

Introduction

- The advent of autonomous vehicles creates the need to observe and model the behaviour of the 'machine - driver', consisting of various sensors exchanging information and acting according to the road context.
- One of the main challenges of automation is the urgent need to handle and process a huge amount of available data transmitting from the vehicles. **Artificial Intelligence (AI) and Machine Learning (ML) techniques** and algorithms have been developed to fulfil this need towards more reliable and advanced behavioral models and understand deeper the dynamic characteristics governing the interaction of the equipped vehicles with the other road users.
- Existing research is mainly focusing on the **interaction between vehicles and their surrounding vehicular traffic** while the investigation of the interaction of autonomous vehicles with other road users is still in its infancy.
- This unpredictability poses significant challenges for automated driving systems, which rely on sensor data and **decision-making algorithms to ensure safe navigation**.
- While AVs are designed to operate based on predefined rules and learned patterns, pedestrians often do not strictly follow traffic regulations and may behave differently depending on situational conditions such as **traffic density, visibility, infrastructure design, and social interactions**.
- Moreover, the increasing presence of AVs in urban environments introduces additional layers of complexity, including communication between vehicles and pedestrians, either implicitly through vehicle motion or explicitly through external **human-machine interfaces**.
- In this context, artificial intelligence (AI) and machine learning (ML) techniques have emerged as powerful tools for analysing large-scale data and **identifying behavioural patterns**.

Methodology

- This study is based on a **structured literature review** aiming to identify and analyse existing artificial intelligence (AI) and machine learning (ML) techniques applied to modelling interactions between automated vehicles and pedestrians.
- The literature search was conducted using major **scientific databases**, including Scopus, Web of Science, and Google Scholar.
- A **combination of keywords** was used to retrieve relevant studies, including "automated vehicles", "autonomous vehicles", "pedestrians", "vehicle-pedestrian interaction", "machine learning", "artificial intelligence", "reinforcement learning", and "trajectory prediction".
- The search focused primarily on **studies published in the last decade**, while earlier seminal works were also included where relevant.
- The selection of studies was based on **specific inclusion criteria**. Papers were included if they: (i) focused on modelling interactions between pedestrians and automated or autonomous vehicles, (ii) applied AI or ML techniques, and (iii) provided sufficient methodological detail regarding the modelling approach.
- Studies focusing exclusively on **vehicle-to-vehicle interactions** or lacking relevance to pedestrian behaviour were excluded.
- In total, a broad set of studies was reviewed, **covering various modelling approaches** such as reinforcement learning, deep learning, inverse reinforcement learning, and multi-agent systems.
- Both **simulation-based and real-world data studies** were considered to capture the diversity of existing methodologies.
- The selected studies were analysed and categorized **according to the type of modelling approach**, the interaction context (e.g., intersections, shared spaces), and the type of data used (e.g., real-world observations, simulation environments).
- This structured approach enabled the **identification of key trends**, methodological differences, and research gaps in the field. It should be noted that, despite efforts to ensure comprehensive coverage, the review may be limited by the availability of published studies and the selection of databases and keywords.

Key Modelling Approaches

Data-Driven & Deep Learning Models

- Capture complex behavioural patterns from large datasets
- Used for predicting pedestrian waiting time, trajectories, and crossing decisions
- More flexible and adaptable than traditional models

Reinforcement Learning (RL & DRL)

- Models decision-making of AVs in dynamic environments
- Applied to:
 - Autonomous braking
 - Trajectory planning
 - Safe speed control
- Enables adaptive and optimized vehicle responses

Inverse Reinforcement Learning (IRL)

- Learns pedestrian behaviour from real trajectories
- Estimates underlying decision-making processes
- Produces realistic and human-like movement patterns

Multi-Agent Systems

- Simultaneously model pedestrians and vehicles
- Capture interaction dynamics more realistically
- Improve safety and coordination in complex environments

