

Explainable AI for Safe and Trustworthy Autonomous Driving: A Systematic Review

Anton Kuznetsov, Balint Gyevnar, Cheng Wang, Steven Peters, Stefano V. Albrecht

Abstract—Artificial Intelligence (AI) shows promising applications for the perception and planning tasks in autonomous driving (AD) due to its superior performance compared to conventional methods. However, inscrutable AI systems exacerbate the existing challenge of safety assurance of AD. One way to mitigate this challenge is to utilize explainable AI (XAI) techniques. To this end, we present the first comprehensive systematic literature review of explainable methods for safe and trustworthy AD. We begin by analyzing the requirements for AI in the context of AD, focusing on three key aspects: data, model, and agency. We find that XAI is fundamental to meeting these requirements. Based on this, we explain the sources of explanations in AI and describe a taxonomy of XAI. We then identify five key contributions of XAI for safe and trustworthy AI in AD, which are interpretable design, interpretable surrogate models, interpretable monitoring, auxiliary explanations, and interpretable validation. Finally, we propose a modular framework called SafeX to integrate these contributions, enabling explanation delivery to users while simultaneously ensuring the safety of AI models.

Index Terms—Autonomous driving, autonomous vehicle, explainable AI, trustworthy AI, AI safety

I. INTRODUCTION

ARTIFICIAL intelligence (AI) has gained a lot of attention in various technical fields in the last decades. Particularly, deep learning (DL) based on deep neural networks (DNNs) provides human-comparable or potentially even better performance for some tasks due to its data-driven high-dimensional learning ability [1], [2], so it has naturally emerged as a vital component in the field of autonomous driving (AD).

Nevertheless, deep learning suffers from a lack of transparency. It exhibits black-box behaviour, obscuring insights into its internal workings. This opacity makes it harder to identify issues and to determine which applications of AI are admissible in the real world. However, in safety-relevant domains such as AD, it is crucial to develop safe and trustworthy AI. Although there are several mitigation processes to handle safety concerns in AI, such as well-justified data acquisition [3], the adequacy of these measures in ensuring

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sufficient safety remains an open question, highlighting the need for further approaches.

Moreover, no standards currently explicitly address the use of data-driven AI in AD. The existing safety standard ISO 26262 - *Road Vehicles - Functional safety* [4] was not explicitly developed for data-driven AI systems and their unique characteristics [5]. The standard ISO 21448 - *Safety of the Intended Functionality* (SOTIF) [6] aims at ensuring the absence of unreasonable risk due to hazards from functional insufficiencies of the system and requires quantitative acceptance criteria or validation targets for each hazard. The concept can be applied to AI-based functions, but these acceptance criteria are not explicitly defined [7]. Moreover, specific guidance for designing AI-based functionality is missing.

As a result, these standards face challenges in addressing safety requirements for data-driven deep learning systems [8]. Although there is ongoing work on the ISO/AWI PAS 8800 - *Road Vehicles – Safety and Artificial Intelligence* [9], its scope and guidance remain unclear due to it still being in a development phase. In general, there is also a relatively high level of mistrust in society regarding AD. The American Automobile Association’s survey on autonomous vehicles (AV) indicates that 68% of drivers in the United States are wary of AVs [10], and AI has been identified as one of the key factors contributing to the non-acceptance of AVs in society [11].

A promising approach to address these problems is explainable AI. XAI aims to provide human-understandable insights into the behaviour of the AI and the development of XAI methods could be beneficial for different kinds of stakeholders [12]. First, it may become an essential tool for AI developers to identify and debug malfunctions [13]. Second, XAI could help users calibrate their trust in automated systems in line with the actual capabilities of AVs [14], thereby preventing misuse. Lastly, assurance companies and regulatory bodies may also benefit, as the increased transparency due to XAI could enable traceability that allows for a more accurate assessment of due diligence and liability in case of accidents [15]. Muhammad et al. [16] go as far as to say that in the future XAI could be *necessary* in terms of regulatory compliance including fairness, accountability and transparency in DL for AD. Given the increasing size of literature on XAI specifically for AD, it is necessary to systematically review which XAI techniques exist and how they are applied to enhance the safety and trustworthiness of AD.

A. Previous Reviews on XAI for AD

We note that some reviews of XAI for AD already exist and we give a brief overview of each in this subsection.

These works provide a good overview of the challenges and stakeholders of the field but have some crucial shortcomings:

- 1) Lack of a systematic and reproducible literature review methodology, leading to potential bias and incomplete coverage;
- 2) No focus on the specific benefits and drawbacks of XAI on the safety and trustworthiness of AD;
- 3) No review of frameworks for integrating XAI with AD.

The work of Omeiza et al. [17] was the first notable survey in the field. They provide a holistic look at XAI for AD, covering the different needs for explanations, regulations, standards, and stakeholders, and an overview of some explainability methods applied in AD. They review the challenges involved in designing useful XAI systems for AD and the associated literature, however, this review is neither reproducible nor complete, especially for the perception and planning tasks.

In addition, Atakishiyev et al. [18] covered very similar topics to Omeiza et al. with a slightly broader coverage of recent XAI technologies for AV perception and planning. Uniquely, they are the first to propose an end-to-end framework for integrating XAI with existing AD technologies, however, they did not explore this direction further. Their literature review was also conducted in a non-reproducible way.

Finally, the literature review of Zablocki et al. [19] identified potential stakeholders and why they might need explanations, the type of explanations useful for them, and when explanations need to be delivered. Based on that, they examine the different methods in the literature. However, they do not focus on the impact of XAI in meeting the requirements for safe and trustworthy AI. Furthermore, the survey has some shortcomings regarding completeness, since they only focus on vision-based methods for end-to-end systems. Accordingly, they do not consider XAI methods for planning and perception that can be applied to modular AD pipelines.

B. Main Contributions

In light of the existing works and the increasing importance of XAI for AD, we make the following contribution:

- 1) We discuss detailed requirements for AI in AD and highlight the importance of XAI in fulfilling them.
- 2) We provide a structured, systematic, and reproducible review of XAI applied for AD with a focus on environmental perception, planning and prediction, and control;
- 3) Based on our review, we identify five paradigms of XAI techniques applied for safe and trustworthy AD which include interpretable design, interpretable surrogate models, interpretable monitoring, auxiliary explanations, and interpretable validation. Moreover, we discuss each paradigm using concrete examples;
- 4) We analyse the limitations of existing modular XAI frameworks for AD and then propose a more concrete and actionable framework for safe and explainable AI called *SafeX* that is based on the summarized XAI techniques.

C. Scope and Structure

Our study gives a comprehensive view of the current state-of-the-art XAI approaches for AD encompassing both modular

and end-to-end pipelines, focusing on perception, planning and prediction, and control. Based on our reviewed methods, we also present a modular framework to incorporate XAI into the design of AVs. However, our survey does not identify stakeholders nor aims to give background on mathematical foundations such as DNNs or reinforcement learning. For these, existing surveys in Section I-A provide good coverage.

The structure of our survey is illustrated in Figure 1. In Section II, we provide foundations, where we define trustworthy AI and identify requirements corresponding to the application of AI in AD. Moreover, we describe the various sources of explanations for AI systems and introduce a taxonomy of XAI concepts as well as terminology for AD components. Section III describes our research questions and the methodology for the survey, assuring reproducibility. Section IV surveys the literature divided into interpretable design, interpretable monitoring, interpretable surrogate models, auxiliary explanations, and interpretable validation. In Section V, we review existing XAI frameworks in AD and propose our framework SafeX. In Section VI and Section VII, we discuss our findings and identify future directions in light of the results of our survey.

II. FOUNDATIONS

We begin in this section with an exploration of the need for trustworthy AI. We then examine the requirements for applying trustworthy AI in AD. Our analysis highlights the critical role of XAI in fulfilling these requirements and identifies the sources of explanations in AI systems. We conclude by reviewing a taxonomy of XAI along with a detailed terminology of AD components.

A. Trustworthy AI

As we begin our discussion of XAI for AD, it is important to understand where the need for explanations in AI stems from. Historically, AI was based on *symbolic* representations, where information was encoded using well-defined mathematical symbols, such as propositional logic or program induction. The first instances of successful AI applications were expert systems [104] which relied on such symbolic representations, lending themselves to varying degrees of inherent interpretability, that usually manifested in the form of causal chains of reasoning.

In contrast, current neural AI methods rely on *sub-symbolic* representations. Under this paradigm, input data is mathematically transformed into output via the learning of millions of parameters from large swathes of training data. This approach allows the modelling of highly complex multi-dimensional relationships which results in high performance. Still, the outputs of sub-symbolic systems are not interpretable due to their sheer size and high levels of abstraction. Therefore, they are often likened to black boxes that lack *transparency*.

While this efficiency versus transparency trade-off is sometimes acceptable (arguably even non-existent [105]), highly complex safety-relevant systems such as AD cannot fully rely on black box systems, as they are not readily certifiable for safety. This is in addition to the countless ethical, social, and legal reasons why neural methods may also be suspect [106].

