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Posted Date: 22 September 2023

doi: 10.20944/preprints202309.1341.v3

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Improving Autonomous Vehicle Reasoning with Non-Monotonic Logic: Advancing Safety and Performance in Complex Environments

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Abstract: The software design of autonomous vehicles (AVs) incorporates artificial intelligence (AI) characteristics to enhance their safety and overall driving performance. Central to vehicle's operation is the ability to reason effectively in complex and uncertain environments. However, traditional logical systems, such as monotonic logic, often struggle to handle the inherent uncertainties and exceptions encountered in real-world scenarios. This paper proposes the utilization of non-monotonic logic in order to enhance the reasoning capabilities of autonomous vehicles. By incorporating non-monotonic reasoning, vehicles can navigate intricate traffic scenarios, make plausible inferences, and adapt their decisions when faced with conflicting information. This research aims to provide a comprehensive review of non-monotonic logic's application in autonomous vehicles, highlighting its advantages over traditional logical systems and its potential impact on safety and performance. Additionally, through this research, we seek to contribute to the advancement of autonomous driving technology by enhancing the reasoning capabilities of vehicles in various scenarios, such as car-following related to critical safety events. The personalized cognitive agent is proposed in driving behavior to consider particularly in their assumptions of homogeneous drivers. The personalized cognitive agent is incorporating heterogeneous driving behaviors, based on individual user preferences, characteristics, and needs. Driving behavior is a complex interplay of various factors, encompassing both human and external elements. Human factors, including age, experience, and gender, contribute significantly to how individuals navigate the roads. These factors influence decisions, reactions, and risk-taking tendencies on the part of drivers. Additionally, external factors such as weather conditions further compound this intricate dynamic, requiring drivers to adapt their behavior to the prevailing environment. The goal of a personalized cognitive agent is to provide tailored and customized experiences to cognitive vehicles, taking into account the unique requirements and individual preferences of occupants inside autonomous vehicles.

Keywords: car–following; non-monotonic logic; reasoning; naturalistic driving studies; safety-critical events; cognitive vehicles

1. Introduction

Despite the growth of vehicle automation, the number of car crashes is still unacceptably high. It seems that safety critical events related to human driving have become more complex and partially uncontrolled due to unexpected circumstances. Studies of human driving behavior are needed to design traffic baselines for mixed traffic, involving traditional, automated and autonomous vehicles. Human driving behavior is affected by various factors such as weather conditions, which reduce visibility in longitudinal car-following (CF) driving behavior [2,10]. *Car-following behavior* refers to how a car- following a leading car reacts to the motion of the lead vehicle. The Car- following behavior describes how a following vehicle reacts to the lead vehicle in the same lane. The limitations of previous works in car-following models, particularly in their assumptions of homogeneous drivers. In reality, drivers exhibit significant heterogeneity in terms of their driving experience, gender, character, emotion, and other sociological, psychological, and physiological aspects. Ignoring this heterogeneity can lead to an incomplete understanding of car-following behavior and limit the accuracy and applicability of the models. The incorporation of driver

 doi:10.20944/preprints202309.1341.v3

heterogeneity is crucial for developing more realistic and accurate car-following models in mixed traffic. By considering the individual differences among drivers, such as their risk-taking tendencies, reaction times, decision-making processes, and driving styles, one can better capture the complexities of real-world driving scenarios. Furthermore, categorizing drivers into just a few types (e.g., aggressive, normal, and inattentive) oversimplifies the richness and diversity of driver characteristics. This simplistic approach fails to capture the nuances and subtleties that exist within different driver profiles. Instead, a more comprehensive approach is needed to account for the wide range of characteristics and behaviors exhibited by individual drivers. Addressing these limitations requires developing models that can effectively incorporate the external heterogeneity between different drivers and the internal heterogeneity within a single driver. The proposed model is based on *personalized cognitive agent*. Each driver is assigned a personalized cognitive agent that can represent the driver profile with accessing local information and learn the driver characteristics. The personalized cognitive agent is based on individual user preferences, characteristics, and needs. The goal of a personalized cognitive agent is to provide tailored and customized experiences to cognitive vehicle, taking into account the unique requirements and individual preferences of occupants inside autonomous vehicle to better understand the driving behavior of all surrounding vehicles in mixed traffic. The rest of this paper is organized as follows: Section 2 gives an overview of related research; section 3 describes the methodology; and sections 4 and 5 present a performance evaluation and conclude the paper.

2. Related Research

Several different driving models have been developed in the literature [1]. Many driving models try to approximate the real driver's road tracking performance, assuming certain driver inputs and outputs. Models of models of driving behavior attempt to capture the driver's decision-making process and behavior, such as how they respond to changes in the road and traffic under external factors, how a driving maneuver is recognized by a cognitive vehicle, observing (by its onboard sensors) the driving behavior of surrounding vehicles [7]. It is expected that there is some level of uncertainty associated with models of driving behavior, as they are based on assumptions and approximations of real-world driver behavior as well as with the inherited uncertainties of onboard sensor measurements and consecutive feature extraction, characterizing the surrounding objects. This uncertainty can have a significant impact on the performance of control systems that are designed using these models. One way to address this uncertainty is by developing a model for the driver model uncertainty [3].

