance with traffic rules and regulations is essential for the safe and efficient operation of roundabouts. Understanding driving behavior at roundabouts can help identify areas in which drivers are not complying with traffic rules, which can inform enforcement efforts and education campaigns (Dwekat et al. 2023; Sackmann et al. 2020).

In this study, we used a data set of roundabouts in Germany to classify driving behavior into three styles, namely conservative, normal, and aggressive, using an unsupervised machine learning for clustering. We also investigated the driving behavior of drivers who interacted with vulnerable road users (VRUs) such as pedestrians and bicycles going through the roundabouts. We compared the resulting behavior of drivers interacting with pedestrians and bicycles and drivers who did not interact with them. To the best of our knowledge, this is the first study in the literature that makes the two aforementioned contributions.

Understanding driving behavior in various traffic environments is crucial for improving road safety and traffic management. Although significant research has been conducted on driving behavior at signalized and unsignalized intersections, there is a notable gap in understanding how drivers behave at roundabouts, especially in mixed traffic environments in which interactions with VRUs such as pedestrians and cyclists are frequent (Ashqar et al. 2019; Elhenawy et al. 2021). Roundabouts, by design, aim to reduce traffic crashes due to their lower traffic speeds and fewer conflict points compared with other intersections. However, the presence of mixed traffic can introduce unique challenges that may affect driver behavior and overall road safety. The importance of this study lies in its potential to enhance road safety by providing a deeper understanding of how drivers and VRUs interact in roundabout settings. Roundabouts are being increasingly used in urban and suburban areas to manage traffic flow and reduce accident severity. However, the presence of mixed traffic, including cyclists and pedestrians, introduces complexities that are not fully understood. By focusing on these interactions, the study identified patterns and behaviors that can inform the design and implementation of safety measures at roundabouts.

Literature Review

Understanding road user behavior is crucial for developing trajectory prediction systems. Additionally, ensuring the safety of automated vehicles (AVs) is essential for their successful introduction to the market. Researchers extensively have studied various data sets and road user trajectories, and some have focused specifically on roundabouts due to their high complexity. Collecting measurement data with naturalistic road user behavior and comprehensive information relevant to specific scenarios is important. Human drivers rely on their understanding of other road users' behaviors to enhance their driving and overall traffic safety. One study examined two three-leg junctions and a roundabout to assess the impact of at-grade intersections on driving behavior, and measured drivers' stress levels using electrodermal activity. The results indicated that roundabouts induced more than twice the stress of standard intersections (Distefano et al. 2020). In another study, researchers utilized data from five different roundabouts along with a distributed questionnaire to investigate driving behavior patterns. The findings revealed that approximately 90% of all drivers breached at least one traffic regulation. The most common violations observed were drivers leaving the roundabouts without signaling and entering the roundabouts without yielding to other vehicles (Al-Saleh and Bendak 2012). Similarly, a different study employed a questionnaire to gather information from drivers, which then was correlated with real-world observations at roundabouts. Data analysis indicated that a significant percentage of drivers possessed a good understanding of roundabout rules. The study also made certain modifications to two roundabouts to compare their performance before and after the changes, using measures of effectiveness. The results demonstrated that, for critical areas and when traffic volumes exceeded 3,000 vehicles/h, the level of service ranged between B and C, and the control delay varied from 10 to 30 s. The study proved to be valuable for traffic planners and designers when making decisions about intersection alternatives, highlighting the importance of considering driving behavior in the process (Alkheder et al. 2020).

Detecting risky driving behavior and predicting drivers' intentions are essential for enhancing road user safety and increasing the success rate of autonomous vehicles. Numerous studies have investigated the characteristics and variability of driving risk at roundabouts, aiming to enable connected vehicles to rapidly assess personalized, real-time risk levels associated with navigating a roundabout. In one study, researchers recorded time-to-collision (TTC) data at roundabouts and employed machine learning techniques to gauge the likelihood of a vehicle choosing the upcoming exit. They developed a risk metric based on TTC data and probability, and found a strong correlation with the coefficient of variation in TTC values at roundabouts. This newfound understanding of risk has the potential to bolster driver-assistance systems in roundabout scenarios (Deveaux et al. 2021). Another study considered factors such as steering wheel angle, angle velocity, and vehicle position to predict whether a driver would take the upcoming exit. They collected driving behavior data to model human interactions with roundabouts, utilizing support vector machines—a supervised machine learning model—for classification and regression analysis. The experimental outcomes indicated that vehicle position estimation significantly improved the reliability of predictions (Zhao et al. 2017). A third study presented two distinct methods for estimating when a driver will exit a roundabout based on their behavior (Ashqar et al. 2021). The first method utilized training data to extract typical behavior patterns, which then were used to classify other drivers' intentions. The second method, independent of training data, generated typical behavior patterns from precise maps and classified arbitrary roundabouts when a map was available. The results demonstrated that the map-based approach performed comparably to the data-driven approach (Sackmann et al. 2020).