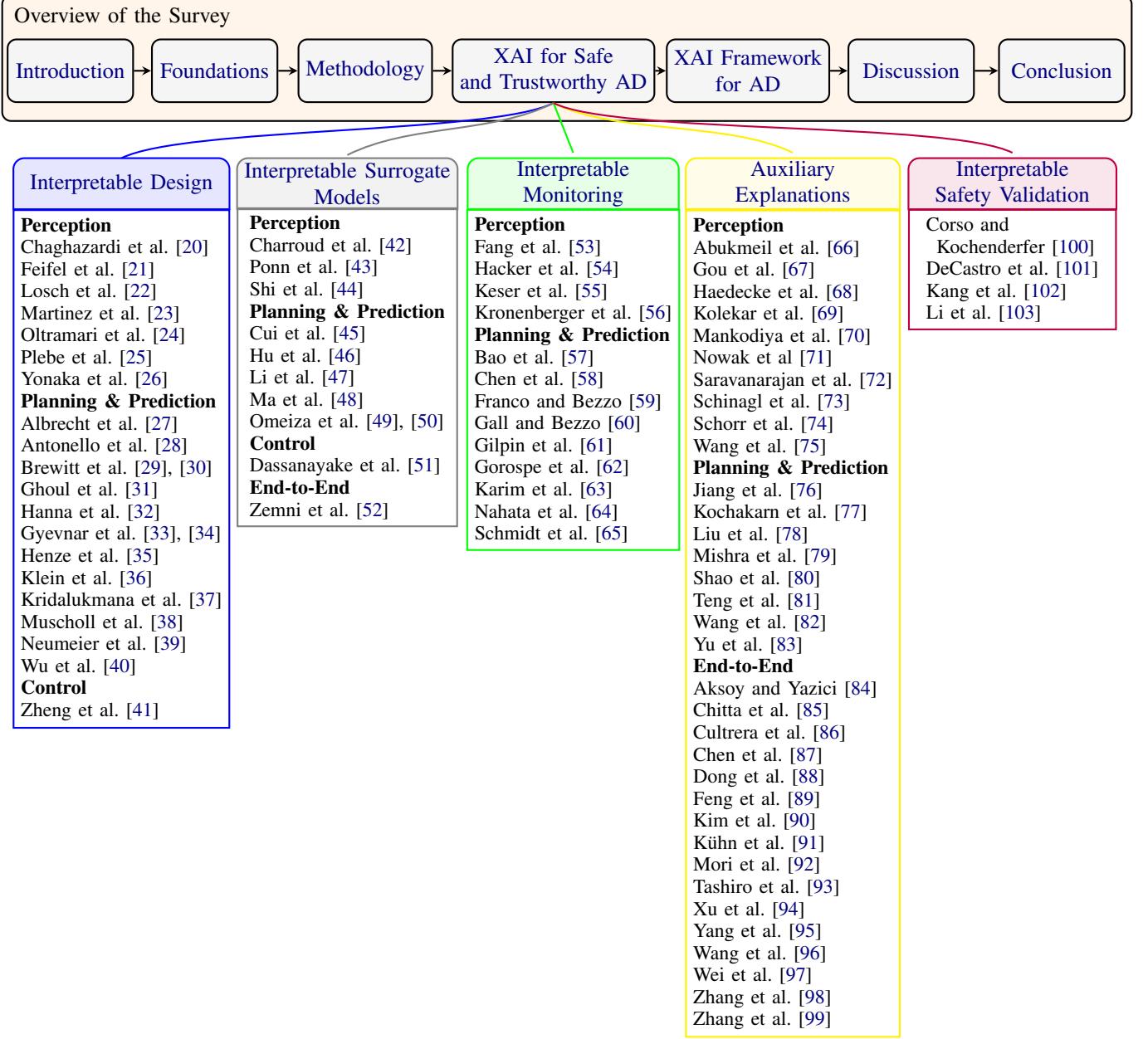


Fig. 1. The structure of the survey. We categorize existing XAI for AD approaches into five branches based on their different applications for AD: interpretable design, interpretable monitoring, interpretable surrogate models, auxiliary explanations and interpretable validation. The more fine-grained categorization is discussed in detail in later sections. Each category to a box with every representative work included.

Symptomatic of these issues is the lack of trust by users of AI systems. To alleviate the many problems that stem from a lack of transparency, methods that automatically explain predictions and decisions to users have become popular [107], forming the field of XAI. However, achieving trustworthy AI is a much more complex issue than could be solved by merely imbuing AI systems with explainability. Instead, trustworthy AI must consider a complex set of socio-technical requirements, among others, human agency, technical robustness and safety, privacy and data governance, diversity, non-discrimination, fairness, and societal and environmental well-being [108]. Our focus on XAI is not to suggest that we can achieve trustworthy AI just via explainable methods but as a

necessary element among the many approaches that support *human-centric AI* which strives to ensure that human values are central to how AI systems are developed, deployed, used, and monitored by ensuring respect for basic human rights.

In the following subsection, we explore in detail the requirements for trustworthy AI specifically for AD. Subsequently, we discuss from which sources and to what extent current AI methods are amenable to explaining and overview a taxonomy of XAI to organise our discussion of these methods.

B. Requirements For Trustworthy AI in AD

Owing to the superior performance in high-dimensional tasks like image processing and object detection [109], black

box methods are now the predominant approach to solving challenges in AD. Unlike many other robotic domains, incorrect behaviour by AVs can cause serious injury or death to humans, meaning safety is a top priority for all stakeholders. Designing safe and trustworthy AI is, thus, becoming urgent for AVs, necessitating the definition of safety requirements.

However, no concrete requirements are published for AI in AD. Instead, we need to take more general requirements for trustworthy AI as a starting point. We discuss whether these requirements map to AI systems in AD and whether new requirements for AI in AD should be defined. One of the well-known AI regulations is the ethics guidelines released by the European Commission [110], in which seven key requirements for trustworthy AI were defined. These are (i) human agency and oversight; (ii) technical robustness and safety; (iii) privacy and data governance; (iv) transparency; (v) diversity, non-discrimination and fairness; (vi) societal and environmental well-being; (vii) accountability.

Another AI risk management framework was developed by the American National Institute of Standards and Technology (NIST) [111]. This also defined seven key characteristics so that trustworthy AI should be (i) valid and reliable; (ii) safe; (iii) secure and resilient; (iv) accountable and transparent; (v) explainable and interpretable; (vi) privacy-enhanced; (vii) fair with harmful bias management. According to this framework, validity and reliability are the bases for other characteristics, while accountability and transparency are overarching concepts related to all characteristics.

The requirements defined in these two proposals are derived from three main sources: data-, model-, and agency-related requirements. We synthesise them in Table I. First, diverse data and data governance are essential to avoid unbiased decisions and protect privacy. Second, an AI model itself ought to be, among others, robust, safe, and accountable. Third, the deployed AI models must be overseen by humans for which human agency is required. Similar requirements are proposed by other individual researchers. For instance, Alzubaidi et al. [112] defined similar requirements for trustworthy AI. They considered accuracy and reproducibility as separate requirements while the EU assigned those requirements to robustness. To avoid unnecessarily conflating conflicting definitions, we take the requirements derived from the two national-level proposals as our starting point, noting that other conceptions of trustworthy AI may be fit to these frameworks.

Requirements From Data: Proper data governance is necessary for AD since privacy- and quality-sensitive data from drivers and external environments need to be processed. For instance, ML-based perception typically uses vision systems to perceive and understand the surroundings, where highly personal data such as pedestrian faces and license plates also appear. However, it is not necessarily the case that technical data must be classified as non-personal [113]. Under EU jurisdiction, for instance, the General Data Protection Regulation (GDPR) [114] may provide a legal basis for processing personal data when using AI-based functionalities, though it is unclear to what extent the unilateral and fully automated processing of personal data in AVs is covered by the GDPR. Moreover, to avoid, among others, unfair bias, we ought to

rely on diverse data to train AI models. Particularly, the non-discrimination of pedestrians is an important requirement for ML-based systems in AD. Despite this, Li et al. [115] showed a bias for missing pedestrians who are children or have darker skin tones. In general, the elicitation of safety-related requirements should be seen as a process that includes multiple stakeholder perspectives to increase diversity [7].

Requirements From AI Models: AD is a safety-critical application where a lack of robustness could lead to traffic accidents. The environment in which an AV operates is complex, uncertain, and changes over time and space. Deep learning-based models need to be robust not only to variations in the physical driving condition (e.g., differing weather conditions, and changes to the car behaviour due to component wear) but also to variations in the behaviours of other drivers, including the possibility that adversarial road users may try to exploit AV systems [116]. In addition, adversarial perturbations can fool deep learning-based neural networks [117], leading to implausible results. Therefore, AI needs to be robust against, among others, noise, distribution shift, and adversarial attacks [16] and must demonstrate safe decisions even in uncertain environments. Moreover, AVs need to be sufficiently transparent for the involved stakeholders such that the decisions of the AV can be understood. For instance, developers need transparency to debug models and thus improve their robustness, while regulators need transparency to audit and certify systems. Furthermore, deployed AI models should be user-centric and designed in a way that all people can benefit from their services regardless of their situation. Finally, establishing accountability for AD systems is important for determining liability in case of accidents [50].

Requirements For Agency: For level 3 AVs [118], human drivers are allowed to do non-driving-related activities while the AV undertakes dynamic driving tasks (DDTs) as long as it remains within the predefined operational design domain (ODD). Nevertheless, a driver should be prepared to take over control at any moment if the system fails or when the ODD is exceeded. In contrast, for more advanced level 4 and 5 systems, human drivers no longer need to stay in the loop which diminishes their oversight, especially when the AI systems are inscrutable. Worryingly, without additional measures, human agency, as a basic human right, will suffer due to the use of black box systems. In particular, the users of AVs may have very little insight into the decision-making processes of AD and could never hope to contest the decisions that may directly impact their bodily integrity. However, obtaining recourse in these situations may not just be a matter of enabling intervention on the AD systems, but rather the provision of explanations that calibrate users' trust according to the system's capabilities. Therefore, depending on the automation level of the system, the requirements for agency may or may not be addressed by existing systems.

In addition to the above three categories of requirements, safety assurance is imperative for AD [119], [120]. We should consider safety at a fundamental level of importance which underlies and complements the three high-level requirements of trustworthy AI for AD. While requirements for trustworthy AI often include safety, safety assurance often places hard

TABLE I
SUMMARY OF THE DEFINED REQUIREMENTS IN THE ETHICS GUIDELINES (EU) AND THE AI RISK MANAGEMENT FRAMEWORK (USA) AND DISCUSSION OF THEIR APPLICABILITY TO AD. THE REQUIREMENTS ARE CLASSIFIED INTO THREE SOURCES: DATA, MODEL AND AGENCY.

Sources	Ethics Guidelines (EU)	AI Risk Management Framework (USA)	Transferable to AD?
Data	Privacy and data governance	Privacy-enhanced	Y
	Diversity, non-discrimination, fairness	Fair with harmful bias management	Y
Model	Technical robustness and safety	Safe	Y
	Transparency	Accountable and transparent	Y
	Accountability	Valid and reliable	Y
	Societal and environmental well-being /	Secure and resilient Explainable and interpretable	Y Y
Agency	Human agency and oversight	/	Y/N

constraints on the behaviour of AI systems as opposed to the more high-level criteria of other aspects of trustworthy AI, and so safety should be viewed as a distinct set of requirements.

However, giving a full account of safety requirements would mandate its publication, so instead we focus on one way of guaranteeing certain safety requirements that also overlap with many of the recommendations of trustworthy AI, namely explainable AI. First, XAI contributes to transparency by delivering (intelligible) explanations of AI models' decisions. To show compliance with data protection regulations, one may call on XAI to provide evidence that personal data is not processed by AD systems and that they can function without personally identifying features in the data. Second, accountability through inquiry and traceability may be achieved, which is essential to show non-discrimination, determine failure cases, and establish a holistic case of their workings for legal proceedings or regulatory conformity. Third, XAI is beneficial for the inspection, debugging, and auditing of AI models, which can contribute to improved robustness and better-calibrated levels of trust in AVs [121]. Fourth, XAI aids in restoring the contestability of AD decisions, which may protect users from undue harm and offer a basis for legal recourse. Therefore, we must conclude, that XAI is an essential tool in meeting the requirements of safe and trustworthy AI for AD.