Uncertainty modeling of driving refers to predicting and managing the uncertainty that comes with driving. This includes modeling human factors, driving behaviors (of human driver, automated or autonomous vehicles), external factors and other factors that can affect driving performance. Driving behaviors are the main cause of road accidents and one of the main sources of insurance claims [14]. Wang and Lu [11] found that the that the difference in driving behavior between males and females remained unchanged, or even increased in some aspects. The differences involved traffic accidents and offenses, although the driving times, attitudes, education, and other background factors were controlled. Furthermore, all drivers involved in traffic accidents and fatalities, however, Younger drivers have the highest rate of accidents. The study of Hiang and Ming [13] aimed to investigate the relationship between age and gender with speeding driving behavior. Results showed young and male drivers averagely travelled at higher velocity before entering the roundabout and at the same time accelerate to higher velocity upon exiting the roundabout compared to old and female drivers. Lee et al. [15] proposed the purpose of this research is (1) to investigate the relationship between crash severity and the age and gender of the at-fault driver, the socio-economic characteristics of the surrounding environment, and road conditions. This research adopts the logit model to investigate how age impacts accident severity and to uncover when age has little effect, using age as a continuous variable. Shahverdy et al [12], introduced a deep learning method for analyzing the driver behavior focused on driving signals, including acceleration and speed to recognize five types of driving styles, including normal, aggressive, distracted, drowsy, and drunk driving. The study [16] examined the factors influencing aggressive driving behavior, considering human factors, personality traits, and demographic characteristics. Regression analysis was used to explore the impact of age and driving experience and their interactions with other variables on aggressive driving behaviors.

Aggressive driving behavior is influenced by a combination of human factors, including age and driving experience, as well as personality traits and demographic characteristics. The analysis revealed a negative correlation between age and aggressive driving behaviors. This implies that as individuals grow older, they tend to engage in fewer aggressive driving behaviors on average. There was a positive correlation found between the personality trait of neuroticism and aggressive driving behaviors. Individuals with higher levels of neuroticism, characterized by emotional instability and heightened negative emotions, are more likely to exhibit aggressive driving tendencies. Significant associations were identified between age, driving experience, and depression. This suggests that older, more experienced drivers may be less prone to depression, potentially reducing their likelihood of engaging in aggressive driving behaviors.

In the context of car-following models, artificial intelligence tools can be used to represent different aspects and behaviors of drivers. A non-monotonic logic-based approach for car- following in autonomous vehicles has been proposed [4,5]. The study develops a reasoning system that incorporates non-monotonic inference mechanisms to handle uncertainties and exceptions in car-following scenarios. The experimental results demonstrate improved adaptability and decision-making performance compared to traditional rule-based systems. An adaptive car- following system that utilizes non-monotonic logic has been introduced to enhance reasoning and decision-making capabilities. The study incorporates context-dependent rules and non-monotonic inference mechanisms to handle exceptions and conflicting information during car- following. Simulation results show improved safety and efficiency in various traffic scenarios. This research investigates the integration of non-monotonic logic into existing car- following algorithms as illustrates Figure 1. The study proposes an architecture that combines rule-based reasoning with non-monotonic inference mechanisms to handle uncertainties and adapt the behavior of autonomous vehicles during car following. Experimental evaluations demonstrate improved performance and adaptability in dynamic traffic conditions. The paper provides a comprehensive overview of the challenges and opportunities of applying non-monotonic reasoning in car- following for autonomous vehicles. It discusses the limitations of traditional rule-based systems and highlights the benefits of non-monotonic logic in handling uncertainties, conflicting data, and context-dependent reasoning. The study also identifies future research directions and potential applications of non-monotonic reasoning in autonomous driving.

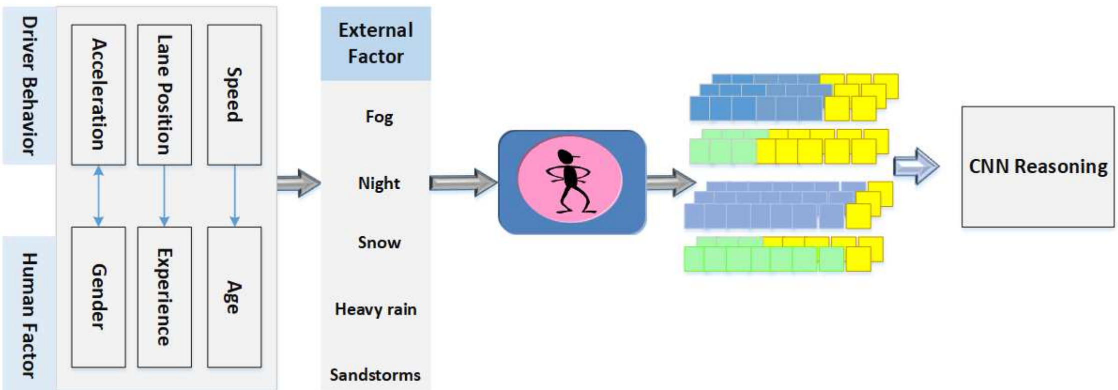

Figure 1. Personalized cognitive agent reasoning.