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Several dynamic factors, including speed, acceleration, and the flow of potentially conflicting vehicles, significantly influence drivers' behaviors. One study analyzed these factors, along with driving behavior characteristics. The researchers applied the random forest algorithm to predict driving behavior. To collect data, a simulator was used to replicate real driving conditions, involving various traffic participants with distinct motion styles. Four representative roundabouts were created for data collection. The random forest model exhibited excellent performance in predicting human drivers' roundabout behaviors. Interestingly, the study found that geometric parameters had minimal influence on predicting driving behavior, whereas the relative velocity between the primary vehicle and surrounding vehicles played a substantial role (Yang et al. 2018). Another study focused on drivers' behavior at turbo-roundabouts, as well as vehicle kinematic parameters such as speed and acceleration. Empirical evaluations of these parameters were beneficial for calibrating traffic microsimulation models and assigning behavior parameters to closed-form capacity models. The study's findings revealed that vehicle speeds in entry lanes generally were low, often below 25 km/h (15 m before the yield line), and ring-lane accelerations typically remained below 1.5 m/s^2 (Guerrieri et al. 2018).

In the present study, k-means clustering was chosen for its ability to identify distinct clusters of driving behavior based on trajectory data. The decision to use this approach was guided by its demonstrated effectiveness in previous studies on driving behavior classification (Khanfar et al. 2022a, b). Specifically, k-means clustering is well-suited for partitioning data sets into distinct clusters based on similarity. Compared with alternative methods such as hierarchical clustering or support vector machines, k-means was deemed to be more suitable for our objectives due to its scalability, interpretability, and ability to handle large data sets efficiently (Ahmed et al. 2020; Ikotun et al. 2023). Additionally, its simplicity and flexibility makes it well-suited for real-time applications and integration into advanced driver-assistance systems (ADAS) (Ahmed et al. 2020; Ikotun et al. 2023).

This study contributes to the existing literature on driving behavior and roundabouts by focusing specifically on the unique challenges posed by mixed traffic environments at roundabouts. Although previous research has explored driving behavior in various contexts, including signalized and unsignalized intersections, the dynamics of roundabouts in mixed traffic scenarios remain relatively understudied. By employing a data-driven unsupervised machine learning approach, this study offers a novel framework for classifying driving behavior at roundabouts, thereby filling a significant gap in the literature. Moreover, the study investigated the interactions between drivers and VRUs, such as pedestrians and cyclists, shedding light on how these interactions influence driving behavior (Ding et al. 2022; Elhenawy et al. 2020; Pathivada and Perumal 2019). By addressing these critical research gaps and offering novel insights, this study significantly advances the understanding of driving behavior and road safety in roundabouts within mixed traffic environments.

Data Set and Methods

Data Set

The objective of this study was to create a classification model capable of categorizing drivers based on road user trajectories using the rounD data set. This data set comprises naturalistic road user trajectories observed at three different roundabouts in the city of Aachen, Germany and has versatile applications, including road user prediction, driver modeling, and scenario-based safety validation for automated driving systems. It encompasses various vehicle classes such as cars, trucks, trailers, vans, buses, as well as pedestrians, bicyclists, and motorcycles. Furthermore, the data set spans a total of 6 h of recordings, encompassing more than 13,746 road users. Additionally, the data were collected at three distinct recording locations on different types of roundabouts, and have a typical positioning error of less than 10 cm (Fig. 1) (Krajewski et al. 2020).