C. Sources of Explanations in AI

Having established the importance of XAI for AD, it is important to understand what sources of explanations arise in existing systems, as this affects their scope of applicability to AD. For this, we clarify definitions related to the basic properties of XAI, particularly the notions of interpretability, explainability, justifiability, traceability, and transparency. We call these properties the *sources of explanations in AI* because an AI system should have at least one of these properties to be amenable to explaining. These are also related and not mutually exclusive concepts, but are often incorrectly used interchangeably so it is important to clarify their meanings. Much of our discussion here is informed by the works of Gyevnar et al. [108] and Miller [122].

Interpretability: we call an AI system interpretable if it is sufficiently low in complexity such that a reasonably experienced user can understand the output of such a system and the causal process that produced that output [123] from the input. Therefore, interpretability is an inherent quality of

a system. Interpretable systems are often argued to be better suited for safety-relevant applications due to the observable chain of causality that led to a decision [105].

Explainability: we call an AI system explainable if the output of the system is accompanied by an additional output that takes the syntactic form of an explanation. The explanation should intelligibly communicate the reasoning process behind how the output was derived [124]. Explainability is not necessarily an inherent quality of the AI system, and may not accurately reflect the causal chain that produced the output.

Justifiability: an AI system's decision is justifiable if one can explain *why* an output was good without necessarily explaining *how* the output was computed [122]. This property depends on a definition of goodness that will inherently depend on the application domain and the ethical framework the designers of the system see fit for use.

Traceability: an AI system is traceable if an external auditor can follow the causal chain of the full decision-making process from input to output. Any system that relies on a black box is not traceable since causality is obscured by design. A system might also only rely on white box systems but still be untraceable due to the sheer size of the models.

Transparency is a broad term that is often used incorrectly to mean any of the same definitions as above. In our view, transparency is not solely the property of the AI system achievable via XAI but the result of a range of measures that enable the understanding and informed use of the system, through a combination of, among others, documentation, XAI, standardisation, and risk assessments [108].

D. Taxonomy of XAI

We now provide a taxonomy of XAI visualised in Figure 2. The taxonomic categories are based on Speith [125] as they are sufficiently high-level and task-agnostic to be concretized in the domain of AD. We consider six categories that we summarise in the following.

Representation of the input within the model has a significant effect on the working of the XAI system. Relating to our discussion of trustworthy AI in Section II-A we can differentiate between *symbolic* and *subsymbolic* systems, as well as *mixed* systems that utilise both. How the designers choose to represent the world will affect downstream design.

Stage relates to when during the decision-making process an explanation is generated and from what representations. *Post-hoc* systems are run after a decision has been made and

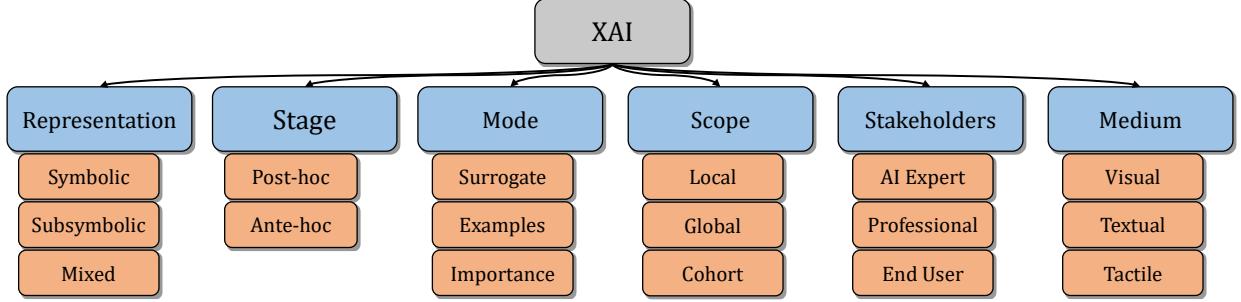


Fig. 2. A taxonomy of XAI covering the most important concepts occurring in the literature of XAI for AD with terminology borrowed from Speith [125].

are usually widely applicable to any sort of decision-making process regardless of representation. In contrast, *ante-hoc* systems are constrained to symbolic or mixed representations as they operate directly with the actual process of decision making which would not be possible with a black box system. These systems have more constrained applicability but are generally more trustworthy and verifiable.

Mode determines the syntactic form and content of the explanation. While there is a large range of explanatory modes, three are particularly popular in XAI. *Importance*-based explanations aim to explain which parts of the input representations are most attended by the model when the system makes a prediction. These models provide a way to shed some light on black box decision making but importance must not be conflated with actual explanations as they can often be altered without affecting the output prediction [126], [127]. *Surrogate* systems aim to condense the overall workings of a complex method into an interpretable model but it is difficult to quantify to what extent these models can faithfully represent their parent models. Finally, representative or counterfactual *examples* are often brought up to explain away some aspect of the decision-making process in terms of an input sample, but these rely on the assumption that the user can understand and then interpret the example correctly.

Scope determines whether the explanation applies to a given input instance only (*local*), to a group of instances (*cohort*), or to the entire model as a whole (*global*). The scope of the explanation is tightly connected to its mode. Example- and importance-based explanations are more suited for local and cohort explanations while surrogate models represent the entire decision-making process and are, thus, global explainers.

Stakeholders are a less frequently considered but crucial aspect, that ought to determine how explanations are designed and delivered [12]. The goal here is to maximise the utility for each stakeholder group which may have very different requirements. Mohseni et al. [128] consider three stakeholder groups: *AI professionals* with access to the AI models and to expert knowledge on these systems, *professionals* with potential access to the AI models but without expert AI knowledge (e.g., judges, regulators, police, etc.), and *end users* without access to either the AI models or expert knowledge.

Medium is the channel through which the explanations are delivered to the stakeholders. How explanations are delivered has a profound influence on efficacy and intelligibility. It is an

important design decision and should complement the correct understanding of stakeholder requirements.

E. Terminology of AD Components

To facilitate the discussion of which XAI technologies are currently being used for which features of AD, we also present a brief introduction of the terminology of the AD components. Although different divisions of AD components exist depending on the level of detail [129], the core competencies of an AV can be generally categorized into three components, which are perception, planning and prediction, and control [130], [131], as illustrated in Figure 3. Perception pertains to the capability to gather data from the surroundings and derive meaningful insights or knowledge from that environmental information. Specifically, *environmental perception* refers to the development of a contextual understanding of the environment, which encompasses the identification of obstacles, detection of road signs and markings, and classification of data based on their semantic significance. *Localisation* refers to the ability of the AV to determine its position within the environment.

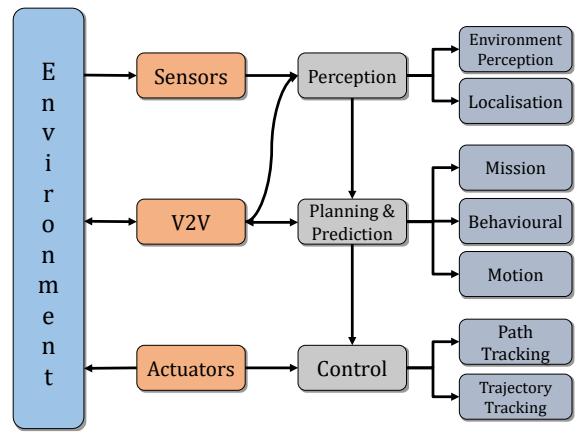


Fig. 3. A typical system overview of autonomous driving systems [130]. Arrows denote the flow of information. Orange boxes are hardware, grey boxes are software components. (V2V: vehicle-to-vehicle communication.)

Planning and prediction involve the strategic process of making informed decisions based on predicted future trajectories of obstacles to achieve the vehicle's higher-order goals. This typically includes navigating the vehicle from a starting point to a desired destination, while simultaneously

avoiding obstacles and optimizing performance based on pre-designed constraints. According to [132], planning can be further divided into mission planning, behaviour planning and motion planning. *Mission planning* represents the selection of a route from its current position to the predefined destination based on the road network. *Behavior planning* is responsible for determining the appropriate driving behaviour at any point of time along the selected route, given the perceived behaviour of other traffic participants and road conditions, etc. Lastly, *motion planning* aims to find a collision-free, comfortable, and dynamically feasible path or trajectory once the behaviour layer signals a driving behaviour in the current driving context.

Finally, control competency denotes its proficiency in executing planned actions, which are formulated by its higher-level processing modules. In *path tracking*, the vehicle is required to converge to and follow a path generated by motion planning without including a temporal law [133]. In contrast, *Trajectory tracking* refers to the following feasible "state-space" trajectories, which specify the time evolution of the position, orientation, and linear and angular velocities [134].

The above modular system description enables the separate development of each component. In addition to modular approaches, there are end-to-end systems that replace the AD architecture with a single neural network [19], though often the control part is separated and the end-to-end network only comprises the planning and perception components. The motivation for end-to-end architectures relies on its simple design by avoiding the consideration of different interconnections between different modules and instead focusing on joint feature optimization of individual modules [135]. In contrast to modular pipelines, end-to-end networks are much less interpretable, so ensuring their safety is more challenging. It is easier to trace the source of errors in modular approaches [136].

III. REVIEW METHODOLOGY

Considering the requirements and interesting challenges in implementing XAI for AD, the field has been growing in popularity. To comprehensively explore the published methods, we have decided to perform a systematic literature review following the recommendations of Kitchenham and Charters [137] and the review methodology section of Stepin et al. [138]. A structured review allows us to systematically explore the field by combining increasingly more fine-grained queries with online indexing databases, while our description of this process enables the reproduction of our results which is beneficial for verifying the validity of our work as well as for obtaining an updated look of the field in the future.

To give an overview of the review process, first, we defined two primary research questions based on which we developed a query hierarchy. We used the resulting queries to search three indexing databases – Scopus, Web of Science, and IEEE Xplore – and applied a three-step process to arrive at a final set of 84 publications. We describe the full process below.

A. Research Questions

RQ1 What are the current methods of XAI that address requirements of safety and/or trustworthiness, and what are their

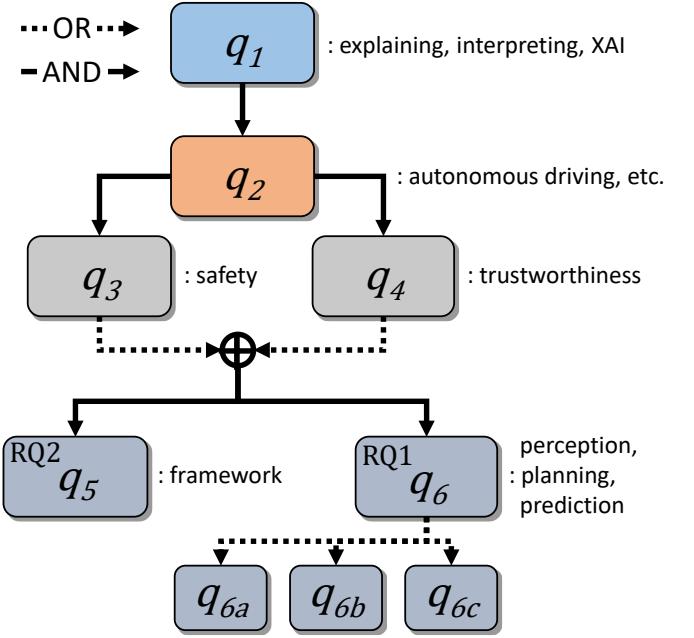


Fig. 4. The query hierarchy used for the survey with a representative list of keywords corresponding to each query. Colours signal various depths of the search hierarchy.

key contributions to meeting these requirements?