3. Methodology

3.1. CNN Reasoning model

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Convolutional neural network (CNN) reasoning refers to the application of CNNs in the context of reasoning and decision-making tasks [6]. The traditional CNN Architecture typically consist of multiple convolutional layers followed by fully connected layers. These layers learn hierarchical representations of input data, enabling the network to capture complex patterns and features. CNNs can be extended or combined with other components to enable reasoning capabilities. This often involves incorporating additional layers, such as recurrent neural networks (RNNs) [6] or attention mechanisms, to capture temporal or spatial dependencies and enable sequential reasoning. Furthermore, CNNs can be employed for visual reasoning tasks, where the model is trained to reason about relationships between objects. The model learns to extract meaningful features from input data and use them to infer relationships and make logical deductions. This paper proposed a hybrid approach that combines multiple techniques to create more accurate and robust driver models as illustrated in Figure 2. A hybrid model uses a deep learning to find causal relationship between human factor and driving behavior based on feature extraction and a statistical model to predict a driver's speed and acceleration, but also incorporate rule-based logic to handle unexpected situations.

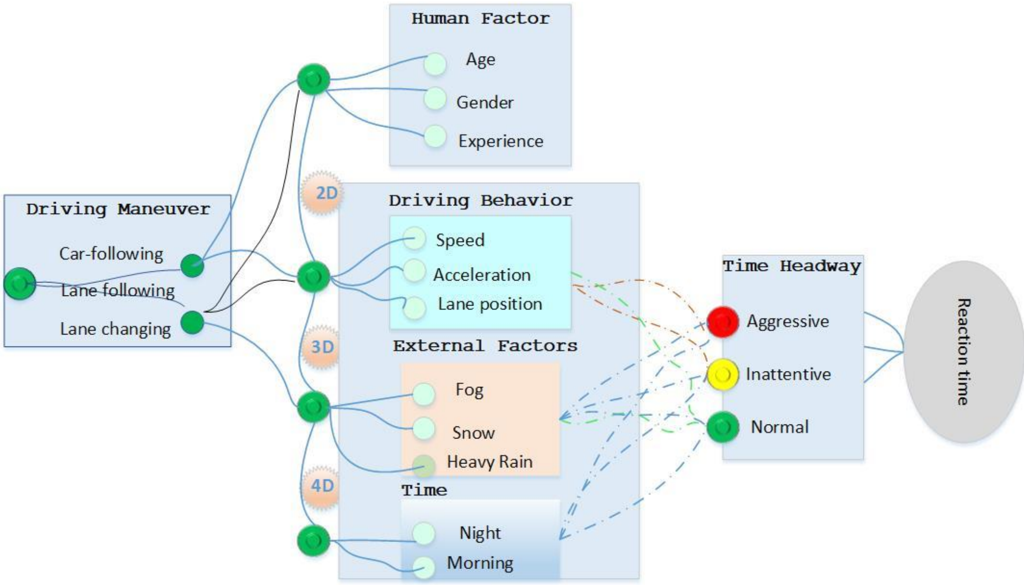

Figure 2. System model.

3.2. Data collection

The dataset used in this research is based on naturalistic driving data taken from the L3Pilot database [8]. A European research project L3Pilot, which tests the viability of automated driving as a safe and efficient means of transportation on public roads, has developed a common data format (CDF) for both data collection and processing and has implemented a consolidated database for processed data collection. The data consist of performance indicators for four driving scenarios, free driving, following a lead vehicle, driving in traffic jams and changing lanes. The used data for training the deep learning algorithm is involving cleaning and formatting the data, selecting relevant features, and splitting the dataset into training, validation, and testing sets. Table 1 summarized the main notation that is used in this paper.

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Table 1. Summary of the Main Notation.

Notation	Description	**Symbol**
Min_ax	Minimum longitudinal acceleration	min(a_x)
Max_ax	Maximum longitudinal acceleration	max(a_x)
SD_ax	Standard deviation of longitudinal acceleration	sd(a_x)
SD_ay	Standard deviation 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)

.

