

RAG-based explainable prediction of road users behaviors for automated driving using knowledge graphs and large language models[☆]

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ARTICLE INFO

Keywords:

Road users' behaviors
Explainable predictions
Pedestrian crossing actions
Lane change maneuvers
Autonomous driving

ABSTRACT

The prediction of road user behaviors in the context of autonomous driving has attracted considerable attention from the scientific community in recent years. Most works focus on predicting behaviors based on kinematic information alone, a simplification of reality since road users are humans, and as such they are highly influenced by their surrounding context. In addition, a large plethora of research works rely on powerful Deep Learning techniques, which exhibit high-performance metrics in prediction tasks but may lack the ability to fully understand and exploit the contextual semantic information contained in the road scene, not to mention their inability to provide explainable predictions that can be understood by humans. In this work, we propose an explainable road users' behavior prediction system that integrates the reasoning abilities of Knowledge Graphs (KG) and the expressiveness capabilities of Large Language Models (LLM) by using Retrieval Augmented Generation (RAG) techniques. For that purpose, Knowledge Graph Embeddings (KGE) and Bayesian inference are combined to allow the deployment of a fully inductive reasoning system that enables the issuing of predictions that rely on legacy information contained in the graph, as well as on current evidence gathered in real-time by onboard sensors. Two use cases have been implemented following the proposed approach: 1) Prediction of pedestrians' crossing actions; and 2) Prediction of lane change maneuvers. In both cases, the performance attained exceeds the current state-of-the-art in terms of anticipation and F1 score, showing a promising avenue for future research in this field.

1. Introduction

Despite the significant progress that the world has experienced in the last years in terms of road safety, road traffic deaths continue to represent a global health crisis, according to the World Health Organization report on road safety (WHO, 2023), especially for Vulnerable Road Users (VRUs), which are involved in 53% of all road traffic fatalities. The same report highlights the fact that 23% of fatal accidents involve pedestrians. As a matter of fact, pedestrians are the most vulnerable road user group also on European Union roads, being involved in 20% of road traffic fatalities (Slootmans, 2021). Similarly, statistics published in 2023 by the National Highway Traffic Safety Administration (NHTSA) reveal an increase in the number of deaths from motor vehicle traffic accidents in the United States of America in 2021 compared to 2020, and a 17.3% increase compared to 2019 (Stewart, 2023), lane change maneuvers being one of the main causes of vehicle

crashes, as the same report indicates that 33% of all road crashes take place during a lane change maneuver. These statistics underscore the need to develop technologies that aim to improve road safety by endowing automated vehicles with the ability to anticipate pedestrian and driver behaviors and motion patterns, such as road crossing actions (for pedestrians) and lane change maneuvers (for drivers).

In the context of autonomous driving, a large number of road user behavior estimation algorithms have been developed to predict the next actions of pedestrians (Kotseruba, Rasouli, & Tsotsos, 2021), cyclists (Pool, Kooij, & Gavrilu, 2021), and drivers (Izquierdo et al., 2023), in an attempt to understand and anticipate their behaviors. However, there is a missing component in the literature, namely a holistic view of road users' behavior and decision-making to identify the extent of factors that affect their behaviors and to explain in what ways they are interrelated. This gap exists because the majority of research works in

[☆] This research has been funded by the HEIDI project of the European Commission under Grant Agreement: 101069538.

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the literature disregard the theoretical findings of traffic interaction and treat the problem as dealing with rigid dynamic objects rather than a social being (Schulz & Stiefelhagen, 2015). Consequently, they focused primarily on observable kinematic numerical data—such as positions, velocities, and accelerations—without fully incorporating the social and contextual cues that are crucial for accurate prediction. Moreover, these models often act as “black boxes”, making it difficult to reason about and interpret their outputs. This issue is significant because the lack of interpretability poses challenges in explaining the models and their predictions to others who may not be familiar with the underlying algorithms. Therefore, explainability is crucial in the automotive industry. We need models that cannot only predict behaviors but also provide clear explanations for their predictions. This is important for the validation and standardization processes that autonomous vehicles must undergo. By offering transparent decision-making, we can ensure safety and build trust among users, which is essential for the acceptance and deployment of autonomous vehicles.

Building on this foundation, in this work, we focus on developing a holistic behavior understanding and prediction system that integrates comprehensive contextual information to anticipate the actions of both pedestrians and drivers. Specifically, by leveraging linguistic contextual information provided to a knowledge graph, we then utilize Bayesian inference as a downstream task on top of the learned embeddings to provide predictions. We then employ retrieval augmented generation to provide explanations of the obtained predictions based on the given contextual inputs. This integrated approach not only enhances prediction accuracy but also provides interpretability and explainability, contributing to the development of trustworthy systems.

For instance, Fig. 1 depicts a situation involving several vehicles driving on a three-lane highway. The green vehicle, which drives along the middle lane, represents the vehicle under interest, also referred to as the target vehicle, while the blue vehicles represent the vehicles around the target vehicle, being denoted as Left Following (LF, i.e., the vehicle driving behind the target vehicle on the left adjoining lane), Right Following (RF, i.e., the vehicle driving behind the target vehicle on the right adjoining lane), and Preceding (P, i.e., the vehicle preceding the target vehicle along its ego-lane, which in this example is the middle lane), respectively. The figure shows the situation at the current time (in solid colors) as well as several future positions of all vehicles (in semi-transparent colors) according to the most likely predictions. In this scenario, the target vehicle is approaching quickly and dangerously the preceding vehicle due to a high difference in velocity between them, thus there is a high risk of collision with P based on the analysis of the estimated time to collision (TTC). Given this context, the target vehicle has two possible courses of action: A) stay on the same lane while decreasing velocity abruptly to avoid a collision with P; B) execute a left lane change maneuver, which seems to be the safer maneuver for all the actors involved in the scene. Action B (left lane change) appears to be a natural behavior that can be executed in a soft, organic manner in coordination with the three surrounding vehicles. Consequently, the behavior understanding and prediction system of LF would regard the left lane change maneuver of the target vehicle as a very likely future behavior and would anticipate and prepare its ego-actions accordingly to accommodate such a potential maneuver of the target vehicle.

So, our model uses linguistic contextual information about the surrounding traffic situation—such as high-risk Time-to-Collision (TTC) with the preceding vehicle and the right following vehicle, and low-risk TTC with the left following vehicle. Then, this information is provided in the knowledge graph. After that, Bayesian inference is carried out on top of the KGE to give the final prediction that the target vehicle will execute (a left lane change maneuver in that case). Finally, Retrieval augmented generation explains this prediction: “The target vehicle is changing lanes to the left to avoid potential collisions due to high-risk TTC with vehicles ahead and to the right, while the left lane offers a safer option with low-risk TTC”.

Overall, accounting for contextual information is essential for understanding behavior in this situation. This context-based reasoning approach can be extended and applied to many other similar situations, involving pedestrians and drivers, where contextual information is the key for understanding and anticipating behavior.

2. Literature and research foundation

2.1. Literature review

A large number of research works have dealt with road users' behavior prediction in the context of autonomous driving. Regarding the prediction of lane change maneuvers, Su, Muelling, Dolan, Palanisamy, and Mudalige (2018) used a Long Short-Term Memory (LSTM) model to predict vehicle lane changes by considering the vehicle's past trajectory and neighbors' states. In the work presented by Benterki, Boukhni, Judalet, and Choubeila (2019), two machine learning models were utilized to predict lane changes of surrounding vehicles on highways. The inputs were longitudinal/lateral velocities, longitudinal/lateral accelerations, distance to left/right lane markings, yaw angle, and yaw rate related to the road. These inputs were trained and tested on Support Vector Machines (SVM) and Artificial Neural Networks (ANN) models. Izquierdo, Quintanar, Parra, Fernández-Llorca, and Sotelo (2019a) predicted lane change intentions of surrounding vehicles using two different methodologies and by only considering the visual information provided by the PREVENTION dataset (Izquierdo, Quintanar, Parra, Fernández-Llorca, & Sotelo, 2019b). The first method was Motion History Image - Convolutional Neural Network (MHI-CNN), where temporal and visual information was obtained from the MHI, and then fed to the CNN model. The second model was the GoogleNet-LSTM model, in which a feature vector was obtained from a GoogleNet CNN model and then fed to the LSTM model to learn temporal patterns. Laimona, Manzour, Shehata, and Morgan (2020) trained LSTM and Recurrent Neural Networks (RNN) models on the PREVENTION dataset to predict surrounding vehicles' lane changing intentions by tracking the vehicles' positions (centroid of the bounding box). Sequences of 10, 20, 30, 40, and 50 frames of (X, Y) coordinates of the target vehicle were considered for comparison. It was concluded that RNN models performed better on short sequence lengths and the LSTM model outperformed RNN at long sequences. The work implemented by Xue, Xing, and Lu (2022) utilized eXtreme Gradient Boosting (XGBoost) and LSTM to predict the vehicle lane change decision and trajectory prediction, respectively, in scenarios in the HighD dataset (Krajewski, Bock, Kloeker, & Eckstein, 2018). The models were based on the traffic flow (traffic density) level, the type of vehicle, and the relative trajectory between the target vehicle and surrounding vehicles. Vehicle trajectory predictions were issued based on historical trajectories and the predicted lane change decisions. In the work by Gao et al. (2023), a dual Transformer model was proposed. The first Transformer was intended for lane change prediction, while the second one was used for trajectory prediction. Similarly, the prediction of pedestrians' crossing actions is another task that has been intensively targeted by the research community, focusing on forecasting whether or not a target pedestrian will cross the road at some point in the near future (typically in the next 1–5 s). This task has been addressed through a diverse range of algorithms and architectures. Among these approaches, it is particularly noteworthy to highlight several methods such as SingleRNN based on Recurrent Neural Networks (RNNs) (Kotseruba, Rasouli, & Tsotsos, 2020), CapFormer which uses a self-attention alternative based on transformer architecture (Lorenzo et al., 2021), a 3D convolutional model (C3D) based on spatiotemporal feature learning (Tran, Bourdev, Fergus, Torresani, & Paluri, 2015), a stacked multilevel fusion RNN (SFRNN) (Rasouli, Kotseruba, & Tsotsos, 2020), and convolutional LSTM (ConvLSTM) (SHI et al., 2015). Despite the abundance of models and research focused on pedestrian crossing predictions, only a limited