RQ2 What concrete general frameworks are proposed for integrating XAI with autonomous driving?

B. Search Process

We chose the Scopus, Web of Science (WoS), and IEEE Xplore online indexing databases to perform our review, as these platforms provide extensive coverage of both technical and non-technical venues as well as the ability to construct and refine detailed queries. To obtain a list of candidate papers, we constructed a search hierarchy as shown in Figure 4. Each level of depth in this tree corresponds to increasingly more refined search terms such that the final list of candidate papers was a set of highly relevant publications with manageable counts. The queries are shown below in the WoS notation, and equivalent queries were constructed for both Scopus and IEEE Xplore. The queries were applied to the title, author keywords, and abstract field of each indexed publication, and the search was carried out between 22 to 26 September 2023.

- $q_1: \text{expla* OR interp* or XAI}$
- $q_2: q_1 \text{ AND (auto* AND (driv* OR vehicle* OR car*) OR self driving)}$;
- $q_3: q_2 \text{ AND safe*};$
- $q_4: q_2 \text{ AND trust*};$
- $q_5: (q_3 \text{ OR } q_4) \text{ AND (pipeline OR architecture OR framework)}$;
- $q_6: (q_3 \text{ OR } q_4) \text{ AND ...}$
- $q_{6a}: \text{sense OR perception OR computer vision OR object detection OR semantic segmentation};$
- $q_{6b}: \text{prediction OR plan*};$
- $q_{6c}: \text{control*}.$

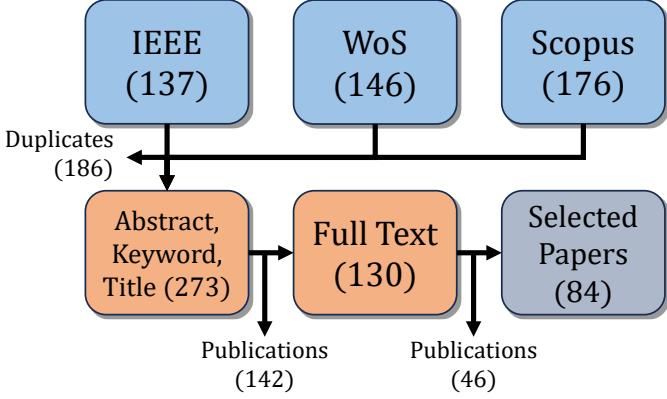


Fig. 5. Overview of the review process as a flowchart. First, papers were retrieved according to the queries (blue boxes), then twice filtered by content (orange boxes). Numbers in parentheses show papers at the end of each step.

TABLE II

THE NUMBER OF PAPERS COLLECTED FOR QUERIES CORRESPONDING TO RQ1 (q_6) AND RQ2 (q_5), WHILE NOT SHOWING q_1-4 AS THESE QUERIES HAD MULTIPLE THOUSANDS OF PAPERS.

	WoS	IEEE	Scopus	Duplicates	Total (w/o dups.)
RQ1	130	135	169	178	256
RQ2	7	11	7	8	17

Our choice for q_1 selects all papers that are related to explaining, interpretation, or any papers that mention XAI. At this point, we did not constrain our search with keywords relating to a particular subject area (e.g., transportation systems) to build a large foundation of papers to select from. We narrowed our search to focus on autonomous driving (and related keywords) using q_2 , and then further filtered papers based on whether they contain keywords relating to trust or safety. To answer RQ1, we take this set of papers and sort them based on whether they relate to a particular subsystem of the AD stack as shown in Figure 3. To answer RQ2, we filter the collected set of papers based on keywords that relate to frameworks or architectures.

The search and selection process was conducted as indicated in Figure 5 and explained below. The total numbers of papers retrieved for the research questions are shown in Table II. After querying for papers we have removed all papers that were duplicates. The remaining set was then filtered based on our exclusion and inclusion criteria (detailed in Section III-C). We then proceeded to filter the remaining papers based on their full text and re-applied the same exclusion and inclusion criteria to determine which papers to include in our final list.

C. Inclusion and Exclusion Criteria

We now describe the inclusion and exclusion criteria that were used for both research questions at each stage of the search process to arrive at the final list. At each stage in the filtering process, we first applied a list of inclusion criteria to determine which papers to keep at that stage. All of these inclusion criteria must have been fulfilled by the paper to pass this stage. We included papers where:

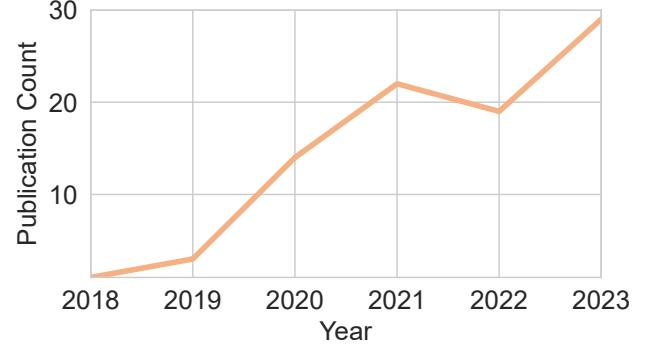


Fig. 6. The number of publications retrieved for RQ1 plotted against the publication year shows an increasing trend.

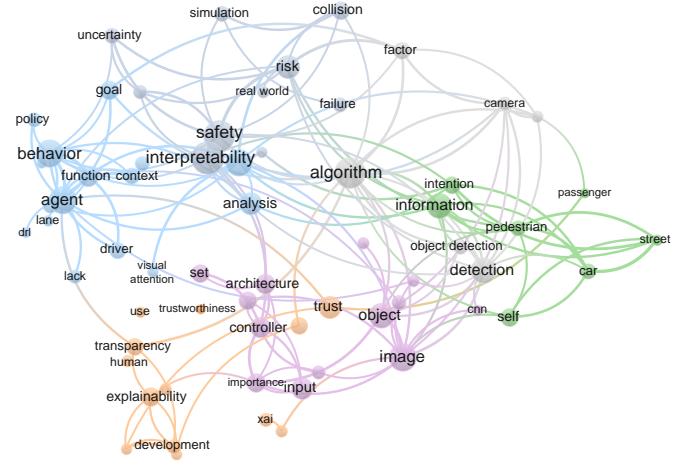


Fig. 7. A map of 61 keyword co-occurrences in the titles and abstracts of all papers selected for the review. Figure generated with VOSViewer [139] using keyword counts occurring at least 6 times with a top 60% relevance score. All nodes in the graph are connected but for ease of visibility we only show edges which connect keywords with at least 8 occurrences.

- The paper was – in part or fully – motivated by a need for safer or more trustworthy technologies; AND
- The paper proposed a concrete system, algorithm, framework, or novel artefact related to artificial intelligence;

After the inclusion process, we applied a list of exclusion criteria which specified more detailed requirements on the papers. We filtered out papers if they met at least one of the exclusion criteria. We excluded papers where:

- It showed no attempt to address any of the sources of explanations (as described in Section II-C); OR
- The main domain of application or evaluation was not autonomous driving; OR
- The paper did not address perception, planning, prediction, or control for autonomous driving;

D. Bibliometric Analysis

We perform a high-level bibliometric exploration of the collected works to provide an overview of the patterns among the publications. As Figure 6 shows, the number of publications related to XAI for AD has been growing since the first

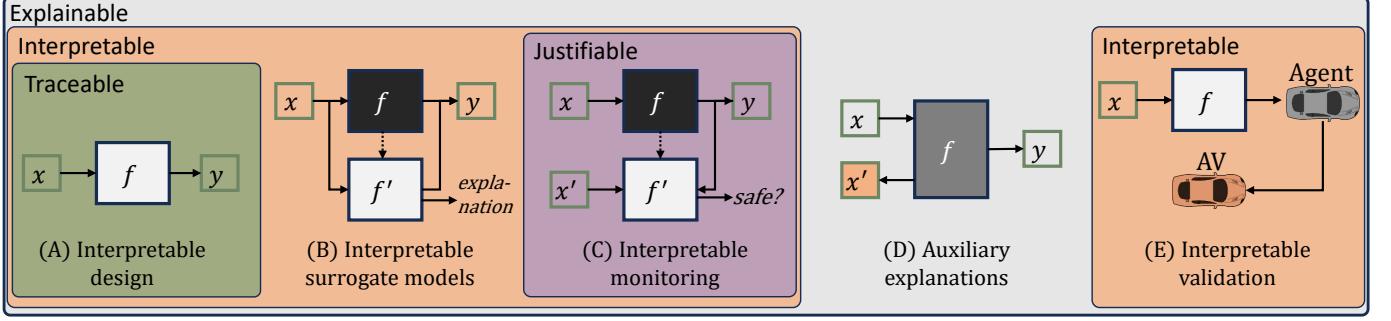


Fig. 8. Categories of XAI for safe and trustworthy AD, sorted by the type of explanations (Section II-C). (A) the AI algorithm is inherently interpretable (white box); (B) surrogate models are used to approximate opaque AI models (black box) and generate explanations for their outputs; (C) a transformed input is fed into an interpretable monitor system (white box) to runtime check the safety of opaque AI models (black box); (D) the AI models can deliver some certain intermediate explanations in addition to their functions (gray box); (E) interpretable algorithms are employed to control agents for validating AVs.

retrieved publications in 2018, a trend we expect to continue observing in the future.

Looking at the keyword relations shown in Figure 7 reveals that the ‘interpretability’ of ‘algorithms’ is most often mentioned with ‘safety’. The mentions of ‘explainability’ in contrast are more associated with ‘transparency’, ‘human’, and ‘trustworthiness’. This provides support for our definitions of the sources of explanations (Section II-C) in that it suggests that interpretability is considered purely an algorithmic concept while explainability is more human-centric.

IV. XAI FOR SAFE AND TRUSTWORTHY AD

After reviewing the collected publications, we determined five main paradigms into which we sorted the reviewed papers. These are interpretable design, interpretable surrogate models, interpretable monitoring, auxiliary explanations, and interpretable validation. An overview and visual illustration of these categories is shown in Figure 8. In this section, we present definitions for each category and describe the corresponding literature.