3.3. Algorithm Description

The algorithm is a hybrid model that consists of a deep learning scheme and statistical tools as illustrated in Figure 3. The deep learning is a subset of machine learning that involves training artificial neural networks to recognize patterns in data. By applying deep learning techniques to analyze large datasets of human behavior and vehicle behavior, you can identify complex patterns and causal relationships that may be difficult to detect using traditional statistical methods. The statistical tools are applied to evaluate the performance of the prediction scheme. The prediction model of drivers' behavior during car- following can be performed for certainty and uncertainty. Driver's certainty during car- following can increase when the driver is familiarity with the situation, consistent behavior of the leading vehicle by maintains a steady speed, consistent acceleration and deceleration, and follows traffic rules. In other hand, there are several factors that contribute to driver's uncertainty during car- following such as Unpredictable behavior of the leading vehicle: Uncertainty arises when the leading vehicle exhibits erratic or unexpected actions, such as sudden braking, lane changes without signaling, or unpredictable acceleration. In additions lack of information or incomplete information about the road conditions, traffic situation, or intentions of the leading vehicle, Furthermore, a driver in weather conditions, these factors can contribute to uncertainty during car-following and driver is feeling anxious and stressed due to external factors.

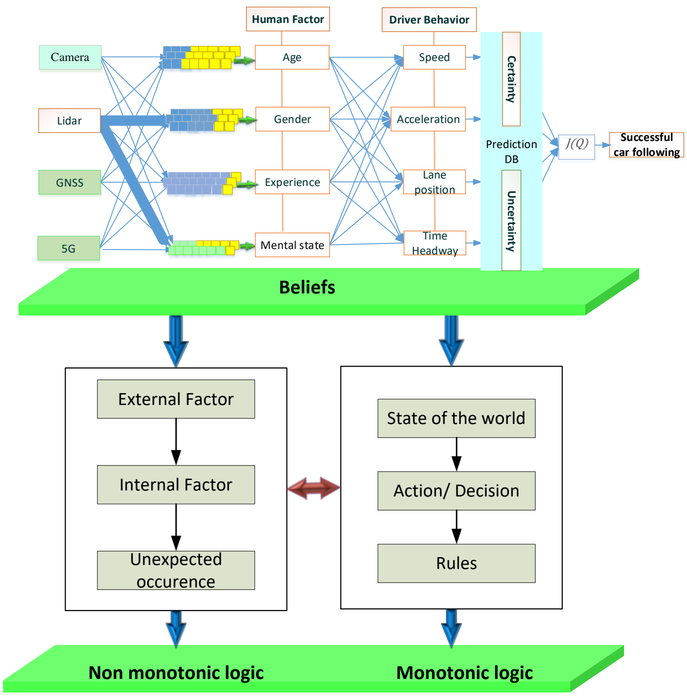

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Figure 3. Hybrid model.

3.4. Feature Extraction

One approach is to use deep learning models to extract features from the data, and then use these features as input to various machine learning schemes, like Nearest Neighbor, Random Forest, Naïve Bayesian network (NBN), Decision Table, etc. Feature extraction based on naturalistic driving data is important for the analysis of driving behavior related to safety-critical events. Human driving behavior can be identified however, it is difficult to control because, although human drivers are affected by external factors that can be estimated and predicted, there are internal factors affecting human cognition which cannot be distinguished or controlled. However, for AVs, both internal and external factors are predictable.

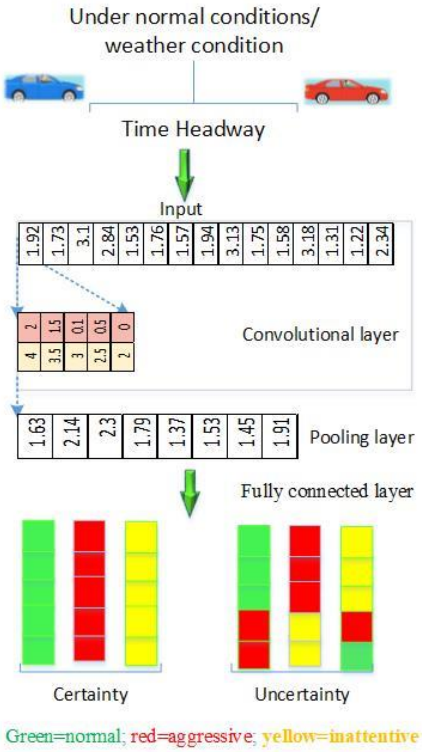

Figure 4. Driving behavior Identification.

The trained CNN can recognize the driver profile based on time headway. The CNN classifies the driver profile in three groups normal, inattentive and aggressive. To evaluate and validate the quality of data clustering results, we used the silhouette, a statistical technique [9] to present graphically how well each object has been classified. For each driver, we calculate its silhouette score using the following formula:

$$S_i = \frac{b_i - a_i}{\max(a_i, b_i)} \quad (1)$$

Where a_i, is the average distance from the *ith* point to the other points in the same cluster as *i*. And b_i is the minimum average distance from the *ith* point to points in a different cluster, minimized over all clusters. The silhouette value is an internal criterion, which is used for interpretation and validation of consistency within a cluster of data and for each point measures how similar that point is to points in its cluster when compared to points in other clusters. Furthermore, we assigned a score according to driver aggressivity degree.