The rounD data set represents a rich and comprehensive resource created through a meticulous process (Krajewski et al. 2020). It involved the extraction of data from an extensive set of 24 distinct recordings of traffic, conducted at 3 different measurement locations within the city of Aachen, Germany. These recordings spanned more than 6 h, with a strategic emphasis on capturing the morning rush hours to ensure a high volume of traffic and substantial interactions among road users. From this extensive data collection effort, the rounD data set successfully compiled a diverse sample of more than 13,000 road users. This diverse group encompasses various vehicle types, including cars, trucks, vans, trailers, buses, and vulnerable road users such as pedestrians, bicyclists, and motorcyclists. This extensive data set is particularly notable for its ability to provide an in-depth understanding of driver behavior within the complex environment of roundabouts. The data set offers detailed insights into how road users navigate roundabouts,

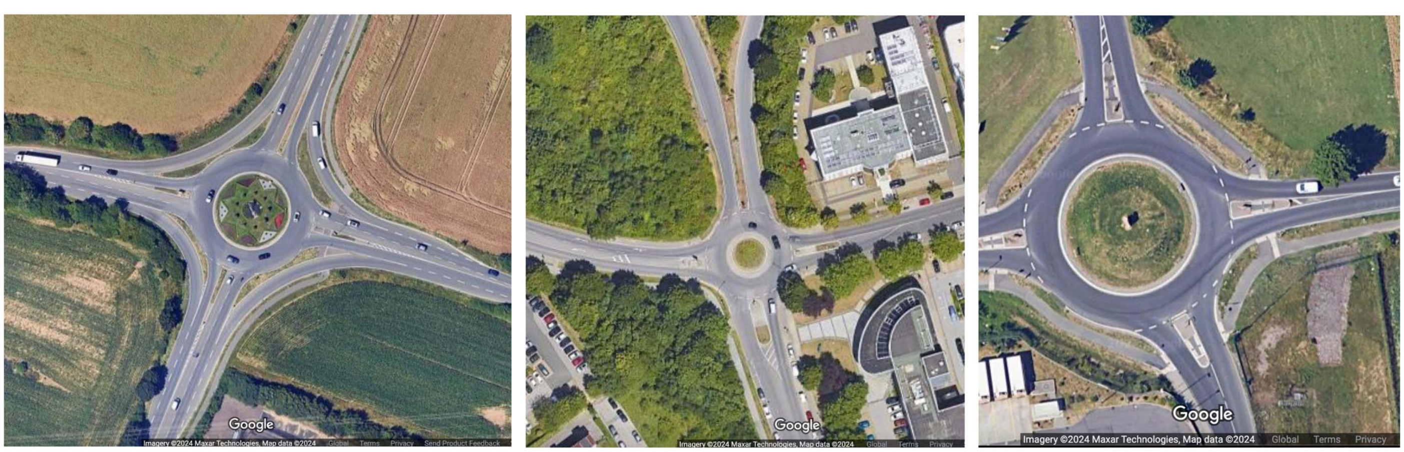

Fig. 1. Maps of the three recording sites included in the rounD data set. (Image © Google, Imagery ©2024 Maxar Technologies, Map data ©2024.)

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including their entry and exit strategies, interactions with other road users, and the signaling of their intentions. Moreover, it encompasses essential information about the roundabouts themselves, encompassing their physical attributes such as size, layout, presence of lane markings, and pedestrian crossings.

The rounD data set is organized into three distinct recording sites located in and around Aachen, Germany. These sites include a four-armed roundabout connecting a highway with Aachen, a roundabout situated in an urban area of Aachen, and a four-arm roundabout located in a suburban setting. Each of these sites presents its own unique characteristics, encompassing varying traffic volumes, lane markings, and pedestrian crossings, providing a comprehensive perspective on roundabout dynamics. The rounD data set is a valuable asset for both researchers and policymakers. It offers a wealth of information on driver behavior and roundabout attributes, serving as a foundation for informed efforts to enhance safety, optimize traffic flow, and improve efficiency within the context of roundabouts. Researchers and policymakers can leverage this data set to gain valuable insights and make data-driven decisions in the realm of roundabout design and operation.