A. Interpretable By Design

Definition IV.1 (Interpretable By Design). *An algorithm is said to be interpretable by design if it is inherently interpretable such that it provides an explicit causal relationship between its input and output.*

1) *Interpretable By Design – Perception:* Chaghazadi et al. [20] introduced an inductive logic programming approach for traffic sign classification where firstly high-level features such as colour, shape, etc. are extracted and then a hypothesis is learned. The design increases transparency and reliability. Moreover, a higher robustness against adversarial attacks compared to other state-of-the-art algorithms was shown. In [21], Feifel et al. proposed a structured interpretable latent space in a DNN for pedestrian detection which learns to extract specific prototypes. The learned prototypes in the latent space can be clustered in a projected 2D-plane via a principal component analysis [140] or a t-SNE projection [141]. Due to the interpretably designed DNN, an ante-hoc analysis is possible which supports the safety argumentation.

Plebe et al. [25] developed a temporal autoencoder for lane and car detections in semantic segmentation consisting of an organized latent space where semantic concepts of lane and car segments are learned. Similarly, Losch et al. [22] proposed semantic bottleneck models for semantic segmentation tasks which aligned every channel with a human interpretable visual concept. The introduction of semantic concepts in the latent space additionally increases transparency in the prediction by the DNN. Oltramari et al. [24] developed a hybrid AI framework for perceptual scene understanding via instructing the latent space of DNNs with knowledge graphs that are extracted from clustering the labelled training data. Martinez et al. [23] developed an interpretable latent space in the DNN by using capsule networks [142] to predict eye fixations in AD scenarios and contextual conditions. A capsule describes a group of neurons whose activity vector represents a specific routable item and is located in the latent space. With these capsules, it is possible to express interpretable relationships between features and contextual conditions on frame-level and pixel-level. In [26], Yonaka et al. trained a CNN to identify the presence of sun-glare in the AD environment. Subsequently, heat maps with a Gradient-weighted activation map approach (Grad-CAM) [143] were calculated to identify the regions of sun glare in the image. The developed heat map approach increases transparency in the decision-making process.

2) Interpretable By Design – Planning & Prediction:

Albrecht et al. [27] proposed an ante-hoc, interpretable, and intelligible prediction and planning system called IGP2 based on rational inverse planning and Monte Carlo Tree Search over high-level macro actions. The method generates driving plans for AVs that are inherently interpretable in terms of rationality principles (safety, efficiency, comfort) and can be justified by design in terms of the actions of other agents and the goals of the ego vehicle. Their evaluation using four scenarios and an open-world environment is promising but computationally expensive. Hanna et al. [32] extends this work by considering occluded factors in the environment. Goal recognition was further investigated by Brewitt et al. [29] who proposed GRIT, a decision tree-based system that is not only inherently interpretable but also verifiable which is a crucial property for safety certification. In a follow-up paper, this work was extended to also work with occluded

environments [30]. Additionally, Gyevnar et al. [33], [34] proposed methods based on IGP2 that use Bayesian networks and trajectory simulations to causally explain the behaviour of the AV in terms of both its intrinsic motivations and the extrinsic behaviour of other traffic participants. Ghoul et al. [31] created an ante-hoc explainability method for goal and trajectory prediction using Discrete Choice Models (DCM) integrated with neural networks. Detected goals inform the trajectory prediction module in which each future time step is represented by a Gaussian distribution parametrised by a neural network. Explainability stems from the inherently interpretable nature of DCMs but this only extends to the goal prediction module. Henze et al. [35] proposed a generally applicable conceptual framework for self-explanations of planning algorithms via natural language for non-expert users. Explanatory features are selected based on input influence, sensitivity analysis of parameters, and traffic rules, however, the framework was not implemented in practice. Klein et al. [36] proposed an ante-hoc interpretable mixture of experts (MoE) classifier based on *motifs* – frequently recurring subsequences in time-series data – extracted from driving trajectories for lane change scenarios designed for AI experts as stakeholders. The system recovers intuitive motifs from the data but the qualitative interpretability benefits of the MoE are not substantially explored and rely on a well-calibrated gating mechanism for choosing among the experts which only performs well with NN-based architectures. Kridalukmana et al. [37] suggested an ante-hoc explainability method with high-level strategic explanations based on a mapping of situational awareness factors [144] to Bayesian Networks (BN) reduced to fuzzy sets. From these, the best actions are picked using set intersection and the Hamming distance. Generated explanations are shown to work for non-experts and their method is computationally efficient but relies on hand-crafted BN models of specific high-level driving maneuvers. Muscholl et al. [38] proposed an ante-hoc explainability method for feature importance extraction for pedestrian interaction prediction. A dynamic Bayesian network models the dyadic (two people) interactions between pedestrians based on three levels of social cues. In addition, the weight of evidence is used to measure the most important low-level features that predict intention to cross. Neumeier et al. [39] proposed an ante-hoc interpretable method for variational auto-encoders by using an expert-driven deterministic decoder that forces the encoded latent space to be more interpretable. They suggest that this could serve as a more general framework for VAE interpretability and show in evaluation that the fixed expert-based decoder does not cause significant degradation in performance. Wu et al. [40] created a mixed ante- and post-hoc, global, rule-based explainable method for decision-making explainability applied for connected autonomous vehicles (CAVs) in an edge computing setting. Their method integrates Markov logic networks (MLN) over high-level interpretable predicates expressed in first-order logic with statistically learned weights from deep Q-networks (DQN) updates from the edge. They show that the MLN can data-efficiently recover the underlying logical formulae governing the behaviour of an autonomous vehicle, although it may also produce illogical formulae.

Antonello et al. [28] proposed a Bayesian inverse planning framework for motion prediction. The framework orchestrates map-based goal extraction, a control-based trajectory generator and a mixture of experts collection of neural networks for motion profile prediction. They showed that modular design allows inspection of each component's influence on the overall performance, thereby providing interpretability.

3) Interpretable By Design – Control: Zheng et al. [41] proposed a model-specific ante-hoc explainable controller in which the output of a neural network-based controller with control barrier function filters is projected onto a safe set in an interpretable manner.

B. Interpretable Surrogate Models

Definition IV.2 (Interpretable Surrogate Models). *An algorithm is said to be an interpretable surrogate model if it is interpretable by design and approximates the behaviour of a black box model such that it provides intelligible explanations of the black box model [123].*

1) Interpretable Surrogate Models – Perception: Charroud et al. [42] focused on explaining a specific deep-learning architecture for AV localization with post-hoc methods for LiDAR data. They first clustered their data, and then used various standard explainability methods (Saliency, SmoothGrad, and VarGrad) to determine the contributions from each cluster that fed into the deep learning model. Ponn et al. [43] introduced a model-agnostic surrogate model for camera-based object detectors. A random forest is trained to predict a detection score according to meta-information about the environment in the training data. Afterwards, Shapley values are calculated to measure the impact of different features from the meta-information which helps interpret the results, such that the behaviour of the object detector under influencing factors in the environment can be estimated. This type of interpretable surrogate model has the potential to increase the transparency and reliability of the network, as detection errors can be analyzed more thoroughly, thereby enhancing the understanding of the model's behaviour. Shi et al. [44] proposed a self-supervised interpretable framework to produce an attention mask corresponding to the importance assigned to each pixel, which constitutes the most evidence for an agent's decisions. The core concept of the framework is a separate explanation model trained for vision-based RL.

2) Interpretable Surrogate Models – Planning & Prediction: Cui et al. [45] combined SHAP and random forest techniques to bring transparency to decision-making determined by DRL. In the framework, SHAP determines the important features associated with the decision made by the DRL model, an RF model is trained using these features and used to explain the decisions of the original DRL model. They demonstrated that the proposed framework could enhance the interpretability of DRL-based AV decisions. Hu et al. [46] proposed a post-hoc interpretation method for neural trajectory prediction with temporal attention. They train a surrogate module that calculates the mutual information between the input and each hidden state of the recurrent neural network to quantify the importance of each time step during the encoding

process. Results are interpretable through the analysis of attention weights and mutual information, but the proposed system is highly model-specific and requires detailed knowledge of the underlying architecture of the neural network. Li et al. [47] designed a post-hoc method for understanding feature importances for lane change (LC) predictions using SHAP [145]. They propose a modified version of SHAP called Maximum Entropy SHAP (ME-SHAP) that they use to explain an XGBoost-based LC decision model. The ME-SHAP model calculates the base value of the SHAP model by solving a constrained optimisation problem that jointly maximises the entropy of classification prediction probabilities and feature contributions. Extensive evaluation shows that the ME-SHAP feature contributions may be rationalised in terms of intuitive driving actions and states, but the qualitative benefits of ME-SHAP over other baselines are not substantiated. Ma et al. [48] also addressed feature importance for LC prediction. They proposed a mixed ante- and post-hoc method using the mean impact value (MIV) with a logistic regression model with three levels of interpretable features. These are individual (relating to the ego), microscopic (relating to the neighbourhood of the ego), and macroscopic (relating to the density of the lanes) features. First an ANN that predicts LC intention is used to select features from the above set via MIV. The selected features are then fed to a logistic regression model which provides the importance scores for the features. Evaluation on the HighD dataset [146] provides some quantitative and qualitative analysis of LC but the benefits of the proposed method are not explored in contrast to baselines. Omeiza et al. [49] deviated from purely importance-based explanations by proposing a post-hoc method for high-level driving decisions for non-expert delivered via natural language text. They integrated random forests with Tree SHAP to measure both the direct and counterfactual contextual feature importance on predictions. The method can then generate intelligible explanations based on the importance scores of features in the tree. Both qualitative evaluation (via examples) and quantitative evaluation (with BLUE and ROGUE to measure n-gram overlap with gold-standard explanations) are presented. However, the method description is incomplete and it is unclear on what sort of data the RFs are trained. In addition, Omeiza et al. [50] designed a post-hoc method for template-based natural language explanations by deriving explanation trees from scene graphs. An extensive user study was used to measure the effects of explanations on the perceived accountability of the AD system and on users' understanding of how the AD system works. However, as with their other proposed explanation algorithm, the method description is limited.

3) *Interpretable Surrogate Models – Control:* Dassanayake et al. [51] analyse the behaviour of a DNN-based controller which stabilizes the dynamic position of an AV under disturbing environmental conditions. A cross-comparable clustering method for the time series data was introduced to interpret the DNN response, such that the internal model understanding and transparency were increased.

4) *Interpretable Surrogate Models – End-To-End:* Zemni et al. [52] proposed an object-centric framework which generates counterfactual explanations for end-to-end decision models.