3.5. Reasoning based non-monotonic logic

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To overcome these limitations of monotonic logic, this paper proposes the application of non-monotonic logic as a promising approach to enhance the reasoning capabilities of autonomous vehicles during car- following. Non-monotonic logic allows for flexible and adaptive reasoning, accommodating exceptions and context-specific information. By incorporating non-monotonic logic into autonomous vehicles, they can make plausible inferences, handle conflicting data, and adapt their behavior to ensure safe and efficient car- following. Thus, the degree of beliefs for driver profiles is clustered into the following stated:

$$Belief\ (A) = normal$$

$$Belief\ (B) = inattentiv\,e$$

$$Belief\ (C) = aggressive$$

The degree of beliefs for the occurrence of accidents is dependent on the driver profiles (A, B, C), and is expressed as follows.

$$\Pr(accident \mid A) = low$$

$$\Pr(accident \mid B) = medium$$

$$\Pr(accident \mid C) = high$$

The degree of beliefs for the occurrence of accidents is dependent on the joint probability of driver profile (A, B, C) and driving related experience (E) and is computed as follows and the probabilities of the state are dependent on the weights as obtained from CNN training:

$$\Pr(accident \mid A \wedge E) = low$$

$$\Pr(accident \mid B \wedge E) = low$$

$$\Pr(accident \mid C \wedge E) = medium$$

$$\Pr(accident \mid A \wedge \overline{E}) = low$$

$$\Pr(accident \mid B \wedge \overline{E}) = high$$

$$\Pr(accident \mid C \wedge \overline{E}) = high$$

The personalized cognitive agent alerts the autonomous control system based on causal relationship between human factors and driver behavior related to time headway. This alert (which is denoted as Alarm) can be represented as combinatorial combination of the involved Boolean variables as showed in Table 2.

Table 2. Alert truth table for a) B=inattentive and E= experienced; b) C= aggressive and E= experienced driver.

B	*E*	*Alarm*
F	*F*	*F*
F	*T*	*F*
T	*F*	*T*
T	*T*	*F*
	a)	

C	*E*	*Alarm*
F	*F*	*F*
F	*T*	*F*
T	*F*	*T*
T	*T*	*F*
	b)	

The personalized cognitive agent creates rules based on obtained beliefs. However, the traditional rule-based systems and monotonic logic have been extensively used for decision-making in autonomous vehicles. However, these approaches often struggle when faced with the non-deterministic and dynamic nature of car -following scenarios. Monotonic logic typically operates

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under the assumption that additional information does not change the validity of previously drawn conclusions. This limitation poses challenges in dealing with exceptions, conflicting data, and context-dependent reasoning, which are prevalent in car- following situations. To overcome these limitations, this paper proposes the application of non-monotonic logic as a promising approach to enhance the reasoning capabilities of autonomous vehicles during car- following. Non-monotonic logic allows for flexible and adaptive reasoning, accommodating exceptions and context-specific information. By incorporating non-monotonic logic into autonomous vehicles, they can make plausible inferences, handle conflicting data, uncertain data, incomplete data and adapt their behavior to ensure safe and efficient car- following.

The primary goal of this research is to explore the potential benefits and challenges associated with integrating non-monotonic logic into autonomous vehicles for car- following by considering human factor, driving behaviors and external factors. The personalized cognitive agent is designing the rules based on defining the relationships between human factors and driving behaviors and logical statements based on the facts to represent knowledge and infer new information as illustrated in Figure 5.

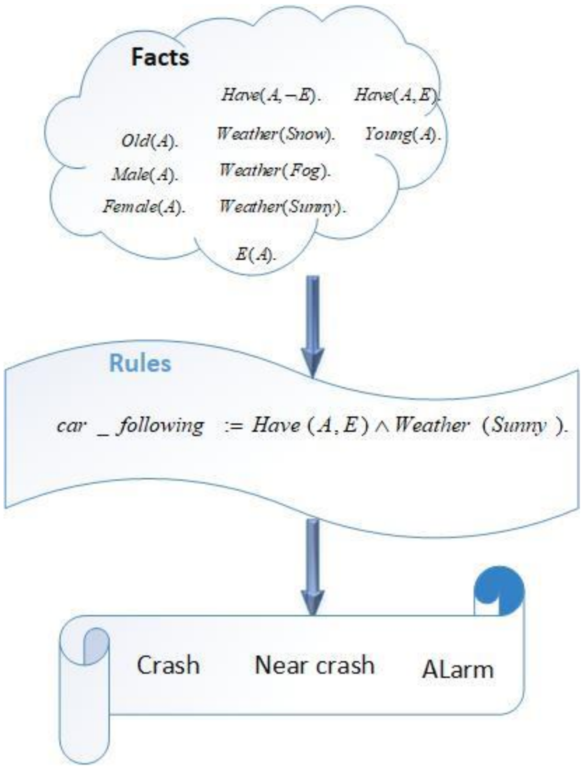

Figure 5. Rules design.