The selection of the rounD data set for this study was based on three main reasons. Firstly, the data set offers a publicly available collection of naturalistic road user trajectories, which ensures that the classification model captures a broad spectrum of driving behaviors and interactions specific to roundabout environments, which are known for their complexity and variability. Secondly, the data set includes a wide range of road users, including various vehicle classes such as cars, trucks, trailers, vans, buses, pedestrians, bicyclists, and motorcycles, which allows for understanding the driving behaviors across different modes of transportation in mixed traffic environments, contributing to the model's robustness and generalizability. Additionally, the data set's extensive duration of 6 h of recordings ensures sufficient data for model training and validation, enhancing the model's accuracy and reliability.

No preprocessing steps were applied to the data set, aligning with the goal of maximizing the framework's applicability in real-time applications. By omitting preprocessing, the framework maintains the authenticity of the naturalistic road user trajectories, ensuring that the extracted features and algorithms accurately reflect real-world driving behaviors. This direct utilization of raw trajectory data enhances the framework's efficiency and effectiveness, because it eliminates the need for time-consuming preprocessing steps that may introduce potential biases or distortions. Furthermore, by leveraging the unedited trajectory data, the framework remains adaptable to dynamic and evolving traffic conditions, enabling it to provide timely and contextually relevant insights for various applications in road safety.

Methods

To classify driving behavior at roundabouts, a previously developed framework from a study of signalized intersections and another study on work zones was utilized (Khanfar et al. 2022a, b). The framework's main components were utilized, but the present study focused on different road infrastructure, namely roundabouts. The first step involved extracting features from each driver's trajectory data using volatility measures (Appendix). Volatility measures are significant safety parameters for identifying driver behavior, and have been used in many studies (Arvin et al. 2019; Khanfar et al. 2022a, b). A higher value of volatility measures implies that a driver is more unstable and riskier, and hence more aggressive (Arvin et al. 2019; Khanfar et al. 2022a, b). Thirteen different volatility measures were used. Next, these extracted features were utilized as input for an unsupervised machine learning algorithm to cluster each driver's behavior in the work zone. The *k*-means algorithm was used in this study, which was successful in previous studies (Khanfar et al. 2022a, b).

The *k*-means algorithm employed in this study is a well-established and widely utilized unsupervised machine learning technique, and is invaluable for the tasks of clustering and data segmentation. Its primary objective is to organize a data set into *k* distinct clusters, the predetermined number of which is specified by the user, based on the inherent similarity between data points. The algorithm operates iteratively, commencing with an initial assignment of data points to clusters, followed by their reassignment to the nearest cluster center, which is determined by the Euclidean distance between each data point and the centroid of the cluster with which it is being compared. Crucially, the centroid, which represents the center of each cluster, undergoes recalculation after each iteration. This recalculation takes into account the mean value of all the data points belonging to the cluster. The iterative process persists until no substantial change is observed in the assignment of data points to clusters, signifying convergence.

The versatility of the *k*-means algorithm extends across numerous domains and applications. For example, it is employed extensively in customer segmentation to group individuals with similar purchasing behaviors or preferences. In image compression, it aids in reducing the file size while preserving essential visual information. Moreover, *k*-means clustering is used in anomaly detection, in which it helps identify outliers or abnormal data points in a data set. The *k*-means algorithm is a foundational tool in machine learning, enabling the effective partitioning of data into meaningful clusters, with applications spanning various fields such as marketing, image processing, and anomaly detection. Its iterative approach, which is grounded in Euclidean distance calculations and centroid re-evaluation, provides a robust means of organizing data for further analysis and interpretation.

Analysis and Results

In this study, *k*-means algorithm played a pivotal role in clustering driving behavior by leveraging volatility measures and finding their respective centroid points. Each centroid point represents the average position of all data points within its cluster. The process of *k*-means clustering entails an iterative assessment of the Euclidean distance between each data point in the data set and the centroid points of potential clusters. Initially, these centroid points are assigned randomly and evolve through each iteration. The *k*-means clustering algorithm is a well-established technique in cluster analysis, and is renowned for its efficacy in various applications (Khanfar et al. 2022b; Mohammadnazar et al. 2021).

To determine the optimal number of clusters for the *k*-means algorithm, the elbow method was employed, using the 13 volatility measures as input. This method aids in selecting the most suitable number of clusters that minimizes total distortion while still retaining a meaningful interpretation. In this case, two or three clusters were considered because they yielded relatively low total distortion and could be interpreted readily in a practical sense. Both scenarios were tested and compared to assess their respective outcomes. Each resulting cluster was labeled 1, 2, or 3, signifying distinct classified driving behaviors. The assignment of specific driving behaviors to clusters was predicated on the mean values of classification features. In labeling each cluster as conservative, normal, or aggressive, we utilized the mean values of the classification features (i.e., centers), to distinct driving behaviors. Higher driving volatility indicates increased driving instability, and is associated with more aggressive behavior (Arvin et al. 2019; Khanfar et al. 2022a, b).