The end-to-end decision model was designed to have an instance-based latent representation. Thereby, the generative model was able to produce new images with slightly changed objects from the original input image. By analyzing changes in the output, the framework helps to understand the influence of objects in the environment on the decisions of the network

C. Interpretable Monitoring

Definition IV.3 (Interpretable Monitoring). *An algorithm is said to be an interpretable monitoring system if it is interpretable by design and it can verify an algorithm's output such that it ensures safer AI deployment.*

1) *Interpretable Monitoring – Perception:* In [56], Kronenberger et al. examined interpretable DNNs for traffic sign recognition. They introduced additional explanations of visual concepts such as colours, shapes and numbers or symbols. These visual concepts are used to verify the decision of the network. Hacker et al. [54] also proposed a monitor for traffic sign recognition. The monitor consists of various mechanisms including an interpretable saliency detector. During operation, the saliency map is computed via occlusion sensitivity [147] and is compared by computing the Euclidean distance to an offline computed saliency map for each traffic sign category. Keser et al. [55] proposed an interpretable and model-agnostic monitor by introducing a concept bottleneck model (CBM) which is used for a plausibility check with the original DNN-based object detector. The interpretability of CBM is achieved by learning human-interpretable labels. Fang et al. [53] constructed a fault diagnosis framework to monitor a system's operational status, while the interpretability of the fault diagnosis is achieved by calculating the contribution of each input feature to the anomaly detection results. The perceptual monitors enhance the reliability of the decision process for the detection algorithm in an interpretable manner. Moreover, robustness is increased. Besides detecting anomalous behaviour of the network, the monitor is also able to detect unsafe inputs.

2) *Interpretable Monitoring – Planning & Prediction:* Bao et al. [57] designed a mixed ante- and post-hoc model for visual explanations. They proposed a two-stage design for traffic accident prediction based on visual attention informed by a Markov decision process specifically designed for visual attention fixation and accident prediction. Stage 1 is based on the post-hoc explainability of CNNs using saliency maps to show visual attention to top-down (focus on a particular region) and bottom-up (consider everything) vision. Stage 2 is a stochastic Markov decision process (MDP) in which the task of an agent is to predict the possibility of an accident and the visual fixation area. The two tasks balance exploration (visual fixation) and exploitation (accident prediction). Visual attention explanations are convincing and several metrics are used to show the connection (both via correlation and causal) between visual attention and accident prediction. However, there was no qualitative evaluation of visual regions and accident predictions. Chen et al. [58] utilized an interpretable SVM to judge the actions chosen by a deep Q network, to prevent the agent from making unsafe actions. Franco and Bezzo [59]

employed decision tree theory to predict if a UAV's action will be safe or not and provide explanations to understand the causes of the prediction. A second decision tree, trained with predefined corrected trajectories, decides what is the minimum distance at which the system must apply the correction. Gall and Bezzo [60] leveraged a decision tree to find the most suitable safe behaviour to adapt the current behaviour and provide associated human-understandable explanations if the monitored safety-critical state variables are predicted to exceed safe bounds. They validated the method by simulating the navigation of an unmanned ground vehicle through rough and slippery terrain. Gilpin et al. [61] designed a high-level antehoc textual explanatory framework for fault detection and explanation for self-driving cars for end-users using natural language. They proposed a hierarchy of systems to synthesise and select explanations generated by lower-level systems based on first-order logic rules and common sense knowledge. Simulated qualitative evaluation in the CARLA simulator shows promising results but no implementation is described with only a framework being proposed. Gorospe et al. [62] proposed a post-hoc, global, rule-based and visual explanation method. They generated a dataset for collision scenarios with different adaptive cruise controllers and emergency braking strategies, then fit ML classifiers to this data to predict the presence of collisions given interpretable features. Finally, decision trees and random forests were used to extract interpretable global rules from the classifiers. Karim et al. [63] proposed a post-hoc attention weight-based method for accident prediction. Explanations rely on the standard Gradient-weighted Class Activation Map (Grad-CAM) [143] method and uses the Car Crash Dataset (CCD) [148]. Quantitative and qualitative evaluation with human participants compared the predicted activation maps to human eye-tracking experiment results and showed significant overlaps between the methods attended areas and eye fixation areas. Nahata et al. [64] trained a decision tree to predict the associated risk with future movements of surrounding vehicles. They argued that they could use the tree to explain why the risk is high and what could be done to decrease the risk. Schmidt et al. [65] proposed a post-hoc decision tree-based method derived from an RL teacher policy trained with proximal policy optimisation for safe driving for a constrained MDP. The constraint was based on the distance to the lead vehicle. The method was shown to be verifiable and easily interpretable.

D. Auxiliary Explanations

Definition IV.4 (Auxiliary Explanations). *An algorithm is said to have the ability to provide auxiliary explanations if the execution of the algorithm creates auxiliary information that provides insight into how the algorithm works.*

1) *Auxiliary Explanations - Perception:* In perception tasks, heat maps are often created to explain the prediction results by highlighting regions that influence the network's decision. A widely used model-specific approach is Grad-CAM [143] which visualizes the activation, typically in the last layer. Kolekar et al. [69] applied Grad-CAM to a DNN for camera-based semantic segmentation. Saravanan et al. [72] also

inspected the behaviour of a DNN for semantic segmentation via Grad-CAM under the synthetically generated haze. In addition to the last layer, Grad-CAM was also applied to two layers in the encoder and one in the decoder resulting in four different heat maps, thus increasing transparency in the decision understanding of the DNN. Abukmeil et al. [66] proposed a variational autoencoder for a semantic segmentation task and generated multiple heat maps by computing the second-order derivatives between the encoder layers and the latent space. The resulting attention maps are aggregated. Additionally, they are fused with the last decoder layer to improve the results. In [71], Nowak et al. computed attention heat maps for a DNN-based bus charger detection. Additionally, these heat maps are used to identify spurious predictions and are further used for training via data augmentation to increase robustness. Besides providing transparency due to the heat maps, the robustness of the DNN is also increased. Mankodiya et al. [70] defined a framework to determine the important area of an image contributing to the outcomes, while the XAI methods used here were Grad-CAM and saliency maps. The aforementioned approaches only focused on camera-based perception tasks. Schinagl et al. [73] proposed a model-agnostic attribution map generation method for LiDAR-based 3D object detection. The heat maps are generated perturbation-based via systematically removing LiDAR points and observing the output changes. They also propose various visual analysis tools which help identify potential misbehaviour of a DNN-based perception system in an interpretable manner. This way, more transparency in the model working is given and the whole development process of the ML system becomes safer. Gou et al. [67] developed the framework Vatld to examine traffic light detection algorithms by analyzing input-output data as well as intermediate representations. Disentangled representation learning was used to extract semantic concepts in the latent representation such as color, background, rotation etc.. Therefore, the analysis tool heavily relies on DNNs that are based on representation learning. In [74], Schorr et al. developed a toolbox with various state-of-the-art visualisation algorithms of a CNN for image classification and semantic segmentation including Grad-CAM and its extensions, saliency maps [149] and guided back-propagation [150]. Wang et al. [75] proposed a framework to interpret 3D-object detection failures by combining macro-level spatiotemporal information and micro-level CNN features. For the micro-level feature extraction, the heat-map algorithm Grad-CAM and the aforementioned Vatld framework were used. Haedecke et al. introduced the analysis toolbox ScrutinAI [68] for semantic segmentation and object detection tasks by offering several visualisation tools. Particularly, ScrutinAI may distinguish between metadata in the input (e.g. different observable body parts in an image for pedestrian detection) to explicitly identify model weaknesses related to semantic concepts of objects.

2) *Auxiliary Explanations - Planning & Prediction:* Jiang et al. [76] proposed a post-hoc method based on attention scores for inter-vehicle trajectory interaction analysis, which sheds some light on which vehicles the model pays the closest attention to in inter-vehicle interactions. The model also predicts ego driver intention which the authors describe

as intra-vehicle explainability. Their evaluation showed that the proposed model is significantly faster than similar methods and performs competitively as compared to baselines, with the added benefit of some interpretability analysis. Kochakarn et al. [77] designed a post-hoc system with spatial and temporal attention for road scene understanding. A self-supervised scene-graph learning algorithm is used to create spatiotemporal embeddings of scene graphs based on graph contrastive learning, which is then used in two downstream tasks. As the final stage of embedding, an attention layer is used to highlight the most important spatial and temporal factors in the scene graph sequence as a form of post-hoc explainability. Liu et al. [78] used a post-hoc heatmap to infer different potential goals on a map, which then guides a neural network-based planner to capture planning uncertainties. Mishra et al. [79] trained a decision tree to explain an RL agent's actions based on states and corresponding actions determined by the optimal policy. They created a visual analytics interface to show the explanations, which was demonstrated to be better than the text-based explanation approach. Similarly, Teng et al. [81] leveraged a Bird's Eye View (BEV) mask, which provided scene semantic information. They argued that the BEV mask can demonstrate how an AV understands the scenarios and thus promote interoperability. Shao et al. [80] also output the intermediate interpretable features for semantic explanation, aiming to enhance safety for the downstream controller. Wang et al. [82] proposed an ante-hoc method that combines a bi-directional long short-term memory (LSTM) with a Conditional Random Field (CRF) predictor to provide scores for interpretable pre-defined features in lane-changing scenarios. Their model also enforces interpretable hard and soft rules that the system must satisfy. Their evaluation is, however, very limited and no qualitative discussion of how the CRF improves the interpretability of the system as a whole. Yu et al. [83] created a post-hoc attention-based method for binary risk prediction from images and scene graph embeddings. Attention layers of the scene graph embedding layer and the final LSTM layer provide some explainability of where the model is focused for its prediction. However, no quantitative evaluation is given and only one qualitatively interesting example is presented of the impact of attention mechanisms on explainability on safety prediction.

3) Auxiliary Explanations – End-To-End: Kim et al. [90] proposed the generation of textual explanations for end-to-end driving tasks. They introduced a dataset called BDD-X (Berkeley DeepDrive eXplanation) with driving videos annotated with driving descriptions and action explanations. In addition to the end-to-end control system, a second attention-based model was trained to predict textual explanations from video sequences. The attention maps of both models were aligned to create a dependency between the controller and the explanations. Based on that, Kühn et al. [91] evaluated the developed baseline on a new dataset called SAX [151] and proposed some improvements over the baseline. They utilized video frames as input and generated natural language action descriptions and explanations using an opaque neural network. Building on this architecture, Mori et al. [92] incorporated throttle into the control in addition to steering and developed

an attention map for visual explanations of AV decisions. Xu et al. [94] introduced the dataset BDD-OIA (object-induced actions) which extracted complicated scenarios from BDD-X and annotated them with new explanations focusing on objects which influence the decision. Additionally, they proposed a DNN architecture which jointly learns action prediction and textual generation. Dong et al. [88] extended the approach by introducing a transformer architecture for the end-to-end network. In this way, the decision and reason generator could include the feature extractor and the attention zones of the transformer architecture. For the decision and reason generator task, Zhang et al. [98] introduced an additional interrelation module in the network expressing interrelationships among the ego vehicle and other traffic-related objects. This module is then combined with global features of the end-to-end network to provide more reliable actions and explanations.