4. Discussion and Analysis

In this section, we discuss the modeling the causal dependencies between human factors, driving behavior for car-following tasks with the aim of keeping a time headway (time distance between a lead and a follow-vehicle). The data provides evidence on the heterogeneity of human driving profiles as the mean THW ranges from near *0s* to *5s* and the minimum of THW ranges from near 0s to more than *3s*. Based on these preliminary findings, we propose the definition of three profiles:

(i) 'aggressive': shorter car time-headway, (*0-2 sec*)

(ii) 'inattentive': longer reaction time (*2-3 sec*), and

(iii) 'normal' for intermediate values of reaction time and car time-headway (bigger than *3sec*), i.e. keeping adaptive cruise control, which is expressed by adaptive relative distance [m] and constant relative speed [m/s].

The definitions of the two driver profiles (aggressive inattentive) are formalized below.

- Aggressive driver profile: A driver i is considered to be aggressive with respect to a threshold t^* on the time headway THW if

$$\overline{THW}(i) := \frac{1}{T}\sum_{t}^{T} THW(i,t) < t^*, \text{ where}$$

T is the time [s]=relative distance [m]/ relative speed[m/s]

- Inattentive driver profile (drivers with long reaction time): A driver i is considered to be inattentive (with a long reaction time) with respect to a threshold $\tilde{t}$ on the time headway THW if

$$\min THW(i) := \min_{t} THW(i,t) > \tilde{t}$$

- Normal driver profile: the drivers whose profiles are neither aggressive or inattentive are called *normal.* They have intermediate values (e.g., < 1 s) of reaction time headway.

Combination between HF and DB

Driving behaviors, such as time headway, speed and acceleration are depended on human factors, such as age, gender, experience and external factors, such as weather condition. However, in this paper, it is considered the human factors. The probability to occur accident is expressed as following,

$$\text{Time Headway} = w_0 * \text{Gender} + w_1 * \text{Age} + w_2 * \text{Experience} + \varepsilon$$

The weight of each human factors is calculated according naturalistic driving.

$$w_0 = \Pr(male) = 0.799$$

$$w_1 = \Pr(18 < age < 29) = 0.352$$

$$w_2 = \Pr(\exp ereince < 15) = 0.409 .$$

The personalized cognitive agent can estimate the probability of accident occurrence according to minimization of the weights. The type of minimization objective function is referred to a loss function, which is also known as cost function. Neural network learning algorithms are formulated with the use of a loss function. The goal was always to minimize the error in prediction L by minimizing the number of misclassifications with respect to all training instances in a data set D containing feature-label pairs

$$Minimize_W L = \sum_{(\overline{X},y)\in D} (y-\overline{y})^2 = \sum_{(\overline{X},y)\in D} (y - sign\{\overline{W}.\overline{X}\})^2$$

The cost function is a special type of functions that helps to minimize error and approach as close as possible to the expected output. It uses two parameters to calculate error: one is an estimated output of the CNN model (also called the prediction) and other is the actual output. The mean squared error (MSE) is indeed a commonly used loss function in various machine learning tasks, including regression problems. Other loss functions, such as root mean square error (RMSE) and mean absolute error (MAE), are also commonly used depending on the specific problem and requirements. Table 3 illustrates a comparison between various machine learning schemes based on statistical measurements error. Nearest neighbor and random forest provide the best classification performance compared to others ML schemes. Furthermore, the two schemes provide the highest accuracy as illustrated in Figure 6.

Table 3. Statistical measurement Error.

	NN	NBN	zeroR	J48 tree	RF	DT
MAE	0.1687	0.186	0.200	0.182	0.169	0.190
RMSE	0.290	0.306	0.316	0.301	0.292	0.307
RAE	84.033	93.07	100	90.676	84.288	95.049
RRSE	91.663	96.83	100	95.241	92.274	96.950

MAE: Mean absolute error; RMSE: Root mean square error; RAE: Relative absolute error; RRSE: Root relative square error. NN: Nearest neighbor; NBN: Naïve Bayes Network; RF: Random forest; DT: Decision Table.