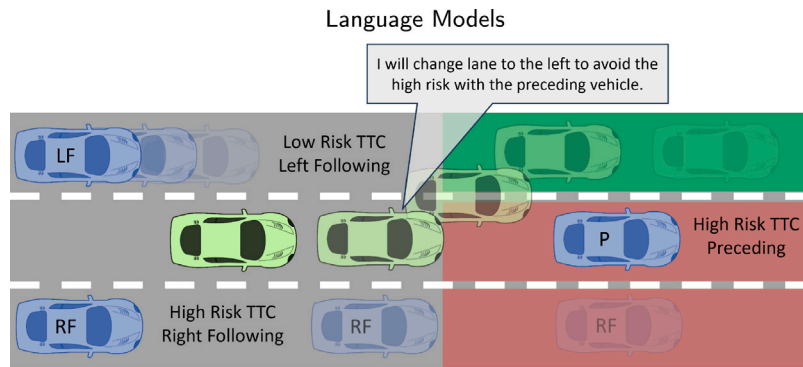


Fig. 1. The target vehicle (green) will most likely make a left lane change maneuver based on the risk assessment of the surrounding (blue) vehicles.

number of them provide insights into explainability or are specifically developed within the context of explainability. For instance, the research by Achaji, Moreau, Aioun, and Charpillat (2023) highlights that Transformers offer an advantage in terms of interpretability, due to their attention mechanism. Moreover, the utilization of pedestrian location and body keypoints as features in predicting pedestrian actions results in more human-like behavior. Muscholl, Klusch, Gebhard, and Schneeberger (2021) propose a dynamic Bayesian network model that takes into account the influence of interaction and social signals. This system leverages visual means and employs various inference methods to provide explanations for its predictions, with a specific focus on determining the relative importance of each feature in influencing the probability of pedestrian actions.

While Deep Learning (DL) techniques have been reasonably successful in solving road users' behavior prediction tasks, they may lack the ability to fully understand and exploit the interdependencies between road users and the semantic relations implicit in a road scene. Not in vain, in real-world applications it is impractical and inefficient to learn all facts and data patterns from scratch, especially when prior and linguistic knowledge is available. As an alternative, neuro-symbolic learning can exploit such information to further improve the ability to really understand road scenes by utilizing well-formed axioms and rules that can guarantee explainability, both in terms of asserted and inferred knowledge (Yi et al., 2018). In neuro-symbolic systems, abstract knowledge extraction is first carried out by means of neural DL techniques, that transform reality into symbols, while logic (or symbolic) reasoning is then performed on the grounds of such symbols. This human-like reasoning approach is interpretable and disentangled, while allowing for compositional, accurate, and generalizable reasoning in rich, complex contexts, such as road scene understanding and autonomous driving, that require identifying and reasoning about entities (road users, road context, and events) that are bundled together by means of spatial, temporal, social, and semantic relations. Knowledge-infused techniques, such as Knowledge Graphs (KG) (Hogan et al., 2021), enable the deployment of neuro-symbolic reasoning given their capacity for representing knowledge and interactions by means of directed graphs that can represent multiple and heterogeneous relations among entities. In addition, Knowledge Graph Embeddings (KGE) (Wickramarachchi, Henson, & Sheth, 2020) is a machine learning task that aims at learning a latent continuous vector space representation (namely, embeddings) of the nodes and edges of a KG, where the nodes represent the road users, the road context, and events, and the edges represent the semantic relations among them. Knowledge completion with KGEs can be used for predicting missing entities (e.g. occluded pedestrians) or relations (e.g. lane change intention) in road scenes that may have been missed by purely data-driven techniques.

2.2. Research gap

Despite advances in behavior prediction models for road users, existing approaches predominantly rely on deep learning techniques that focus on numerical kinematic data such as positions, velocities, and accelerations. As a result, these models often function as “black boxes”, lacking interpretability and the ability to incorporate the rich contextual and semantic information present in road scenes. Furthermore, they typically do not fully exploit the interdependencies between road users, the environment, and the implicit semantic relations that influence behavior. Moreover, traditional models struggle to utilize prior knowledge or linguistic information that could enhance prediction accuracy and explainability. This limitation arises because they are generally impractical for learning all facts and data patterns from scratch, especially in complex, real-world scenarios where understanding subtle cues and relationships is crucial. This limitation hinders their ability to generalize across diverse environments and to provide transparent reasoning behind their predictions. Therefore, there is a need for models that can integrate comprehensive linguistic contextual information—including human factors, social interactions, and environmental conditions—and that can reason about this information in an interpretable manner. Such models should not only predict behaviors but also provide explanations for these predictions, enhancing trust and facilitating the adoption of autonomous systems.

2.3. Research objective

In this work, we aim to address the need to understand and predict road users' behaviors by incorporating contextual features into a knowledge-based representation that can also encode other sources of information, such as human knowledge representing driving experience. For that purpose, we propose a neuro-symbolic approach that will combine expressive features (representing road users' context) and human experience (in the form of linguistic descriptions and/or rules) in a Knowledge Graph (KG) representation.

1. **Integration of Linguistic Contextual Information through Knowledge Graphs:** We construct a knowledge graph that encodes linguistic contextual information beyond mere kinematic data. This allows the model to capture complex relationships and dependencies among various factors influencing road users' behaviors, enabling generalization across different road environments involving both vehicles and pedestrians.
2. **We perform behavior prediction by applying Bayesian inference as a downstream task on the grounds of the learned embeddings derived from the knowledge graph,** which will enable us to perform a fully inductive reasoning system based on KGE. This principled approach leverages the rich contextual information captured in the embeddings to provide probabilistic predictions about future behaviors.

3. To address the interpretability challenge, we use retrieval augmented generation to provide explanations for the obtained predictions based on the given contextual inputs. This step makes the model's reasoning transparent and understandable, enhancing trustworthiness by allowing users to comprehend why certain predictions were made. The explanations developed in this work are intended to justify the decisions of AVs and support the traceability required for AV standardization processes. Additionally, these explanations can enhance the decision-making module itself, enabling it to produce more grounded and reasoned decisions.

The rest of this article is organized as follows: Section 3.1 describes the procedure followed to build a Knowledge Graph that encodes road users' behavioral models; Section 3.2 presents the road users' behavior prediction system using KGE and Bayesian inference; Section 3.3 dives into the details of how to achieve explainability with the proposed approach; Section 4 introduces the implementation and experimental results and Section 5 describes the conclusions and future work.

3. Proposed method

This section introduces the proposed method for providing an explainable prediction of road user behaviors. Our method incorporates three main components: (1) a knowledge representation of the real world, (2) a road user behavior prediction approach, and (3) an explainability component. The section first provides context, detailing feature extraction and transformation, and explains how these are used to design an ontology for two use cases focusing on pedestrians and drivers. Next, the proposed prediction approach is detailed in all its phases, and finally, the explainability component is presented from multiple perspectives.

3.1. Modeling road user's behaviors using knowledge graphs

In the realm of knowledge representation, the Knowledge Graph (KG) stands as a key tool encoding triples that reveal real-world facts and semantic connections (Peng, Xia, Naseriparsa, & Osborne, 2023). A triple, the fundamental building block within the KG, comprises three elements: subject, predicate, and object (alternatively termed as head, relation, and tail). Conceptually, a KG manifests itself as a graph where the edges represent relations and the nodes denote entities. As previously mentioned, one of the applications of KGs focuses on transforming them into low-dimensional vectors that encode entities and relationships, a technique known as Knowledge Graph Embedding (KGE). The resultant vector is employed for learning and reasoning within embedding-based machine learning models, which can rely on distance-based measures or similarity-based scoring (Choudhary, Luthra, Mittal, & Singh, 2021). In this work, we employ two different models for KGEs: a distance-based model known as TransE (Bordes, Usunier, Garcia-Duran, Weston, & Yakhnenko, 2013) and a similarity-based model named ComplEx (Trouillon, Welbl, Riedel, Gaussier, & Bouchard, 2016).

It is important to highlight that the KG provides a generalizable approach applicable across various road scenarios and road user behaviors. By enabling knowledge representation based on either data or expert insights, this approach captures real-world scenarios through entities and relationships. For our study, we evaluate the effectiveness of our approach through two real-world use cases focusing on different road user behaviors, including both pedestrians and drivers.

The KG design process centers on modeling road user behavior by leveraging available features and contextual understanding of each scenario. Each use case was carefully evaluated, drawing from a collection of real-world scenarios that pedestrians and drivers encounter daily. From these scenarios, we identified a list of features that offer meaningful information about the context. These features were then systematically incorporated into the KG design to ensure a comprehensive representation of road user behavior.

3.1.1. Pedestrian use case

The pedestrian use case focused on predicting whether a pedestrian will cross the road in the next 30 frames. The entire pipeline has been trained and tested using two datasets:

- **Joint Attention for Autonomous Driving (JAAD).**² This dataset comprises 348 short video clips, each extensively annotated to depict various road actors and scenarios across diverse driving locations, traffic, and weather conditions. The dataset annotations encompass spatial, behavioral, contextual, and pedestrian information. Details of the dataset are described in Rasouli, Kotseruba, and Tsotsos (2017)
- **Pedestrian Situated Intent (PSI).**³ The dataset comprises 104 training videos, 34 validation videos, and 48 testing videos, collectively covering 196 scenes. It includes bounding box annotations for traffic objects and agents, which are accompanied by text descriptions and reasoning explanations. Details of the dataset are described in Chen et al. (2022).

Both datasets provide valuable scenarios captured in varied locations with different pedestrians, offering significant insight into pedestrian street behaviors. However, they present some limitations due to the imbalance between pedestrians who cross the street and those who do not. In both datasets, approximately 72% of pedestrians actively cross the street, while the remaining 28% do not. Using the data as originally provided leads to overfitting towards pedestrian crossing behavior, with most predictions indicating crossing. To improve the reliability and quality of the experiments, the data were balanced before implementation, as detailed in Section 4.1.