Feng et al. [89] proposed to expand the textual reasoning about the driving actions with explanations including the surrounding environment based on semantic segmentation by extending the BDD-OIA dataset with additional annotations, although they did not qualitatively show the added benefit of the new annotations. In [99], Zhang et al. extended the BDD dataset by BDD-3AA by providing explanations and corresponding object segmentations. The interpretation was provided by importance value scores for the objects on the image. Human evaluation showed that object-level explanations are more persuasive than pixel-level explanations while the additional textual explanations increased trust for users and manufacturers. However, the decisions and explanations do not necessarily correlate, and the explanations need to be validated for reliability.

Wang et al. [96] proposed intermediate outputs in the end-to-end design to improve interoperability. Besides the planned trajectory as an output, they also provide future semantic maps from the intermediate perception part in Birds-Eye-View (BEV). A similar approach was proposed by Chen et al. [87] where a semantic BEV mask containing a map, ego state, surrounding objects and routing was delivered. The generation of intermediate perceptual outputs modularises end-to-end networks. Yang et al. [95] proposed two frameworks generating attention maps of end-to-end controllers to better understand scenes. The first one was model-specific and produced feature maps from the convolutional layer. In contrast, a second model-agnostic approach was proposed which compared the controller outputs between the raw input images and occluded ones. By examining changes in the output, a pixel-wise heat map could be delivered. Cultrera et al. [86] proposed attention blocks in the DNN-based end-to-end controller to create attention maps. Aksoy and Yazici [84] developed an end-to-end controller which explicitly provided a saliency map prediction as an intermediate output and as an input for the action prediction. Chitta et al. [85] proposed an end-to-end system which provides a trajectory and a BEV semantic prediction as an output. Moreover, attention maps of the DNN are computed to increase interpretability. Wei et al. [97] trained an end-to-end method that directly plans the future trajectory for the ego vehicle. Their method includes an attention mask over a CNN backbone that they claim can increase the safety

and interpretability of the system by allowing the inspection of the LiDAR input data. However, their evaluation does not analyse the benefits of this system. Tashiro et al. [93] also produced heat maps as an intermediate output for an end-to-end controller. For the heat map generation, they quantised the network activations to pay limited attention to specific bits and showed improved performance to other attention map generation methods. In addition, the visual intermediate outputs lead to a similar transparency that modular AD architectures can provide. This could also help identify errors in complex end-to-end systems more accurately. However, the reliability of the intermediate output is not guaranteed and the intermediate explanations do not necessarily help in understanding the behaviour of the end-to-end system.

E. Interpretable Safety Validation

Definition IV.5 (Interpretable Safety Validation). *An algorithm is said to provide interpretable safety validation if it provides an interpretable way to generate adversarial behaviours of surrounding agents for the validation of AVs.*

Corso and Kochenderfer [100] utilized signal temporal logic (STL) to generate high-likelihood failures for AVs, while they argued STL is easily understood because of its logical description between temporal variables. DeCastro et al. [101] leveraged parametric signal temporal logic (pSTL) to construct an interpretable view on modelling a relationship between policy parameters to the emergent behaviours from deploying that policy, while the behaviour outcome is expressed by pSTL formulas. As pSTL provides a way to construct formulas that describe the relationships between spatial and temporal properties of a signal, the formally-specifiable outcome can be obtained by configuring the parameters, allowing proactively generating various desired behaviour of an agent for testing AVs. Kang et al. [102] proposed a visual transformer to predict collisions supplemented by attention maps. Subsequently, a time series of attention maps is further analysed to identify spatiotemporal characteristics and based on the situation interpretation, accident scenarios for safety assessment are extracted. The extraction is based on the definition of functional scenarios by the PEGASUS project [152] on 6-layer information including road levels, traffic infrastructure, events, objects, environments, and digital information. In [103], Li et al. introduced a risk assessment phase for the perception and prediction of dangerous vehicles as well as traffic lights. A visual explanation for the classification is provided by computing saliency maps via RISE algorithm [153], which supports safety assurance in the risk assessment phase.

V. XAI FRAMEWORK FOR AD

We now provide an overview of existing XAI frameworks for AD and analyze their limitations. As part of our systematic review, we identified three relevant XAI frameworks, which illustrate high-level AD modules and describe various ways to integrate them. Subsequently, we propose our XAI framework for AD – *SafeX*: a framework for safe and explainable AD – based on the concrete XAI methods summarized in Section IV.

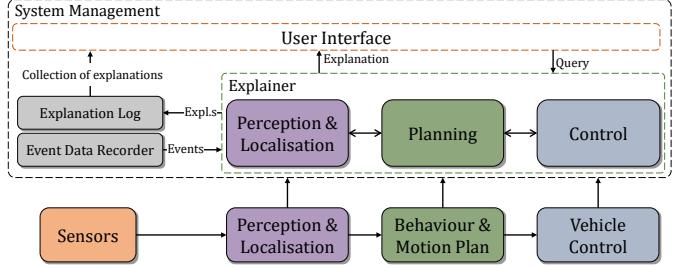


Fig. 9. Reproduction of the framework from [17] with three main components: the user interface, the explainer, and the AD modules. The explainer serves as a middleware between users and AD modules and interacts with them.

A. Existing XAI frameworks

Omeiza et al. [17] defined an explainer as the bridge between an AV and users, allowing explanations to users' queries based on the information from AD modules, as shown in Figure 9. Instead of focusing on a specific AV function, their framework remains at a high level to illustrate the general role of XAI in AD. Atakishiyev et al. [18] introduced a similar conceptual framework for end-to-end autonomous control systems by including XAI components that realise safety-regulatory compliance. In this framework, an XAI component aims to provide explanations of each driving action taken in the given environment. Regulatory compliance is confirmed by simulation and real-world testing based on these explanations.

The framework defined by Brajovic et al. [154] consists of four steps for the entire development cycle of AI. These are use case definition, data collection, model development, and model operation. The use case describes the task that the AI aims to solve, while the data affects whether the AI is biased and robust. The developed model is aimed to achieve an appropriate level of accuracy, robustness, explainability, and other desirable requirements. Finally, the model operation shall be equipped with a monitoring system that is proportionate to the nature of the AI and its associated risks. Although this framework provides useful guidance, its application to AVs is not addressed and users' queries are not considered.

B. SafeX: A Safe and Explainable Framework for AD

Inspired by our literature review, we propose a novel framework for safe and explainable AD shown in Figure 10, which we call SafeX. Different from the frameworks proposed in previous work, we present a more fine-grained application of XAI to AD, focusing on the integration of the concrete surveyed methods within the full AD stack in a way that also enables safety monitoring and intelligible explanation delivery.

The overall structure of SafeX is shown in Figure 10a. We define an explainable monitoring system (EMS) as a bridge between users and an AV. On one hand, the EMS generates intelligible explanations to users based on their queries by extracting the necessary information from the AV. On the other hand, it includes a monitor for each AD module to deliver safety feedback regarding the module's output. These two functions of the EMS are not only aimed at increasing a user's understanding and trust in the AV but also at providing a safer AV for the user. To accomplish the two roles

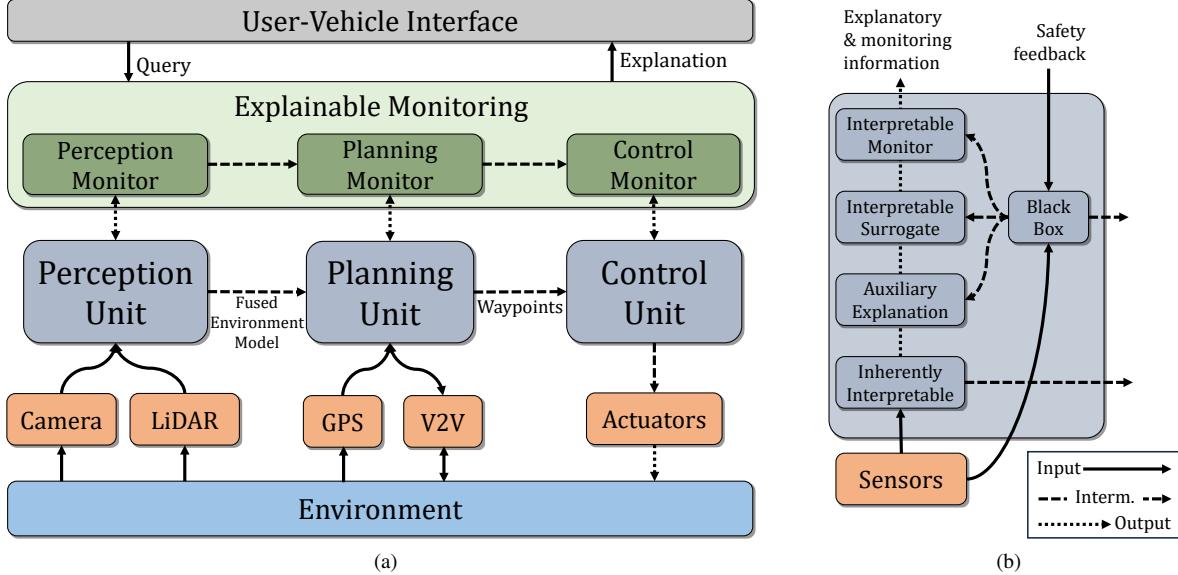


Fig. 10. *SafeX*: our framework for safe and explainable AI for AD integrates concrete XAI techniques with AD in an actionable way. (a) Explainable monitoring generates intelligible explanations to users’ queries using information from AD modules to achieve trustworthiness while monitoring the output of each module by providing safety feedback to ensure safety; (b) Each unit in SafeX may contain interpretable surrogate monitors and models, while auxiliary explanations can be applied for the black boxes in each AD module. Alternatively, the functions in AD modules are designed to be inherently interpretable.

of the EMS, each AD module must be carefully designed. Figure 10b uses the four identified XAI categories from our survey to deliver explanatory and monitoring information to the upstream EMS for each AD module. For black boxes in an AD module, interpretable monitors, interpretable surrogate models, and auxiliary explanations can be applied. In addition, the functions in the module can also be inherently interpretable to deliver traceable explanatory information if the interpretable functions meet the performance requirements. They may also serve as a fallback if the monitoring systems report unexpected and unverifiable behaviour from the black box systems.