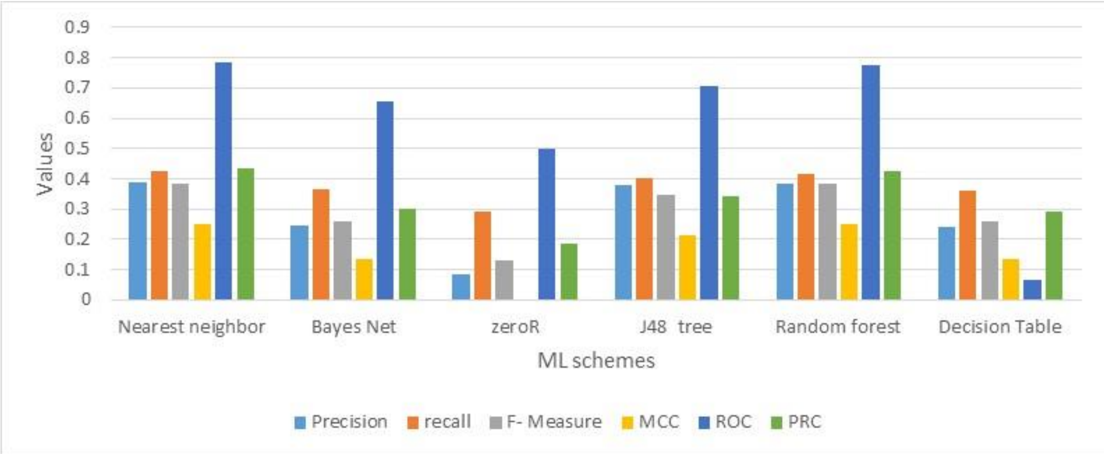

Figure 6. Comparison between ML schemes.

5. Simulation Results

The causal relationship between human factors and driver behavior related to time headway is complex and influenced by various factors. Human factors can play a significant role in determining how drivers perceive, interpret, and respond to the need for maintaining a proper time headway. Figure 7 illustrates the driver profile which has been classified in aggressive, inattentive and normal according to time headway. Drivers with an aggressive driving style may be more inclined to follow vehicles closely and maintain shorter time headways. Experienced drivers often have a better understanding of lane discipline and the importance of staying within their designated lane. They are more likely to maintain a consistent and centered lane position. However, inexperienced drivers may have a limited understanding of lane discipline which is increasing the risk of collisions. Inexperienced drivers may find the acceleration of a vehicle thrilling or exhilarating, especially if it's their first time driving or if they are not yet accustomed to the sensation. In addition, Inexperienced drivers may feel nervous or anxious during acceleration, particularly in situations where they are still learning to control the vehicle's speed and acceleration smoothly. Figure 8 illustrates the involvement of young driver in age between 20-24 in car accidents. Figure 9 illustrates that females are involved in car accident less than the males. Figure 10 illustrates that the type of car accident and the most accident occur with adjacent car.

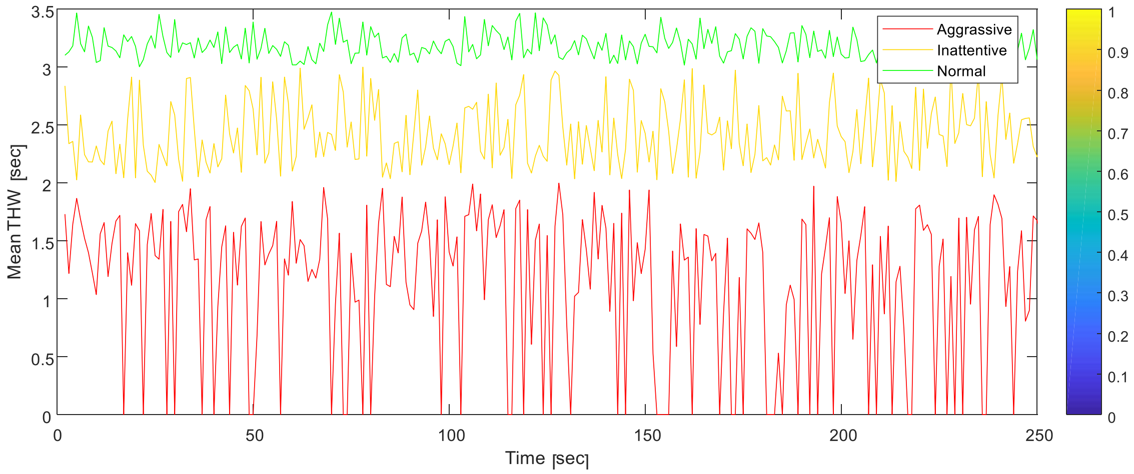

Figure 7. Driver profile.

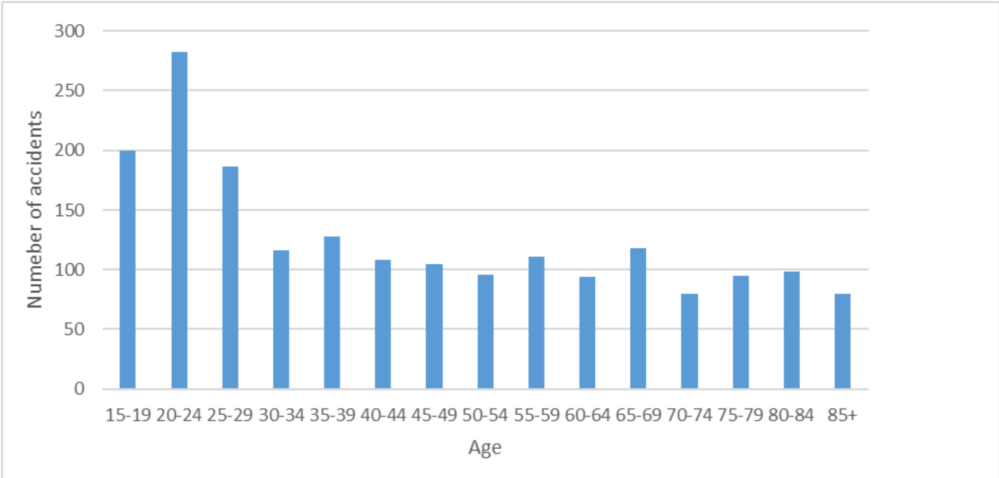

Figure 8. Age versus number of the accidents.