The process of modeling pedestrian behavior first considers feature extraction and linguistic transformation. From the mentioned datasets, a set of pedestrian features is extracted using a deep learning approach, and then they are transformed from numerical to linguistic values, as detailed in Melo, Herrera-Quintero, Salinas, and Sotelo (2024). The features extracted for each annotated pedestrian include:

- **Motion Activity:** States the motion activity of the pedestrian
- **Proximity to the road:** Transforming from an assessment of road segmentation and pedestrian location to a linguistic representation indicating the pedestrian's proximity to the road in three levels, based on their closeness to it.
- **Distance:** Transforming from an estimated distance in meters to a linguistic representation that indicates the pedestrian's proximity to the ego-vehicle.
- **Body Orientation:** Transforming from an angle ranging from 0° to 360° to a linguistic representation that encodes the pedestrian's body posture from the perspective of the ego-vehicle.
- **Gaze:** Transforming from a binary value to a linguistic indicator that denotes whether the pedestrian is observing the ego-vehicle.

Once features are extracted and transformed, a pedestrian behavior ontology, referred to as PedFeatKG in this study, is designed from pedestrian features and was outlined in Table 1. It encompasses the classes (entities in the KG), their descriptions, the instances of each class representing linguistic values, and the potential relations associated with each class. In the PedFeatKG ontology, each pedestrian from the dataset's training set was represented by a class with a unique ID (noted as **Pedestrian ID**). At the same time, the Pedestrian ID was associated with a specific pedestrian instance at a particular frame (noted as **Pedestrian instance ID**). This latter class comprised the pedestrian dataset ID and the frame number. For instance, if a

² JAAD dataset is publicly available at: https://data.nvision2.eecs.yorku.ca/JAAD_dataset/.

³ PSI dataset is publicly available at: <http://pedestriandataset.situated-intent.net/>.

Table 1
Pedestrian behavior ontology.

Class	Class description	Instance	Possible relation
Pedestrian	Generic entity pointing to every child pedestrian	Pedestrian	Any
Pedestrian ID	Individual Pedestrian ID	Ped1	HAS_CHILD
Pedestrian instance ID	ID for a pedestrian at a particular frame	Ped1-30	INSTANCE_OF PREVIOUS NEXT MOTION
Motion Activity	Pedestrian motion activity	Stand, Walk, Wave, Run, Na	LOCATION
Proximity	Pedestrian closeness to the road	NearFromCurb, MiddleDisFromCurb, FarFromCurb	EGO_DISTANCE
Distance	Pedestrian closeness to the ego-vehicle	TooNearToEgoVeh, NearToEgoVeh, MiddleDisToEgoVeh, FarToEgoVeh	ORIENTATION
Orientation	Pedestrian body orientation	VehDirection, LeftDirection, OppositeVehDirection, RighthDirection	ATTENTION
Gaze	Pedestrian attention	Looking, NotLooking	ACTION
Cross Action	Crossing behavior of the pedestrian	crossRoad, noCrossRoad	

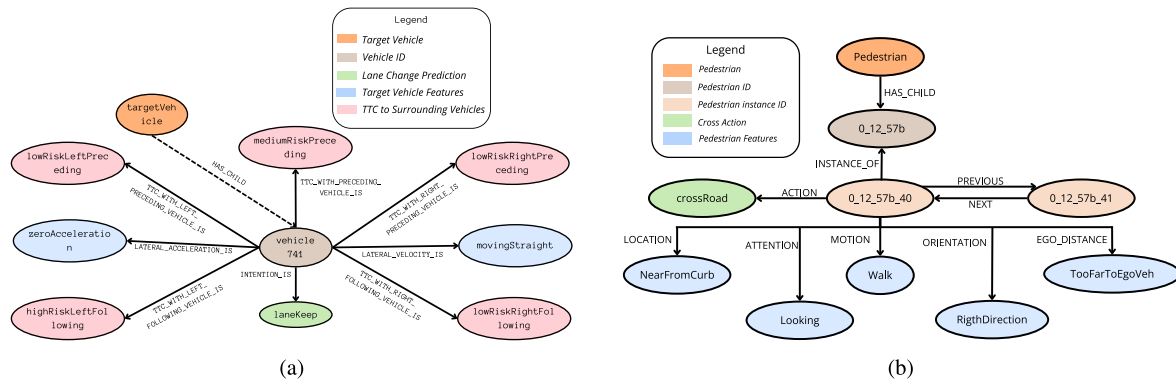


Fig. 2. 2(a) One KG instance where the vehicle has zero lateral acceleration and has medium TTC risk with the preceding vehicle and high TTC with the left following vehicle. (b) PedFeatKG from explainable features with 1 instance.

pedestrian has the ID “ped1”, there will be as many classes as frames considered in the following structure: “ped1–30”, “ped1–32”, “ped1–34”, and so on. Linking the pedestrian ID with the pedestrian instance ID enabled the association of all pedestrian instances, indicating to the KG that they represent the same pedestrian across different frames. Additionally, each pedestrian instance ID was linked with its previous and next pedestrian instance ID, thus providing temporal association information regarding pedestrian behavior in a road scene within the KG. Likewise, all pedestrian ID classes extracted were associated with a generalization class called **Pedestrian**, enabling any specific pedestrian to be linked to a general one. This linkage is considered a path reification link. On the other hand, each pedestrian instance ID was subsequently linked with the five pedestrian features that represent the pedestrian’s state in the following triple format: $\langle \text{pedestrian-instance-ID}, \text{FEATURE_RELATION}, \text{value} \rangle$. In addition, it can be observed that the pedestrian instance ID was also linked with a crossing behavior, delineated by two possible class values: **crossRoad** or **noCrossRoad**. Fig. 2(b) shows a generated KG instance from the PedFeatKG ontology. In this example, it represented the state of the pedestrian with ID 0_12_57b in frame 40, its features, and its future crossing action.

3.1.2. Drivers use case

In the lane change prediction use case scenario, the *HighD*⁴ dataset is used. It is a German dataset that was recorded using a camera mounted on a drone, providing a collection of naturalistic top-view scenes of vehicle movements and interactions on German highways. Details of the dataset are described in Krajewski et al. (2018).

⁴ The dataset is publicly available through the following link <https://levelxdata.com/highd-dataset>.

The process of modeling lane change behavior first considers feature extraction and linguistic transformation. The inputs that will be used to construct the KG are vehicle lateral velocity and acceleration, the target vehicle intention, TTC with the preceding vehicle, and TTC with the left/right preceding and following vehicles. These inputs are extracted from the highD dataset in numerical format. Then, they are converted to linguistic categories. For example, the lateral acceleration numerical value is converted to a category from a set of linguistic categories like accelerating left, zero lateral acceleration, and accelerating right. To divide each numerical feature into some linguistic categories, some thresholds are determined. Following the structure proposed in Manzour, Ballardini, Izquierdo, and Sotelo (2024), we used the normal distribution of the lateral velocity and acceleration separation thresholds. Regarding the other TTC numerical variables, the thresholds are based on the studies in Manzour et al. (2024), Saffarzadeh, Nadimi, Naseralavi, and Mamdoohi (2013) and Ramezani khansari, Moghadas Nejad, and Moogeh (2021).

Once features are extracted and transformed, a driver behavior ontology, referred to as DriverKG in this study, is based on the reification of nodes and relationships obtained from the HighD dataset, to get reified triples. For example, if the vehicle is accelerating in any direction and the TTC risk with the left following vehicle is high, then the reified triples will be $\langle \text{vehicle}, \text{LATERAL_ACCELERATION_IS}, \text{zeroAcceleration} \rangle$, and $\langle \text{vehicle}, \text{TTC_WITH_LEFT_FOLLOWING_VEHICLE_IS}, \text{highRiskLeftFollowing} \rangle$. Table 2 shows the KG ontology for the lane change prediction case. The table is divided into four columns. The first column shows the possible classes in the KG. The description of each class is indicated in the second column. The third column shows the possible reified instances that can be assigned to that class, given that the class can take only one instance at a frame. The last column shows the relation that points to that class. In this ontology, a generic entity named *vehicle* is linked to various child vehicles via the *HAS_CHILD*

Table 2
Vehicle behavior ontology.

Class	Class Description	Instance	Possible Relation
intention	Lane changing intention of the vehicle	LLC (Left Lane Change) LK (Lane Keep) RLC (Right Lane Change)	INTENTION_IS
latVelocity	Vehicle lateral velocity	movingLeft movingStraight movingRight	LATERAL_VELOCITY_IS
latAcceleration	Vehicle lateral acceleration	leftAcceleration zeroAcceleration (No lateral acceleration) rightAcceleration	LATERAL_ACCELERATION_IS
ttcPreceding	TTC with the preceding (front) vehicle	highRiskPreceding mediumRiskPreceding lowRiskPreceding	TTC_WITH_PRECEDING_VEHICLE_IS
ttcLeftPreceding	TTC with the left preceding (front) vehicle	highRiskLeftPreceding mediumRiskLeftPreceding lowRiskLeftPreceding	TTC_WITH_LEFT_PRECEDING_VEHICLE_IS
ttcRightPreceding	TTC with the right preceding (front) vehicle	highRiskRightPreceding mediumRiskRightPreceding lowRiskRightPreceding	TTC_WITH_RIGHT_PRECEDING_VEHICLE_IS
ttcLeftFollowing	TTC with the left following (rear) vehicle	highRiskLeftFollowing mediumRiskLeftFollowing lowRiskLeftFollowing	TTC_WITH_LEFT_FOLLOWING_VEHICLE_IS
ttcRightFollowing	TTC with the right following (rear) vehicle	highRiskRightFollowing mediumRiskRightFollowing lowRiskRightFollowing	TTC_WITH_RIGHT_FOLLOWING_VEHICLE_IS
vehicleID	Child vehicle ID which changes every frame	vehicle ID number (e.g. '741')	HAS_CHILD
vehicle	Generic entity pointing to every child vehicle	–	Any

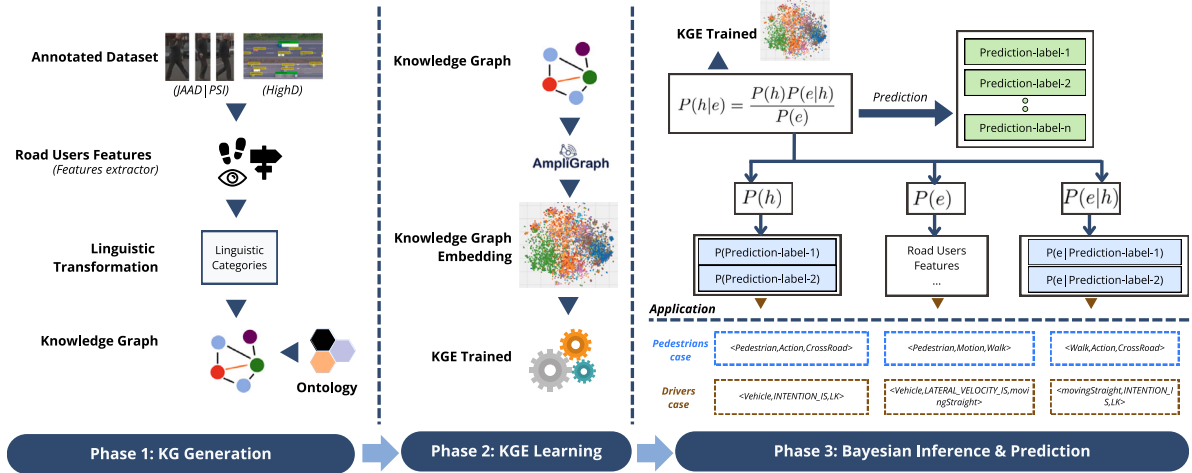


Fig. 3. Pipeline architecture for modeling road user's behaviors.

relation. Each child vehicle is assigned a unique ID (known as *vehicleID*) for each frame. It is important to note that even if it is the same physical vehicle across different frames, it will receive a new *vehicleID* in each frame. Consequently, while both IDs in reality refer to the same vehicle, they are treated as distinct vehicles within the ontology when generating triples and constructing the KG.