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Table 1. Scaled cluster centers at roundabouts for $k = 2$ and 3

Volatility measure	$k = 3$			$k = 2$	
	Cluster 1 (conservative)	Cluster 2 (normal)	Cluster 3 (aggressive)	Cluster 1 (conservative)	Cluster 2 (normal)
DV_1	3.03	2.92	5.76	2.92	3.03
DV_2	0.74	0.73	0.63	0.73	0.74
DV_3	116.80	−103.26	−6,152.43	−107.88	116.80
DV_4	71.82	69.06	75.97	69.07	71.82
DV_5	−68.78	−67.45	−79.26	−67.46	−68.78
DV_6	2.64	2.54	4.95	2.54	2.65
DV_7	0.408	0.38	0.44	0.38	0.41
DV_8	93.56	−83.72	−222.80	−83.82	93.56
DV_9	54.03	50.89	65.79	50.89	54.03
DV_{10}	−53.44	−52.75	−41.83	−52.74	−53.44
DV_{11}	361.17	−98.33	243.79	−98.06	361.72
DV_{12}	52.33	51.53	51.65	51.53	52.33
DV_{13}	−10.36	−10.49	−8.69	−10.48	−10.36
Sample size	6,967	6,535	5	6,967	6,540

By examining the mean values of the volatility features, we categorized clusters exhibiting higher volatility as aggressive, reflecting a tendency for risk-taking and assertive driving maneuvers. In contrast, clusters with lower volatility were deemed to be conservative, representing cautious and restrained driving behaviors. The remaining clusters, which had an intermediate range of volatility, were labeled normal, signifying a balanced and moderate approach to driving. This criterion enabled us to define clear boundaries between driving styles based on the degree of volatility of each cluster, facilitating a clear understanding of driving behavior in diverse traffic scenarios. The k-means algorithm was conducted with all possible features for both $k = 2$ and 3, and the results indicate the clustering outcomes and their corresponding driving behavior classifications (Table 1).

According to the clustering results, we found that most drivers proceeding through a roundabout can be classified into two driving styles: conservative, and normal. This is due to many factors. First, it usually is a drivers' responsibility when approaching a roundabout to yield to the traffic already in the roundabout (or to pedestrians and bicyclists if there is a crosswalk or a bike lane), and merge only when there is a safe gap in the traffic. Thus, roundabouts generally are considered to reduce traffic crashes, because traffic speeds in roundabouts are relatively lower than at other signalized and unsignalized intersections. Furthermore, there are fewer conflict points in roundabouts than at any other road infrastructure.

The other goal of this study was to investigate the behavior of the drivers that interacted with a VRU (i.e., a pedestrian or a bike). There were about 113 VRUs and 13,507 vehicles. Of those, about 3,681 drivers interacted with a pedestrian or a bike while proceeding through the roundabouts. We found the interaction between the VRUs and drivers of the other vehicles near the roundabouts by matching the position during a specified interval of time. The clustering drivers who interacted with VRUs compared with drivers that did not interact with VRUs is presented in Table 2.

The results showed that the percentage of conservative drivers who interacted with VRUs (about 77.21%) was significantly higher than the percentage of conservative drivers that did not interact or the percentage of all conservative drivers. We also found that most of the drivers that were identified as aggressive (about four-fifths) also were drivers who interacted with VRUs as they proceeded through the roundabouts. This means that although drivers tend to slow as they approach roundabouts, they tend to behave abnormally (conservatively or aggressively) when they interact with VRUs on the roads. This raises a concern that conservative behavior might increase the risk of crashes, especially rear-end collisions. Comparing the effect of the surrounding environment and the interaction with other modes of transportation is crucial for policymakers to determine the effective and suitable safety countermeasures in multimodal intersections.