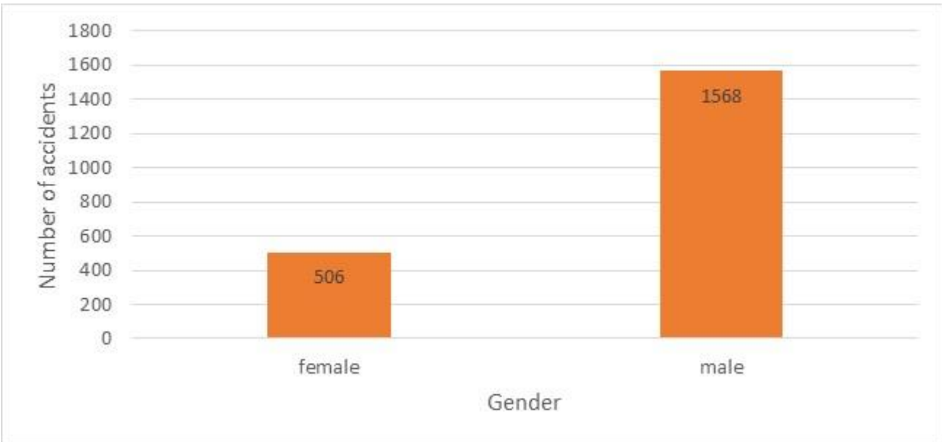

Figure 9. Gender versus number of accident.

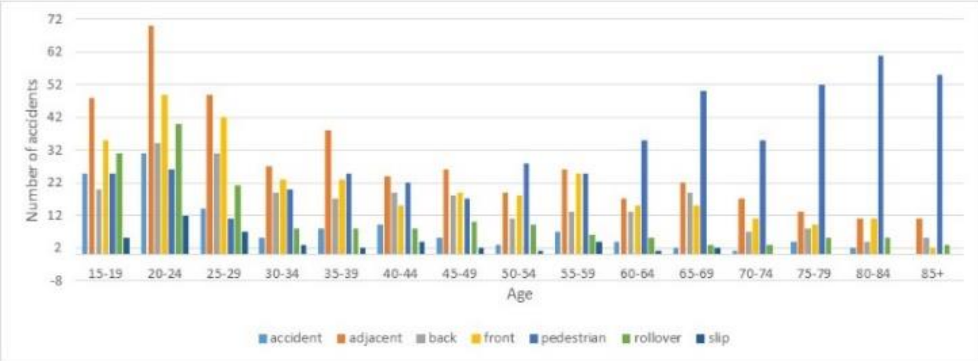

Figure 10. Age versus type of accident.

6. Conclusion

In conclusion, the integration of non-monotonic logic in autonomous vehicles' reasoning for car-following holds great potential for enhancing safety, adaptability, and decision-making in dynamic traffic environments. Traditional rule-based systems and monotonic logic often struggle to handle exceptions, conflicting data, and context-dependent reasoning, which are prevalent in car- following scenarios. By employing non-monotonic logic, autonomous vehicles can overcome these limitations and achieve more robust and intelligent behavior. Through the application of non-monotonic logic, autonomous vehicles can handle uncertainties, adapt to changing conditions, and make plausible inferences based on incomplete or uncertain information. The incorporation of non-monotonic logic allows for the modeling of non-monotonic dependencies of driver behavior, enabling the autonomous vehicle to respond effectively to unexpected actions, variable speeds, and context-specific behaviors exhibited by human drivers. This improves safety, efficiency, and the overall performance of the autonomous driving system. Furthermore, the use of AI characteristics, such as sensor fusion, perception, decision-making, predictive analytics, and continuous learning, enhances the safety of autonomous vehicles. AI enables the vehicles to perceive the environment, make informed decisions, and monitor their performance in real-time. The combination of non-monotonic logic and AI characteristics provides a comprehensive approach to develop cognitive and safe autonomous vehicles. However, it is important to continue researching and addressing challenges associated with integrating non-monotonic logic and AI in autonomous vehicles. These challenges include the interpretation and handling of complex scenarios, the validation and verification of non-monotonic reasoning, and the development of robust and reliable AI algorithms. Future work will combine features describing the human factors and vehicle behavior into cognitive hypotheses of a hierarchical cognitive Bayesian network. This will represent an extension of the approach of [7] for recognition of vehicle behavior, like car-following, lane following and lane changing. By addressing these challenges, we can further improve the safety, reliability, and acceptance of autonomous vehicles on our roads.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare no conflict of interest.

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