Fig. 2(a) shows a generated KG instance based on the previously mentioned ontology. In this instance, the vehicle with ID 741 is a child of the generic entity vehicle. This can be described in a triple with format $\langle \text{targetVehicle}, \text{HAS_CHILD}, 741 \rangle$. This child has *latAcceleration* class assigned to *zeroAcceleration* instance. Also, 741 has *mediumRiskPreceding* and *highRiskLeftFollowing* TTC. *vehicle 741 INTENTION_IS LK*.

3.2. Road users' behavior prediction approach

Both Road Users' Behavior Predictions use cases to leverage the proposed architecture based on feature extraction, KGs and their associated ontologies. The overall workflow, depicted in Fig. 3, comprises three main phases: (1) KG Generation, (2) KGE Learning, and (3) Bayesian Inference and Prediction. This section provides the details of the three phases.

3.2.1. Phase 1: KG generation using all types of knowledge

To capture and encapsulate the data concerning road users' behaviors, the initial step involved extracting the data and features that describe each scene from both the driver's and pedestrian's perspectives. The subsequent step was to convert the extracted features into linguistic values. Following this, utilizing the Ampligraph 2.0.0 library (Costabello et al., 2019), the KG is constructed in the form of

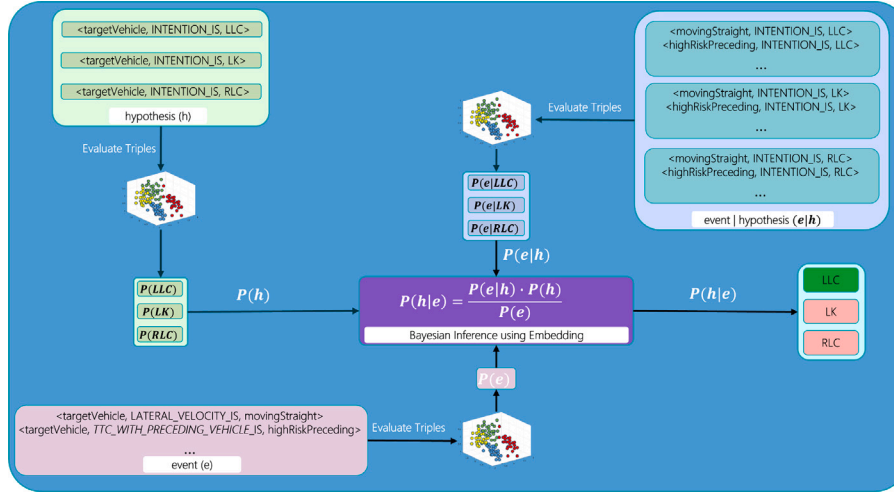


Fig. 4. Calculating the lane change probabilities in the Bayesian Inference and Prediction phase.

triples, where a set of triples represents the scene in a frame. Building the KG is a process executed based on a KG ontology that generalizes the data applicable to each road scene. This knowledge can originate from various sources and formats, including annotations in datasets, fuzzy rules, and textual explanations concerning road user behavior.

3.2.2. Phase 2: KGE learning

In the second phase, Ampligraph 2.0.0 was employed to construct a KGE model using the KG generated in the previous phase. We used the *ScoringBasedEmbeddingModel* to implement a neural architecture that encodes concepts from a KG into low-dimensional vectors, using a scoring layer such as ComplEx and TransE. The training and validation process using the KGE model is conducted using the Ampligraph library. As a result of this phase, optimal embeddings representing the KG are obtained. These embeddings are then utilized in the subsequent phase for inference and prediction over the KG.

3.2.3. Phase 3: Bayesian inference & prediction

Our approach is designed to leverage inductive reasoning by incorporating specific structures, known as reifications, into the knowledge graph by leveraging the properties of the ontology. This allows us to perform Bayesian inference (phase 3 in Fig. 3) on the embeddings derived from the KG learning phase (phase 2). These embeddings are trained on the contextual and linguistic data extracted from the datasets, as detailed in Section 3.1.1 and Section 3.1.2. Once these embeddings are obtained, it is then possible to calculate the probabilities of reified triples $P(h, r, t)$ using the evaluation method from the AmpliGraph library. Then, the Bayes rule in Eq. (1) is used to compute the probability of a hypothesis given some evidence, denoted as $P(h|e)$, where h represents the hypothesis (such as the likelihood of a pedestrian intention to cross the road) and e stands for the evidence, which in this context is data measured by onboard sensors at a specific moment. The datasets (like JAAD for pedestrians and HighD for vehicles) provide this sensory data.

$$P(h|e) = \frac{P(h)P(e|h)}{P(e)} \quad (1)$$

For instance, if the hypothesis is that a pedestrian intends to cross the road and the evidence includes observations such as (i) the pedestrian's attention state is looking and (ii) the pedestrian's location is near to the vehicle, then the probability of the hypothesis $P(h)$ is determined by evaluating a reified triple, e.g., reifying the intention of a pedestrian to cross the road into the triple $\langle \text{pedestrian}, \text{INTENTION_IS}, \text{crossRoad} \rangle$. Concerning the calculation of $P(e)$, which involves a series of multiple pieces of evidence, we employed Eq. (2) since each piece of evidence is considered independent. Additionally, each element e_i is reified from

the graph. For example, assuming that the evidence is composed of two elements e_1 and e_2 indicating respectively that the pedestrian is looking to the ego-vehicle and the pedestrian is near to the ego-vehicle, the associated probabilities are given by the reification of following two triplets $\langle \text{pedestrian}, \text{action}, \text{looking} \rangle$ and $\langle \text{pedestrian}, \text{egoDistance}, \text{nearToEgoVeh} \rangle$.

$$P(e) = P(e_1) \times \dots \times P(e_n) \quad (2)$$

The probability of the evidence given the hypothesis $P(e|h)$ is calculated based on Eq. (3). It is computed as the product of the probabilities of all pieces of evidence assuming the condition that the hypothesis is true. These conditioned pieces of evidence are also reified. For example, calculating the probability of a pedestrian near the vehicle given the hypothesis that this pedestrian will cross the road can be reified as $\langle \text{nearToEgoVeh}, \text{INTENTION_IS}, \text{crossRoad} \rangle$. The computation of this conditional probability implies that we take for granted that the object entity is a pedestrian who will cross the road. Under these conditions, the likelihood of the pedestrian being close to the vehicle in these circumstances will be calculated. After that, all computed conditioned probabilities are then multiplied together to determine $P(e|h)$. Finally, with all these probabilities available from the graph through the embeddings, the probability of a hypothesis given the evidence $P(h|e)$ can be calculated using the Bayes rule in Eq. (1).

$$P(e|h) = P(e_1, \dots, e_n|h) = P(e_1|h) \times \dots \times P(e_n|h) \quad (3)$$

By analogy, the same concept applies to vehicle lane change prediction. For example, let us suppose that we are interested in calculating the probability that a vehicle will make a left lane change given that the vehicle is moving straight while having a high TTC risk with the preceding vehicle. For better illustration, Fig. 4 shows how Bayesian inference operates over the KG to calculate the lane change probabilities. The probability $P(h)$ is computed by evaluating the triple $\langle \text{targetVehicle}, \text{INTENTION_IS}, \text{LLC} \rangle$ from the KGE. Then, the probability $P(e)$ is calculated by multiplying the two evaluated triplets (1) $\langle \text{targetVehicle}, \text{LATERAL_VELOCITY_IS}, \text{movingStraight} \rangle$ and (2) $\langle \text{targetVehicle}, \text{TTC_WITH_PRECEDING_VEHICLE_IS}, \text{highRiskPreceding} \rangle$. Similarly, the probability $P(e|h)$ is computed by the multiplication of the two evaluated triplets (1) $\langle \text{movingStraight}, \text{INTENTION_IS}, \text{LLC} \rangle$ and (2) $\langle \text{highRiskPreceding}, \text{INTENTION_IS}, \text{LLC} \rangle$. Finally, $P(h|e)$ is calculated using Eq. (1). This process combines structured knowledge representation with probabilistic Bayesian inference to make predictions based on observed data. This process is repeated for each label, so the probability of LLC is computed given the generated linguistic

inputs, the same computation is done for *LK* and *RLC*, and the score with the highest probability will be the model's prediction. In the pedestrian use case, the probabilities of *crossRoad* and *noCrossRoad* are computed given the generated linguistic inputs, and the highest probability will be considered as the model's prediction.

3.3. Explainability

Although the KG inherently offers some insights into explainability, in our study we chose to integrate additional tools to support prediction explanations. Hence, we incorporated the fuzzy logic approach and the Retrieval Augmented Generation (RAG) technique. In this section, we provide a detailed overview of both approaches to enhance explainability.