Results

- While the reviewed studies highlight the **strong potential** of AI and ML techniques for modelling vehicle-pedestrian interactions, several important limitations remain.
- A key issue is the **extensive reliance on simulated and synthetic data**, which, although useful for controlled experimentation, often fails to capture the complexity, variability, and unpredictability of real-world conditions.
- This limits the **generalizability of models** when applied to real traffic environments characterized by behavioural uncertainty, environmental noise, and unstructured scenarios.
- Different AI and ML approaches also present **distinct strengths and challenges**. Reinforcement learning methods are effective for modelling adaptive decision-making but require large datasets and careful reward design, while deep learning techniques can capture complex patterns but often lack interpretability, raising concerns for safety-critical applications.
- Multi-agent models provide more **realistic interaction** representations but introduce increased computational complexity and scalability challenges.
- Additionally, accurately **modelling pedestrian** behaviour remains difficult due to its dependence on cognitive, social, and contextual factors.
- Another **critical challenge** is the transition from simulation to real-world deployment.
- Addressing this **gap requires** the integration of high-quality real-world data, such as trajectory datasets and naturalistic observations.
- However, data collection **remains complex** due to cost, privacy, and technical constraints, often relying on methods such as video analysis, LiDAR, and sensor-based systems.
- Finally, the influence of road infrastructure and environmental **conditions is often underexplored**.
- Factors such as **urban versus rural settings**, traffic density, weather, and lighting conditions significantly affect both pedestrian behaviour and model performance, further challenging model robustness.
- **Future research** should therefore focus on developing context-aware and interpretable models, leveraging hybrid approaches that combine real-world and simulated data, and creating diverse datasets that better reflect real-world variability.

Discussion

- Table 1 summarizes the main **artificial intelligence and machine learning approaches** used for modelling vehicle-pedestrian interactions.
- Each method offers **distinct advantages** depending on the application. Deep learning techniques are effective in identifying complex patterns and are widely used for trajectory prediction, while reinforcement learning approaches focus on decision-making and control, enabling automated vehicles to adapt to dynamic environments.
- Inverse reinforcement learning provides a **more realistic representation of pedestrian behaviour** by learning from observed actions, whereas multi-agent systems capture the interaction between multiple road users, offering a more comprehensive modelling framework. Hybrid approaches combine different techniques to improve overall performance and robustness.

Table 1: AI/ML Methods for Vehicle-Pedestrian Interaction Modelling

Method Type	Purpose	Strengths	Limitations	Typical Application
Deep Learning	Pattern recognition & prediction	Captures complex nonlinear behaviour	Low interpretability	Trajectory prediction
Reinforcement Learning (RL/DRL)	Decision-making & control	Adaptive, dynamic behaviour	High data & training cost	AV control, braking
Inverse RL (IRL)	Learn human behaviour	Realistic behaviour modelling	Requires high-quality data	Pedestrian modelling
Multi-Agent Systems	Model interactions	Realistic multi-user dynamics	High complexity	AV-pedestrian interaction
Hybrid Models	Combine approaches	Improved robustness	Complex implementation	Real-world applications

Conclusions

- The era of autonomous vehicles **imposes the need** of their safe coexistence with their surrounding traffic and mostly with pedestrians and other vulnerable road users.
- **Modelling the behaviour of automated vehicles and pedestrians** when interacting in various types of intersections is not an emerging field; it is continuously enriched with more advanced methods and techniques as the amount of data is also rapidly increasing.
- This work attempted to **enlighten this issue** by analyzing existing literature and various methods developed and applied for modelling the interaction between these two agents based on machine learning and artificial intelligent techniques.
- The **shortcomings and advantages** of each method can be served as a valuable tool for researchers aiming to further analyze this type of interaction and contribute to increase the safety levels for pedestrians when an automated vehicle is approaching.
- The review revealed the **lack of availability** of real automated and autonomous vehicle trajectory data as most of the studies use simulated generated data or data from driving simulators and virtual reality experiments.
- Finally, there is **limited research on studying and investigating vehicle behaviour** during their interaction with pedestrians at random locations where human decide unpredictably to cross deteriorating the safety levels.

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