The interaction of vehicles and pedestrians at roundabouts can have a significant impact on traffic flow. Pedestrians and cyclists are vulnerable road users who require special attention from drivers, especially at roundabouts, in which the flow of traffic can be complex and unpredictable. Drivers need to be aware of the presence of pedestrians and cyclists and yield to them as necessary. The presence of pedestrians and cyclists at roundabouts can cause delays and disruptions to the flow of traffic. Pedestrians may cross the roundabout at unmarked or marked crosswalks, causing drivers to slow or stop. Cyclists also may use the roundabout, and drivers need to be aware of their movements and adjust their speed accordingly. In addition, the interaction between pedestrians and cyclists can also impact traffic flow, because they may cross each other's paths and cause further delays. Efforts to improve the interaction of vehicles and pedestrians at roundabouts can help to improve traffic flow. For example, providing marked crosswalks and bicycle lanes can help to better define the paths of pedestrians and cyclists, reducing the likelihood of conflicts with vehicles. Improved signage and education for drivers also can help to increase awareness of the

Table 2. Results of clustering all drivers, drivers with interaction, and with no interaction

Driving style	All drivers		Drivers with no interaction		Drivers with interaction	
	Number	Percentage (%)	Number	Percentage (%)	Number	Percentage (%)
Conservative	6,967	51.58	4,125	42.06	2,842	77.21
Normal	6,535	48.38	5,692	57.93	843	22.68
Aggressive	5	0.04	1	0.01	4	0.11
Total	13,507		9,826		3,681	

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presence of pedestrians and cyclists at roundabouts, reducing the likelihood of accidents and delays.

Moreover, the interaction of vehicles and pedestrians can impact driving behavior in a number of ways. When drivers encounter pedestrians, they may need to slow or stop, which can lead to changes in their speed and acceleration. This can affect the flow of traffic and cause congestion, particularly in areas with heavy pedestrian traffic. Additionally, drivers may need to be more attentive to their surroundings when pedestrians are present, which can lead to changes in their driving behavior such as increased lane changes, braking, or steering. Pedestrians also can impact the behavior of other road users, such as bicyclists or motorcyclists, who may need to take extra precautions to avoid collisions with pedestrians. Overall, the interaction of vehicles and pedestrians can create complex and dynamic traffic scenarios that require careful attention and awareness from all road users.

Conclusion

The issue of identifying driving behavior is important because the driving habits of drivers have a significant impact on road safety. Roundabouts are particularly intriguing due to the high level of user engagement that a driver or an automated vehicle must consider while proceeding through. Using data-driven unsupervised machine learning to categorize driving behavior at roundabouts, we extracted the volatility measures to classify driving behavior and investigate the effect of interaction between drivers and pedestrians or cyclists.

We found that most drivers proceeding through a roundabout can be classified into two driving styles: conservative, and normal. Roundabouts generally are considered to reduce traffic crashes, because traffic speeds in roundabouts are relatively lower than at other signalized and unsignalized intersections. In addition, there are fewer conflict points in roundabouts than at any other road infrastructure. The results also showed that the percentage of conservative drivers that interacted with VRUs (about 77.21%) was significantly higher than the percentage of conservative drivers that did not interact with VRUs or the percentage of all conservative drivers. Drivers tend to behave abnormally when they interact with VRUs on the roads. This raises a concern that conservative behavior might increase the risk of crashes, especially rear-end collisions. Driving behavior is considered to be one of the most critical criteria in traffic safety studies. The results of this study could be helpful in improving the safety of roads by allowing policymakers to determine the effective and suitable safety countermeasures. The results also will be beneficial for advanced driver-assistance systems as the technology is deployed in a mixed traffic environment.

Based on the study findings, policymakers are urged to implement targeted safety countermeasures at multimodal roundabouts to mitigate the risks associated with driving behavior, particularly in interactions with VRUs. Because a significant proportion of drivers exhibit conservative behavior when interacting with VRUs, measures should be devised to enhance awareness and promote safer interactions between motorists and pedestrians or cyclists at roundabouts. This could include implementing educational campaigns to raise awareness about the importance of yielding to VRUs and adhering to designated crossing points. Additionally, infrastructure improvements such as enhanced signage, designated crosswalks, and dedicated cycling lanes can facilitate smoother interactions and reduce the likelihood of conflicts between different road user groups. Policymakers also should consider integrating ADAS into roundabout designs to provide real-time assistance and warnings to drivers, particularly in scenarios involving VRUs. ADAS could leverage real-time data on driving behavior to provide proactive warnings and assistance to drivers, alerting them to the presence of VRUs and promoting responsible and cautious driving practices. Additionally, the study's identification of potential risk factors for crashes, such as rear-end collisions resulting from conservative behavior, underscores the need for ADAS interventions aimed at mitigating these risks.