3.3.1. Explanation using fuzzy rules

To integrate explainability into our approach we first adopted a fuzzy logic approach, characterized by its multi-valued nature that mirrors human thought and interpretation. The generation of fuzzy rules entailed a rule mining process employing various learning algorithms and classification systems. In this study, we employed the IVTURS-FARC system (Sanz, Fernández, Bustince, & Herrera, 2013), which utilizes interval-valued restricted equivalence functions to enhance rule relevance during inference. The learning process of this system involved the FARC-HD algorithm (Alcala-Fdez, Alcalá, & Herrera, 2011) for fuzzy association rule extraction. The rule mining process began with the extracted pedestrian features from JAAD and PSI datasets, then, employing the mentioned methods, we extract a set of rules structured as follows:

$$\text{Rule } R_j : \text{ if } x_1 \text{ is } A_{j1} \text{ and...and } x_n \text{ is } A_{jn} \quad (4) \\ \text{ then Class} = C_j \text{ with } RW_j$$

In the given expression R_j denotes the label of the j th rule, $x = (x_1, \dots, x_n)$ represents a n -dimensional pattern vector (related to pedestrian features in our context), A_{ji} stands for an antecedent fuzzy set indicating a linguistic term, C_j signifies the class label, and RW_j denotes the weight of the rule (Ishibuchi & Nakashima, 2001). In this work, we initially applied the fuzzy logic approach to the pedestrian use case. In the pedestrian use case, the rule mining process produced 60 rules from the PSI data, while 51 rules originated from the JAAD data. To gain insights into pedestrian behavior, we utilized these rules and integrated them into the KG. Each fuzzy rule was transformed into two classes (as illustrated in Fig. 5) which were focused on: (1) combining all feature values into one class and (2) integrating the crossing action and rule weight. Introducing these two new entities in the KG required modifying the associated ontology to reflect the changes. Therefore, we established another ontology labeled as **PedFeatRulesKG**, where pedestrians, alongside their feature states, are linked with rules relevant to their states, thus offering more insights into their behavior. The PedFeatRulesKG ontology can be considered as an extension of the PedFeatKG ontology (see Section 3.1.1). Fig. 6 illustrates an example of the mentioned ontology for a pedestrian in a frame, showcasing the explainable features associated with its state and the correlation with fuzzy rules that apply to this state.

3.3.2. Explanation using RAG

Retrieval Augmented Generation (RAG) is a machine learning model that combines the power of pre-trained language models with the ability of a retrieval system to retrieve relevant information from a large database and then use this information to generate precise and contextually rich responses to the user's query (Lewis et al., 2020). This large database can be a public database or a private database that is specified for a certain domain. The private database can be obtained by leveraging external knowledge sources, which enhances the model's responses to be more accurate, informative, and specific to that certain task or domain. The RAG process, schematically depicted

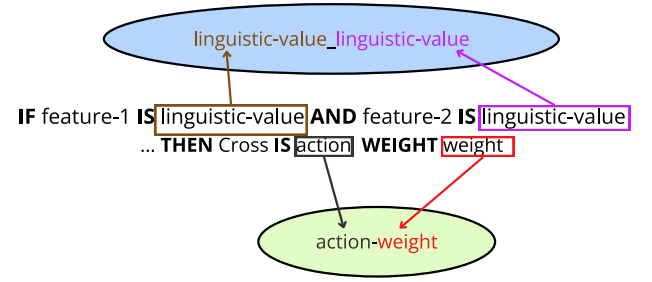


Fig. 5. Fuzzy rule conversion definition.

in Fig. 7, consists of three modules: retrieval module, augmentation module, and generation module. First, the document which forms the source database is divided into chunks. These chunks, transformed into vectors using an embedding model like OpenAI or open source models available from the Hugging Face community, are then embedded into a high-dimensional vector database (e.g., Chroma and LlamaIndex).

When the user inputs a query, the query is embedded into a vector using the same embedding model. Then, chunks whose vectors are closest to the query vector, based on some similarity metrics (e.g., cosine similarity) are retrieved. This process is contained in the retrieval module shown in the figure. After that, the retrieved chunks are augmented to the user's query and the system prompt in the augmentation module. This step is critical for making sure that the records from the retrieved documents are effectively incorporated with the query. Then, the output from the augmentation module is fed to the generation module which is responsible for generating an accurate answer to the query by utilizing the retrieved chunks and the prompt through an LLM (like chatGPT by OpenAI, hugging face, and Gemini by Google). We used the RAG procedure described in Fig. 7 for both our use cases, pedestrian crossing behavior prediction, and vehicle lane change prediction. The only difference is the source of knowledge and the query that will be fed to the retrieval module.

4. Implementation and experimental results

In this section, we provide a detailed description of how our behavior prediction approach was implemented for both pedestrian and driver scenarios. While both scenarios share a common KGE learning strategy and the Bayesian inference scheme, as described in previous sections, here we highlight specific details associated with each scenario, beginning with the datasets and experiments considered. Subsequently, we present and analyze the extensive experimental activity we performed to evaluate the results concerning other state-of-the-art approaches.

4.1. Implementation details — pedestrian use case

The implementation of our approach for the pedestrian use case can be delineated in three segments: (1) Feature extraction, (2) Modeling pedestrian behaviors utilizing KG, and (3) Explainability using RAG. Firstly, we build a modular architecture employing Python and PyTorch to extract the features specified in Section 3.1.1. These extractions were facilitated by various neural networks and processed estimations as briefly described in Table 3. All implementation details and feature extraction processes are expounded upon in Melo, Salinas, and Sotelo (2023).

Secondly, we employed Python, TensorFlow, and the AmpliGraph 2.0.0 library to execute the pipeline for modeling pedestrian behaviors utilizing KG. In this implementation, we utilized the ComplEx scoring model, the Adam optimizer, and the SelfAdversarialLoss. In terms of training parameters, we utilized an embedding size of $k = 150$. The number of corruptions generated during training ranges from 5 to 20,

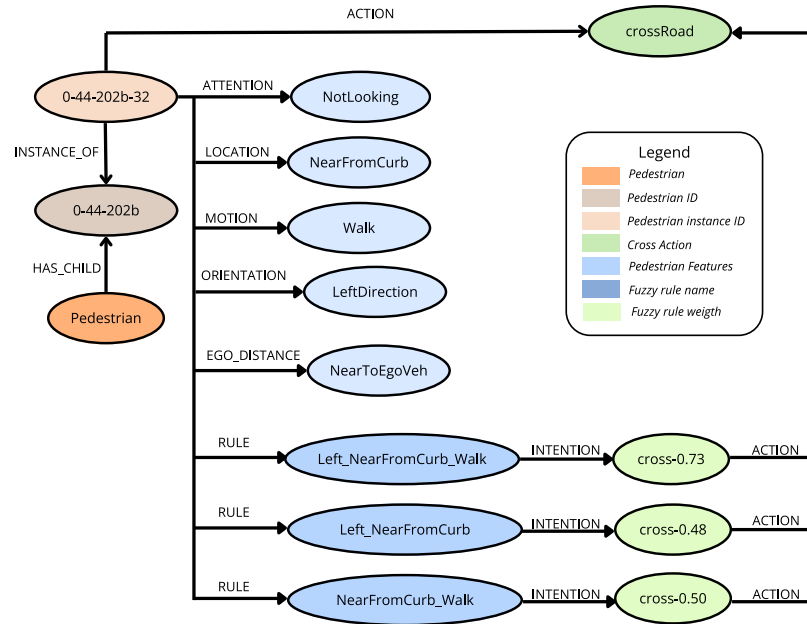


Fig. 6. PedFeatRulesKG from explainable features with 1 instance.

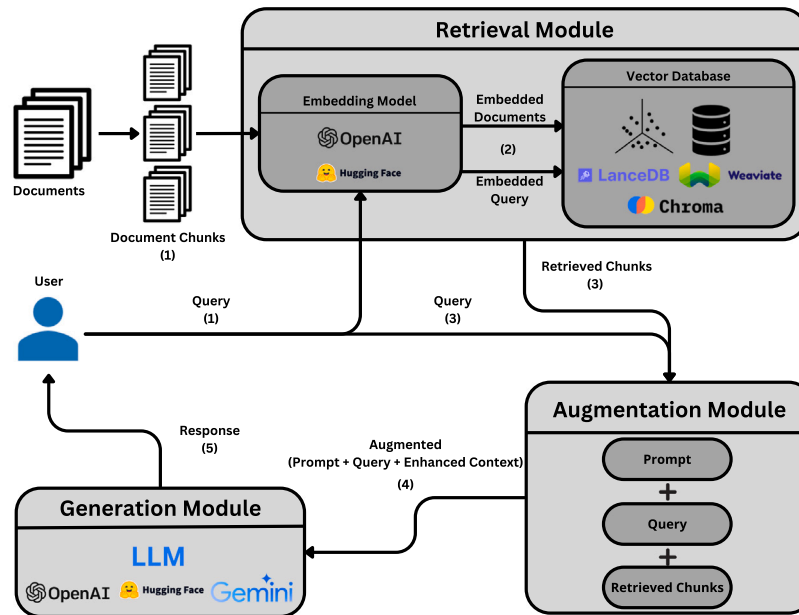


Fig. 7. RAG workflow (the numbers show the arrangement of the RAG process flow throughout the figure).

Table 3
Pedestrian Features Extraction.

Feature	Extraction type	Description
Motion activity	Neural network	We implemented a transformer architecture that processes the 2D body pose and outputs the pedestrian action. From YOLOPv2 (Han, Zhao, Zhang, Chen, Zhang, & Yuan, 2022) was obtained from the drivable road area segmentation and lane detection. Based on an experimental minimum distance it is estimated whether the pedestrian is near to the road or not.
Proximity to the road	Neural network and estimation	
Distance	Estimation	Estimated using the triangle similarity Using the PedRecNet (Burgermeister & Curio, 2022) the joint positions of the human body and the body orientation from the azimuthal angle φ were obtained.
Orientation	Neural network	
Gaze	Estimation	We used the 2D body pose detection and the positions of the nose, left eye, and right eye keypoints.

Table 4
Number of triples in the experimental setup.

Dataset	Ontology	Triples
PSI	PedFeatKG	238 795
	PedFeatRulesKG	302 574
JAAD	PedFeatKG	139 624
	PedFeatRulesKG	197 381

depending on the quantity of triples and the dataset. Additionally, we set $learningRate = 0.0005$, $batchSize = 10000$, and implemented an early stopping criterion using the Mean Reciprocal Rank (MRR) as is described in Melo et al. (2024). MRR is used to evaluate the effectiveness of embeddings by averaging the reciprocal positions of the first correct answer in a list of queries. We observed that higher MRR scores for the embeddings directly correlate with improved prediction accuracy.

From the datasets selected in Section 3.1.1 and the ontologies described before (PedFeatKG and PedFeatRulesKG), two KGs were generated, each composed of a specific number of triples and entities, as detailed in Table 4.

Finally, the third segment was focused on RAG implementation. To accomplish this explainability module, we utilized pedestrian features extracted from the JAAD and PSI datasets to generate a human-readable document that incorporates a basic explanation of why pedestrians have or do not have the intention to cross the road, for instance: “*The pedestrian will not cross the street because, the pedestrian is looking, is oriented to the left, is running, is at a moderate distance from the road and the vehicle is too far*”. Then, we utilized this document containing all descriptions in the RAG module, based on the LangChain framework. Within this module, we segmented the document into chunks and transformed them into embeddings using the OpenAI model. The embeddings were then stored in the Chroma vector database. Subsequently, the final response was generated using the OpenAI GPT-4 Large Language Model (LLM), based on a prompt tailored for the pedestrian use case and a query derived from the pedestrian features within the prediction frame, as detailed in Fig. 8.

Regarding the experimental setup, we selected datasets as outlined in Section 3.1.1, using a set of videos for both training and testing. To ensure experiment reliability, we initially chose videos that met specific criteria for visibility and high quality. For JAAD, 136 videos were used for training and 35 for testing, while for PSI, 104 videos were allocated to training and 48 to testing. Additionally, during training, videos were prioritized based on quality and relevance, with the most representative videos positioned at the start of the training set. The performance evaluation of the proposed pipeline was carried out using precision, recall, and F1-score metrics. Precision is defined as the ratio of correctly predicted positive cases to the total predicted positives, recall as the ratio of correctly predicted positive cases to the total actual positives, and F1-score as the harmonic mean of precision and recall.

4.2. Implementation details — drivers use case

This section addresses two main branches regarding the driver use case. The first one focuses on training the generated KG obtained from phase 1. The training utilizes the Ampligraph library, which creates the KGE from the HighD dataset. The second branch discusses the generation of explanations using the RAG technique. The dataset was divided based on tracks, to ensure a clear distinction between training, validation, and testing data, taking into account the vehicles’ behaviors across different tracks. This division was crucial to prevent the overlap of behaviors, especially since vehicles on the same track could exhibit similar behaviors, such as vehicles moving to the right because there is an exit on the right at the end of the road. Consequently, the dataset was organized so that the first 48 tracks (80% of the data), were allocated for the training and validation phases. The remaining

Table 5

Comparing the pedestrian behavior predictor with various methods. The table includes the available results.

(a) $JAAD_{test}$				
Model	F1	Precision	Recall	Accuracy
C3D	0.65	0.57	0.75	0.84
PCPA	0.68	—	—	0.85
Decision Tree	0.78	0.78	0.78	0.78
Fuzzy Logic	0.75	0.69	0.81	0.69
PedFeatKG	0.86	0.77	0.96	0.79
PedFeatRulesKG	0.87	0.86	0.88	0.83
(b) PSI_{test}				
Model	F1	Precision	Recall	Accuracy
eP2P	0.66	—	—	0.76
Ours Black Box	0.75	0.74	0.75	0.62
Decision Tree	0.63	0.63	0.63	0.63
Fuzzy Logic	0.72	0.74	0.70	0.59
PedFeatKG	0.81	0.75	0.89	0.69
PedFeatRulesKG	0.84	0.75	0.94	0.72

12 tracks (20% of the data) were reserved exclusively for testing. A variety of triple counts are explored for validation, including 500, 1000, 2000, 4000, and 10 000 triples. Despite this range, the evaluation score during testing remained consistent across these different triple counts. Therefore, a decision was made to proceed with 2000 triples for validation, leveraging the *train_test_split_no_unseen* function provided by the Ampligraph library to facilitate this choice. The final distribution of triples for the dataset was established as 351 736 for training, 2000 for validation, and 12 222 for testing.

Two distinct scoring models are compared: *TransE* and *ComplEx*. To ensure a fair comparison, the training parameters are fixed. This includes setting the embedding size (k) to 100, employing the Adam optimizer with learning rate = 0.0005, utilizing the SelfAdversarialLoss, generating five negative triples for every positive triple by corrupting both the subject and object, and setting a batch size of 10 000. Additionally, validation parameters were specified, with a burn-in period and frequency both set at five, alongside a validation batch size of 100. An early stopping criterion is also used to monitor the MRR metric during validation, with a patience threshold of five validation epochs. F1-score is the used evaluation metric to choose the best model. Also, precision and recall metrics are used to compare results with other works. The machine used to carry out this experiment is a Lenovo Legion laptop with Windows 11, i9-13900HX CPU, 32 GB of RAM, and NVIDIA GeForce RTX 4090.

Regarding the RAG section the data is divided into chunks with the size of 384 tokens. Each chunk represents a KG of one sample in the form of triples. Chunks were transformed into embedding vectors using *all-MiniLM-L6-v2* Hugging Face embedding model and stored in the Chroma vector database. After that, OpenAI GPT-4 LLM was used in the generation module to generate the final response. The query is formed by extending the linguistic inputs which are fed to the KGE and Bayesian inference model with the lane change prediction output obtained from that model. Then, this query is fed to the RAG model. Fig. 8 shows the used system prompt to implement few-shot learning with an example where the query is provided together with the type of expected answer so that the LLM model can follow similar behavior while generating the responses.

4.3. KG-based prediction results — pedestrian use case

The performance of our knowledge-based predictor approach was evaluated over the test set of each dataset. The results provided were compared with the following methods:

- In JAAD:

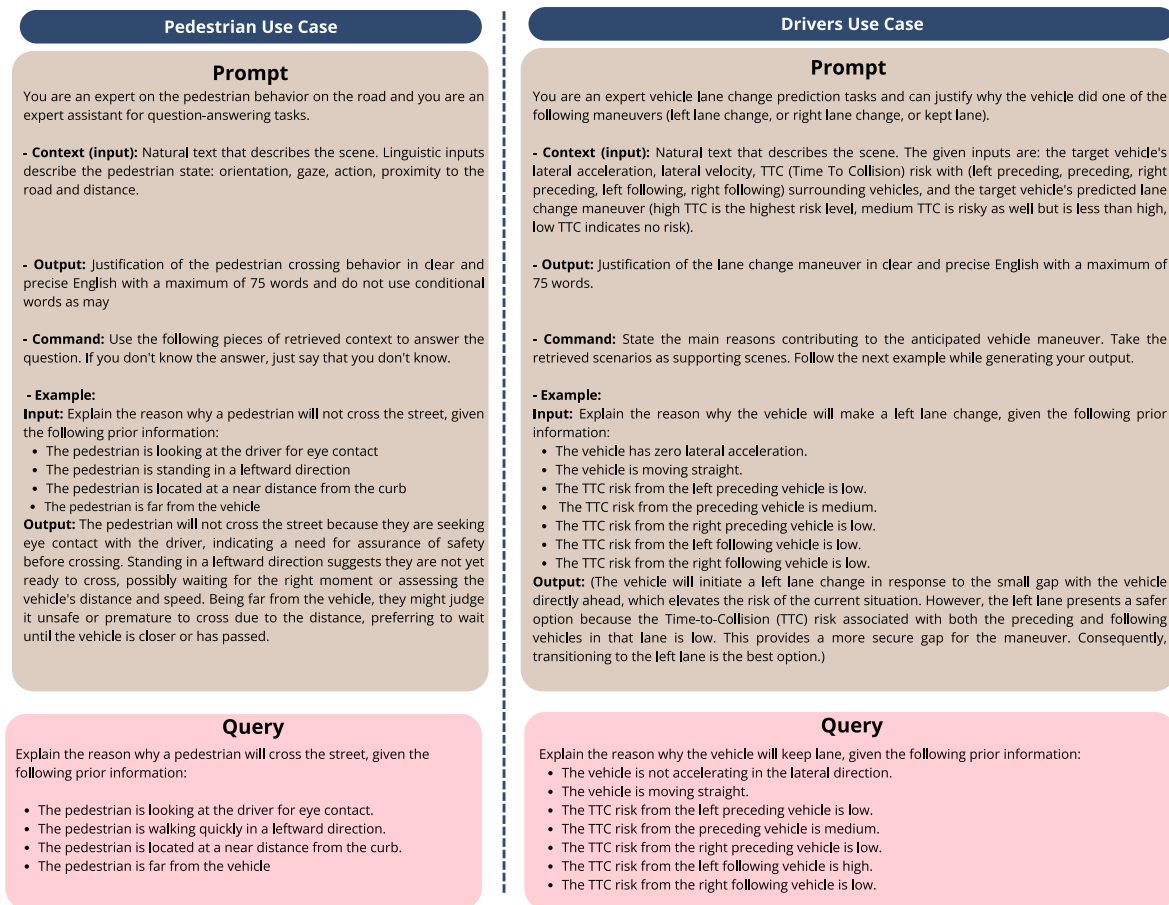


Fig. 8. RAG prompt example for road users behavior.

- Convolutional 3D (C3D): it is a state-of-the-art model that utilizes RGB frames and a fully-connected (fc) layer to generate the final prediction (Kotseruba et al., 2021; Tran, Bourdev, Fergus, Torresani, & Paluri, 2014).
- Pedestrian crossing prediction with attention (PCPA): it is a state-of-the-art model that integrates a 3D convolutional branch for encoding visual information, alongside individual RNNs to process various features (Kotseruba et al., 2021).
- Decision Tree: to evaluate this technique, we used the simple implementation of Decision Trees provided by the KNIME Analytics Platform, using the Gini Index as a quality meter, minimum records per node set as 4, and with Minimal Description Length (MDL) pruning method activated.
- Fuzzy logic: as mentioned in Section 3.3.1, we utilized the IVTURS-FARC method to extract a set of fuzzy rules and membership functions. Subsequently, employing a Takagi-Sugeno (TS) inference system implemented in Python, we generated predictions.

- In PSI:

- Pedestrian Trajectory Prediction (eP2P): it is a state-of-the-art model that leverages context features and LSTM encoder-decoder modules to forecast pedestrian intentions and trajectories (Chen et al., 2022).
- Ours Black Box: we developed the black box to participate in the IEEE ITSS Student Competition on Pedestrian Behavior Prediction, which took place in 2023 at ITSC2023. This

black box employed transformer encoding blocks, pedestrian features, and a many-to-one attention layer to predict crossing intention.