Future plans include expanding the scope to investigate a wider range of driving behaviors and interactions at roundabouts in diverse geographic locations and traffic conditions. Furthermore, ongoing research efforts will focus on integrating the study results into practical applications, such as the development of ADAS tailored for roundabout environments. Despite its contributions, this study has certain limitations that should be acknowledged. For example, the classification model's performance may vary depending on factors such as environmental conditions and driver demographics, necessitating further validation and refinement. Additionally, although the study focused on driving behavior, other factors such as road infrastructure and traffic regulations also may influence safety outcomes at roundabouts, and should be considered in future research endeavors.

Appendix. Volatility Measures Used as Inputs to Unsupervised Machine Learning Algorithm

Volatility measure	Description	Equation
DV_1	Standard deviation of speed	$\sqrt{\frac{\sum_{i=1}^{N}(V_i-\bar{V})^2}{N}}$
DV_2	Standard deviation of longitudinal deceleration or acceleration	$\sqrt{\frac{\sum_{i=1}^{N}(AD_{\mathrm{long}_i}-\overline{AD}_{\mathrm{long}})^2}{N}}$
DV_3	Coefficient of variation of speed	$100\times\frac{\sqrt{\frac{\sum_{i=1}^{N}(V_i-\mathrm{V})^2}{N}}}{V}$
DV_4	Coefficient of variation of longitudinal acceleration	$100\times\frac{\sqrt{\frac{\sum_{i=1}^{N}(A_{\mathrm{long}_i}-A_{\mathrm{long}})^2}{N}}}{\overline{A}_{\mathrm{long}}}$

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Appendix. (*Continued.*)

Volatility measure	Description	Equation
DV_5	Coefficient of variation of longitudinal deceleration	$100 \times \frac{\sqrt{\frac{\sum_{i=1}^{N}(D_{\text{long}_i} - \overline{D_{\text{long}}})^2}{N}}}{\overline{D_{\text{long}}}}$
DV_6	Mean absolute deviation of speed	$\frac{\sum_{i=1}^{N} \lvert V_i - \bar{V} \rvert}{N}$
DV_7	Mean absolute deviation of longitudinal acceleration	$\frac{\sum_{i=1}^{N} \lvert A_{\text{long}_i} - \overline{A_{\text{long}}} \rvert}{N}$
DV_8	Quantile coefficient of variation of normalized speed	$100 \times \frac{Q_{V_3} - Q_{V_1}}{Q_{V_3} + Q_{V_1}}$, where Q_1 and Q_3 = sample 25th and 75th percentiles.
DV_9	Quantile coefficient of variation of longitudinal acceleration	$100 \times \frac{Q_{A_{\text{long}_3}} - Q_{A_{\text{long}_1}}}{Q_{A_{\text{long}_3}} + Q_{A_{\text{long}_1}}}$
DV_{10}	Quantile coefficient of variation of longitudinal deceleration	$100 \times \frac{Q_{D_{\text{long}_3}} - Q_{D_{\text{long}_1}}}{Q_{D_{\text{long}_3}} + Q_{D_{\text{long}_1}}}$
DV_{11}	Percentage of time mean normalized speed exceeds mean plus 2 standard deviations	$100 \times \frac{\sum_{i=1}^{N}(V_i \geq \bar{V} + 2 \times \alpha)}{N}$, where $\alpha = DV_1$
DV_{12}	Percentage of time mean of longitudinal acceleration exceeds mean plus 2 standard deviations	$100 \times \frac{\sum_{i=1}^{N}(A_{\text{long}_i} \geq \overline{A_{\text{long}}} + 2 \times \alpha)}{N}$, where $\alpha = DV_2$
DV_{13}	Percentage of time mean longitudinal deceleration exceeds mean plus 2 standard deviations	$100 \times \frac{\sum_{i=1}^{N}(D_{\text{long}_i} \geq \overline{D_{\text{long}}} + 2 \times \alpha)}{N}$, where $\alpha = DV_2$

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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