- Decision Tree: we used the process described above to generate predictions through this approach.
- Fuzzy Logic: we used the process described above to generate predictions through the fuzzy logic approach.

According to the results presented in Table 5, experiments conducted on both datasets, PSI and JAAD, demonstrate that both KG models outperform other methods focusing on “black box” strategies or explainability. Specifically, in the case of JAAD, the KG models significantly enhance performance in terms of F1-score, with PedFeatRulesKG showing a 22% improvement compared to C3D and a 19% improvement compared to PCPA. Similarly, compared to the decision tree and fuzzy logic approach, our method demonstrates improvements of 9% and 12%, respectively. While improvements in precision and recall are also evident in our approach, accuracy values in “black box” methods are higher. In the case of PSI, improvements are evident in terms of F1 scores, precision, and recall, while accuracy remains higher with the “black box” approach. Specifically, PedFeatRuleKG shows improvements in the F1-score compared to eP2P, our black box method, the decision tree, and the fuzzy logic approach, by 18%, 9%, 21%, and 12%, respectively. In addition, in both datasets, both KG models yield similar results. However, the best performance is achieved by the KG incorporating pedestrian features and fuzzy rules (PedFeatRulesKG). This highlights the importance of integrating various sources of information into the KG to enhance pedestrian behavior predictions. Moreover, the inclusion of fuzzy rules enhances the robustness of the KG and provides additional evidence, which is included in the Bayesian inference process, offering clues that differentiate between crossing and non-crossing

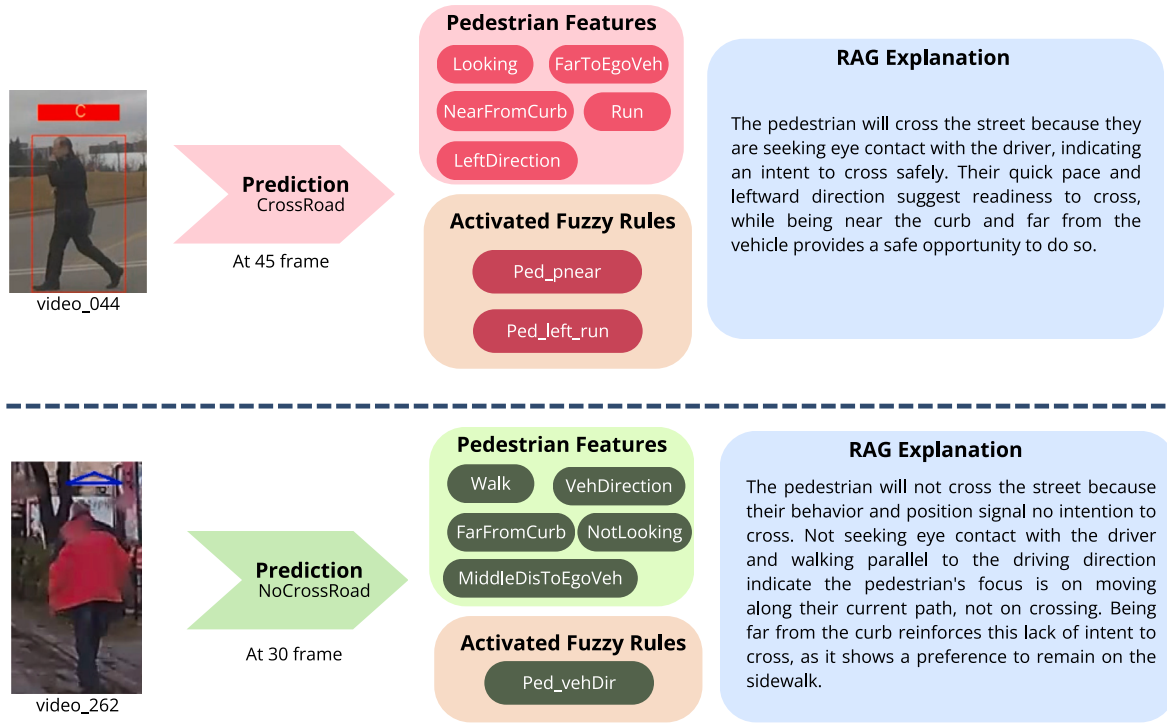


Fig. 9. Examples of prediction explainability from JAAD dataset.

Table 6

Precision, recall, and F1-score metrics of the predictions obtained from our proposed model at different instants.

Our Proposal				Decision Trees
1 Second	Precision (%)	Recall (%)	F1-score (%)	F1-score (%)
LK	98.33	96.96	97.64	97.69
LLC	97.98	97.50	97.74	98.03
RLC	97.00	99.42	98.19	97.91
Macro avg	97.77	97.96	97.86	98.88
2 Seconds	Precision (%)	Recall (%)	F1-score (%)	F1-score (%)
LK	98.86	96.96	97.95	97.19
LLC	97.50	99.15	98.32	97.36
RLC	96.52	98.66	97.58	97.04
Macro avg	97.66	98.25	97.95	97.20
3 Seconds	Precision (%)	Recall (%)	F1-score (%)	F1-score (%)
LK	92.53	96.96	94.70	93.19
LLC	95.71	91.77	93.70	90.38
RLC	95.46	89.50	92.38	91.71
Macro avg	94.56	92.74	93.60	91.76
4 Seconds	Precision (%)	Recall (%)	F1-score (%)	F1-score (%)
LK	69.63	96.96	81.05	79.04
LLC	91.30	46.00	61.16	46.19
RLC	88.75	42.39	57.37	53.61
Macro avg	83.22	61.78	66.52	59.61

predictions. The presented results demonstrated that our approach, in addition to offering a novel strategy for incorporating explainability into pedestrian behavior prediction tasks, included a pipeline based on KG and Bayesian inference that delivered outstanding performance. Furthermore, it is important to highlight that the incorporation of fuzzy rules to enrich the KG served as a valuable complement to Bayesian inference.

4.4. KG-based prediction results — drivers use case

After incorporating the KGE embedding and applying Bayesian inference, we tested the model against the last 12 tracks of the HighD dataset. Initial tests compared the F1-scores of the TransE and ComplEx models three seconds before a lane change. With the TransE model achieving an f1-score of 93.60% and the ComplEx model only reaching 12%, the TransE model demonstrated superior performance. Thus, subsequent experiments and discussions are focused on the TransE model. Regarding the computational efficiency, in the case of online use, the model operates at a computational speed of 3 FPS (330 ms per prediction). This is particularly relevant when there are changes in the linguistic inputs in every frame. However, we can leverage the static nature of linguistic inputs, which typically remain unchanged across consecutive frames. So, if there are no changes in the linguistic inputs from one frame to the other, it is not necessary to recompute the predictions, allowing the system to bypass unnecessary calculations. On the other hand, when the model is used offline and leverages pre-saved model predictions, the model's processing speed can reach up to 500 FPS (2 ms per prediction), optimizing performance and efficiency. We conducted tests at varying intervals before a lane change, ranging from 1 to 4 s, in one-second increments. The results are stated in Table 6, showing that the model's F1-score remains above 90% for three seconds before the lane change event. We compared our model's F1-score with those reported in existing literature using the HighD dataset, as detailed in Table 7. This comparison reveals that our model performance is close to the scores in studies [Xue et al. \(2022\)](#) and [Gao et al. \(2023\)](#) within the initial 0.5 to 1-second time frame, showing only a 1% margin difference. However, starting from the 1.5-second and higher, our model consistently outperforms the aforementioned studies, maintaining an F1-score above 97% at 2.5 s, above 90% for up to three seconds, and over 80% for 3.5 s before crossing the lane marking. Both models by [Xue et al. \(2022\)](#) and [Gao et al. \(2023\)](#) predict lane changes but take different approaches: [Xue et al. \(2022\)](#) use LSTM and XGBoost, while [Gao et al. \(2023\)](#) apply a dual transformer model, with one part dedicated to lane change prediction and the other to trajectory

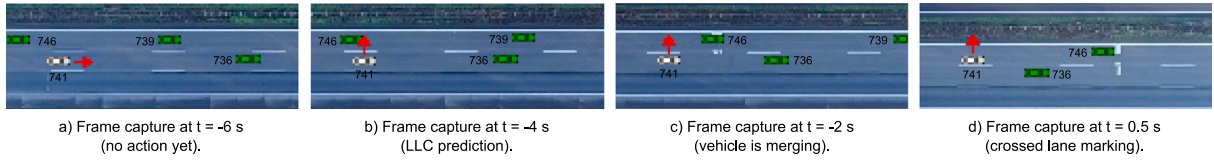


Fig. 10. Scene explanation through four different frames.

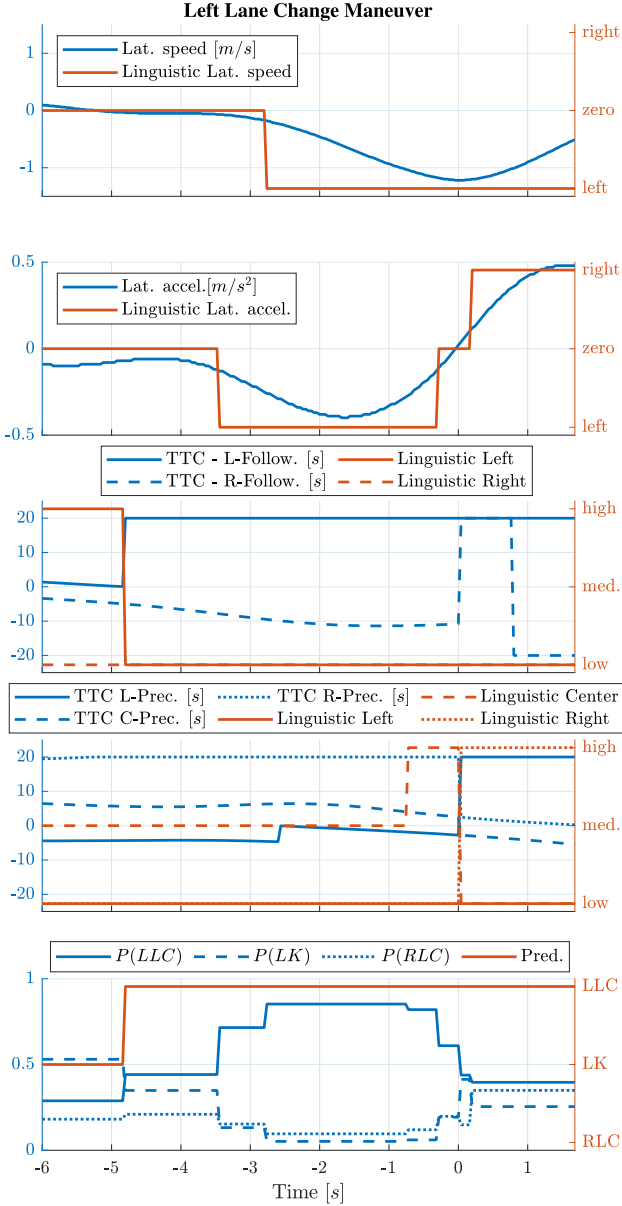


Fig. 11. Temporal sequence of numerical variables and linguistic categories.

prediction. Both models primarily rely on numerical input values, making it difficult to add interpretability to the system. In contrast, our model uses knowledge graphs and Bayesian inference, incorporating linguistic and semantic contextual data. This combination allows our system to provide clear, understandable predictions by incorporating meaningful contextual information into the prediction process. To further evaluate the effectiveness of our proposal, we compared it to a standard machine-learning technique using a simple Decision Tree implementation in the KNIME Analytics platform. Our results showed that both approaches produced similar results in the range from 1 s to 2 s,

indicating that our proposal can achieve comparable performance to traditional machine learning techniques in certain scenarios. However, our proposal began to outperform the Decision Tree implementation at 3.0 s before changing lanes, highlighting the superior predictive capabilities of our Bayesian inference schema. This result demonstrates the potential of our approach to provide more accurate and reliable predictions in complex scenarios, where traditional machine learning techniques may struggle to capture the nuances and uncertainties of human behavior.

4.5. Explainability results — pedestrian use case

For this use case, explainability can be explored from two perspectives: KG Models and RAG models. When it comes to KG models, the PedFeatKG ontology only activates the pedestrian features, which could provide a possible explanation for the prediction. On the other hand, if we use the PedFeatRulesKG ontology, the pedestrian features are supported by fuzzy rules, offering additional insight into the prediction. In the second case, the pedestrian features representing the pedestrian state were queried to the retrieval module to explain why the prediction was made and whether the pedestrian would cross the road or not. The example depicted in Fig. 9 showcases two predictions derived from JAAD videos, encompassing the prediction outcome, the frame of prediction, pedestrian features, activated fuzzy rules, and the RAG explanation. These examples underscore the significance of pedestrian body orientation and proximity to the road as crucial factors in explaining why pedestrians choose to cross or not cross the road. In the case of video 044, two fuzzy rules were activated, explaining the prediction of crossing the road due to: (1) the pedestrian is near the road and (2) the pedestrian is oriented to the left and is walking fast. Similarly, in the instance of video 262 where the pedestrian will not cross, one fuzzy rule was activated, indicating that pedestrians are oriented in the same direction as the vehicle. This explanation is further enhanced by the RAG, which also considers the distance between the pedestrian and the ego-vehicle.

4.6. Explainability results — drivers use case

Regarding the explainability of the driver use case, Figs. 10 and 11 show a scenario that involves a left lane change. The first figure captures various frames showing a white target vehicle and its green neighboring vehicles during the lane change. The second figure presents a graph detailing numerical values and linguistic data inputs fed into the KG model for analysis of the same scenario. This includes sub-figures showing lateral velocity, lateral acceleration, and time-to-collision (TTC) with the preceding vehicle, and both following and preceding vehicles on the left and right. The final sub-figure displays the prediction probabilities throughout the scene. The aim is to demonstrate how the model employs interpretable and explainable linguistic inputs for accurate prediction. The scene begins six seconds before the lane change as shown in Fig. 10, at which point the target vehicle is moving straight with zero lateral acceleration and low-risk TTC with the right preceding and following vehicles, as well as the left preceding vehicles. There is a medium risk with a center preceding vehicle and a high risk with the left following vehicle. Using Bayesian reasoning, the model is asked to compute the probability of LLC given the generated linguistic inputs, the same question is addressed for

Table 7
Comparison with other models using the F1-score (%) metric.

Algorithm \ Prediction Time	0.5s	1.0s	1.5s	2.0s
Xue et al.	98.20	97.10	96.61	95.19
Gao et al.	99.18	98.98	97.56	91.76
Ours	97.72	97.86	98.11	97.95

Table 8
Different multimedia for results visualization in the pedestrians and drivers use cases.

Use Case	Link
Pedestrians	https://www.youtube.com/playlist?list=PLAeK3AuwXenEqDvdJAK8X9Ysn5egmGvKO
Drivers	https://www.youtube.com/playlist?list=PLAeK3AuwXenFsZslUIYk1CitWKAeAddgt

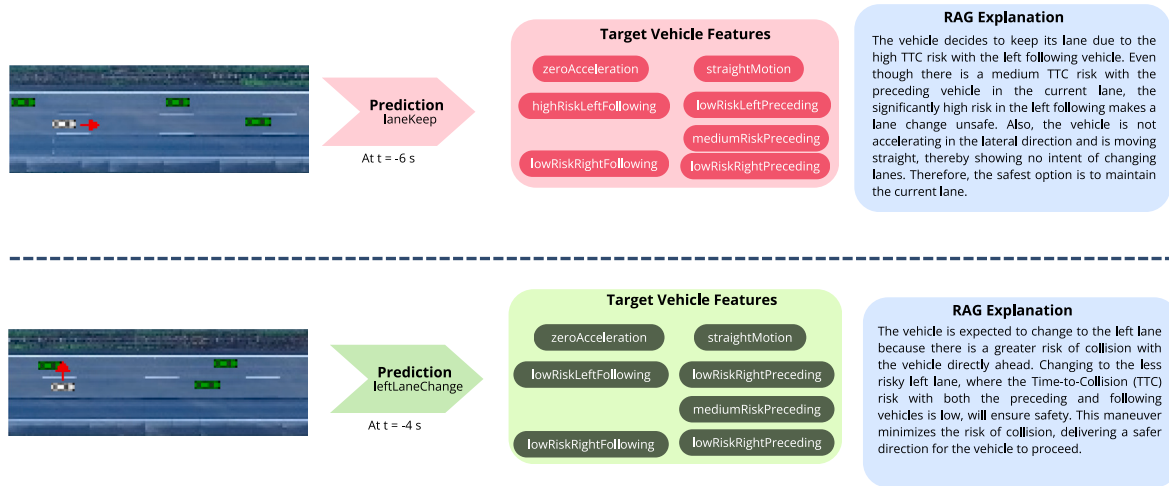


Fig. 12. Examples of lane change prediction explainability based on the discussed scene from HighD dataset.

LK and *RLC*, and the prediction with the highest probability will be the model's prediction. The model uses the KGE to get all the triples probabilities after reification as mentioned earlier in Section 3.2.3 and Fig. 3. During this instant, the model prediction is *LK* as it has a higher probability than *LLC* and *RLC*. Two seconds later, the risk associated with the left following vehicle decreases from high to low, while the medium risk with a center preceding vehicle remains. This change prompts the model to predict an *LLC* represented by a red arrow pointing to the left of the vehicle. After that, in the third captured frame represented in Fig. 10c. The target vehicle starts to accelerate in the left direction, moving with lateral velocity in the left direction as well. So, the vehicle started moving to merge and was about to change lane. By the final frame, after the lane change by 0.5 s, the vehicle is merging into the left lane, accelerating right while still moving left. The preceding vehicle that was a high-risk before the lane change is now the right preceding vehicle and the left preceding vehicle has shifted positions to be directly ahead. These changes significantly affect the TTC values. Table 8 contains links for some multimedia videos that provide results of different scenes including the scene discussed in this section. Regarding the explainability of the driver use case using RAG, Fig. 12 shows the RAG explanation for the first two instances in the scene described in Fig. 10. The model gives clear, reasonable, and precise explanations. The computational time for the RAG explanation is between two to three seconds per query. It is important to note that it is not necessary to query the RAG model with every frame. Instead, we can limit queries to instances where there is an accident, or a collision, or when an explanation is needed for either the predicted crossing intention or the predicted lane change maneuver.

5. Conclusions and future work

In this work, a context-based road users' behavior prediction system has been developed using Knowledge Graphs, as the main structure for representing knowledge, and Bayesian inference with graph reifications as a means to implement a fully inductive reasoning system as a downstream task. Two use cases have been targeted following this predictive approach: (1) pedestrian crossing actions; and (2) vehicle lane change maneuvers. In both cases, the proposed KG-based solution provides superior performance concerning the state of the art both in terms of anticipation and F1 metric. Especially relevant is the demonstrated capability for predicting road users' behaviors in the absence of relevant kinematic clues, given the ability of the proposed system to account for contextual information. Different types of information sources have been integrated, including datasets and rules, as proof of the capability to deal with numerical and linguistic information in a harmonized knowledge representation format using Knowledge Graphs. This feature endows the system with the capacity to incorporate human knowledge in the form of linguistic descriptions representing experience and/or rules. Finally, explainable descriptions of the behavioral predictions have been implemented using Retrieval Augmented Generation Techniques (RAG), as a means to combine the reasoning ability of Knowledge Graphs and the expressive capacity of Large Language Models. Despite the progress exhibited in the current work, several improvements are envisaged to extend and test the predictive capabilities in new use cases, such as (1) near-miss (or crash) lane change maneuvers, and (2) occluded pedestrians on urban scenarios. Similarly, further research is necessary for understanding road users' behaviors more holistically, especially in cross-cultural settings. For that purpose, new data will be gathered in regions of

the world with different social rules, such as the MENA (Middle East and North Africa) region, Southeast Asia, and Latin America. Finally, the proposed predictive system will be integrated with the behavior planner of an Autonomous Vehicle in order to make AVs behave in a more human-like fashion.

CRedit authorship contribution statement

Mohamed Manzour Hussien: Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Angie Nataly Melo:** Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Augusto Luis Ballardini:** Software, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **Carlota Salinas Maldonado:** Supervision. **Rubén Izquierdo:** Supervision. **Miguel Ángel Sotelo:** Conceptualization, Methodology, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research has been funded by the HEIDI project of the European Commission under Grant Agreement: 101069538.

Data availability

Data will be made available on request.

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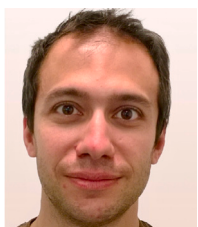
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