In contrast to existing frameworks, SafeX is based on concrete state-of-the-art methods, and we design SafeX according to the modular components identified in Section IV. The resulting modular design allows future research and development to focus on deeply investigating and refining specific components independently. By stacking multiple forms of XAI methods, we can enable developers to integrate the appropriate methods with their AD stack based on specific stakeholder and regulatory requirements, and the desired degree of safety. Moreover, the proposed EMS can simultaneously achieve both the safety monitoring of the AV and the delivery of intelligible explanations to users’ queries.

VI. DISCUSSION

We set out to answer two research questions based on a systematic literature review. The overall bibliometric results (Section III-D) confirmed that there is an increasing interest in developing XAI methods for AD, and keyword associations showed that the current methods are largely focused on safety via algorithmic interpretability or human-centric explainability. In closely scrutinising the retrieved publications for RQ1, we found that state-of-the-art literature is trying to resolve the challenge of safe and trustworthy AI in AD by focusing on

five core XAI design paradigms, namely interpretable design, interpretable surrogate models, interpretable monitoring, auxiliary explanations, and interpretable validation.

Though some surveys of the field of XAI for AD exist [17]–[19], we are the first to carry out a reproducible and systematic survey to our best knowledge. While the previous surveys have focused on a more holistic understanding of the entire field, we decided to focus on the concrete tasks of perception, planning and prediction, and control. Here, it is interesting to note, that there is a significant imbalance in the number of publications for each task. Control is consistently more neglected across all five XAI design paradigms than perception and planning, despite the intensive research into neural network-based safe RL control methods [155]. Furthermore, XAI for LiDAR-based perception and various fusion approaches remains highly unexplored compared to camera-based detectors. This is noteworthy even though the majority of state-of-the-art perception architectures incorporate LiDAR sensors due to their provision of accurate depth information [109]. In contrast, end-to-end methods enjoy significant attention from the field, however, most methods for these systems are constrained to auxiliary explanations.

However, herein lies an important challenge. It has been shown many times, that the post-hoc analysis methods of auxiliary explanations based on Shapely values, attention maps, or saliency maps are neither consistent nor necessarily correct (see for some examples [126], [127], [156]). While these methods are undoubtedly useful for building explanations, they are also not sufficient, if our requirements of trustworthy and safe AI are to be upheld in, for example, regulations and courts. This challenge is then further exacerbated by the fact that the evaluation of auxiliary methods is usually cursory with hard-to-interpret quantitative metrics and no qualitative insights at all. One way to increase safety for AD is to integrate

multiple XAI techniques into one framework in a “Swiss cheese” model of safety that assures that malfunctions do not go unnoticed through the AD stack.

This is why our analysis of **RQ2** is relevant, and why we propose a new framework called SafeX to integrate concrete XAI methods with AD. We found that the number of existing works about frameworks or pipelines is limited and these frameworks provide only a very high-level overview of the ways XAI may be integrated with AD on a lower level of the AD stack. Given these limitations and the urgent need for safe and trustworthy AI for the AD stack, our framework SafeX modularly integrates the identified techniques of XAI with each AD module. A modular approach in SafeX allows the combination of multiple sources of explanations in a way that may reduce the risks of using AI for AD. One may also combine multiple modalities of predictions which, when used with our proposed explainable monitoring system, can act both as a bridge between users and the AD system and as a tool for comprehensive safety guarantees. The EMS is, thus, designed to enable the delivery of explanations to users while ensuring the safety of each AD module through runtime monitoring.

We also observed that interpretable safety validation, one of the five XAI design paradigms, has received less attention in the field. This is relevant because the safety testing of AVs is one of the most pertinent and difficult challenges that currently faces the AD field due to the heavy-tailed distribution of driving scenarios [157]. As we saw in Section IV-E, one way to mitigate this problem is the extraction of varied scenarios from real driving data that is achieved through an interpretability analysis uncovering the relevant factors of the environment in the scenario. Through interpretability, we can also understand the causal factors in the scenarios so that we can manipulate them and extract new scenarios.

In our study, we narrowed our focus on perception, planning and prediction, and control, while not considering studies about data diversity, ethics, or AI model oversight. This is because the former three are arguably the most pressing if we aim to address the requirements of safe and trustworthy AI in a way that also translates to more deployable and reliable AVs. While the latter three are undoubtedly important, their solution may present less of a stride towards creating real-world AVs.

In addition, natural language processing and generation for interacting with users and delivering intelligible explanations were not considered, though our review has picked up on a few methods [17], [34], [37] that directly consider human-robot interactions as a significant part of the explanatory process. What this suggests, is that there exists a disconnect between research that focuses on the needs of end users and research that addresses explainability of the driving stack. The problem with this gap is that explanations ought to change depending on the requirements of the user and the design of explanations need to take this dependency into account otherwise risking invoking mistrust or confusion in users.

Furthermore, our focus on XAI is only a partial measure of how safe and trustworthy AI should be achieved. As discussed in Section II-A, trustworthiness, safety, and transparency are overarching concepts that require the cross-disciplinary collaboration of people. Other measures such as uncertainty

quantification, rigorous testing, thorough documentation, standardisation, etc. are also necessary. Still, we have also seen that XAI is a diverse and popular field that addresses some of the key requirements of trustworthy and safe AI.

In summarizing the above discussion, we identify the following recommendations for the field of XAI for AD:

- *Explainable perception architecture*: investigate more explainable approaches for other sensors such as LiDAR and Radar not just camera-based perception; explore XAI for various fusion architectures, particularly combining XAI methods for different sensors that are integrated;
- *Rigorous testing for auxiliary methods*: auxiliary explanations methods like Shapely values, saliency and attention maps are prone to gaming, inaccuracies, and misinterpretation. It is necessary to thoroughly evaluate these methods not just quantitatively but also with extensive qualitative insights that focus especially on the failure cases of the methods;
- *Modular and layered monitoring*: to improve the safety of AD, one method does not suffice. Our proposed framework, SafeX, instead suggests that multiple layers of independent and co-supervisory explanatory functions should verify and monitor the workings of underlying black box systems and each other, potentially providing fallback options in emergencies;
- *Cross-disciplinary collaboration*: XAI methods are usually developed in isolation. To better understand stakeholder requirements and to adapt explanations to the varied socio-technical interactions of the real world, it is crucial to develop methods that are rooted in actual problems and not merely motivated by a vague sense of need for safety and trustworthiness.

VII. CONCLUSION

In this paper, we investigated the applications of XAI for safe and trustworthy AD. We began the survey by defining requirements for trustworthy AI in AD, noting that XAI is a promising field for addressing several of these requirements. Subsequently, we gave an overview of the sources of explanations in AI and presented the taxonomy of XAI. Based on a systematic literature survey founded on two research questions, we derived five key applications of XAI for safe and trustworthy AI in AD and an appropriate framework to integrate these applications into AD. Our key findings are:

- Actual XAI for AD research can be sorted into five categories: interpretable design, interpretable surrogate models, interpretable monitoring, auxiliary explanations, and interpretable validation;
- There is a lack of detailed general XAI for AD frameworks that address safety requirements and are also rooted in concrete research. We propose to fill this gap with a new framework SafeX that can incorporate all categories of XAI methods designed for AD;
- XAI for AD, as an emerging topic, is gaining increasing attention according to the published literature per year. We expect that the number of studies will further increase with the development of AI.

Looking to the future, we can expect legal and social pressures to increase on the development of AD. Growing up to this challenge will require joined initiatives from multiple disciplines and the involvement of various stakeholders. Here, we expect XAI to act as a bridge that could connect cross-disciplinary gaps. Emerging fields will also continue to influence the field. With the advent of large language model-based (LLM) systems, there will be a pronounced need for XAI more than ever, as models continue to improve and emergent behaviour is discovered every day. Calls for this in other fields are already emerging (e.g., mechanistic interpretability [158]), however, the use of LLMs in AD further complicates the black box problem. In addition, LLMs themselves could one day become the explainers, but it will only be through the involvement of various stakeholders and disciplines that this may become a reality for safe and trustworthy AD.

REFERENCES

- [1] A. Mathew, P. Amudha, and S. Sivakumari, "Deep learning techniques: an overview," *Advanced Machine Learning Technologies and Applications: Proceedings of AMLTA 2020*, pp. 599–608, 2021.
- [2] A. A. Jammal, A. C. Thompson, E. B. Mariottini, S. I. Berchuck, C. N. Urata, T. Estrela, S. M. Wakil, V. P. Costa, and F. A. Medeiros, "Human versus machine: comparing a deep learning algorithm to human gradings for detecting glaucoma on fundus photographs," *American journal of ophthalmology*, vol. 211, pp. 123–131, 2020.
- [3] O. Willers, S. Sudholt, S. Raafatnia, and S. Abrecht, "Safety concerns and mitigation approaches regarding the use of deep learning in safety-critical perception tasks," in *International Conference on Computer Safety, Reliability, and Security*, 2020, pp. 336–350.
- [4] ISO, "ISO 26262-1:2018(en), Road vehicles — Functional safety," 2018. [Online]. Available: <https://www.iso.org/standard/43464.html>
- [5] R. Salay and K. Czarnecki, "Using machine learning safely in automotive software: An assessment and adaption of software process requirements in iso 26262," *arXiv preprint arXiv:1808.01614*, 2018.
- [6] ISO, "ISO 21448:2022: Road vehicles—Safety of the intended functionality," 2022. [Online]. Available: <https://www.iso.org/standard/77490.html>
- [7] S. Burton, C. Hellert, F. Hüger, M. Mock, and A. Rohatschek, "Safety assurance of machine learning for perception functions," in *Deep Neural Networks and Data for Automated Driving: Robustness, Uncertainty Quantification, and Insights Towards Safety*. Springer International Publishing Cham, 2022, pp. 335–358.
- [8] D. Gesmann-Nuissl and I. Tacke, "Funktionale sicherheit ki-basierter systeme im automobilsektor," in *the 14th Workshop Fahrerassistenz und automatisiertes Fahren*, 2022, pp. 85–98.
- [9] ISO, "ISO/CD PAS 8800:road vehicles - safety and artificial intelligence," 2023. [Online]. Available: <https://www.iso.org/standard/83303.html>
- [10] B. Moye. (2023) Aaa: Fear of self-driving cars on the rise. [Online]. Available: <https://newsroom.aaa.com/2023/03/aaa-fear-of-self-driving-cars-on-the-rise/>
- [11] S. Reig, S. Norman, C. G. Morales, S. Das, A. Steinfeld, and J. Forlizzi, "A field study of pedestrians and autonomous vehicles," in *Proceedings of the 10th international conference on automotive user interfaces and interactive vehicular applications*, 2018, pp. 198–209.
- [12] M. Langer, D. Oster, T. Speith, H. Hermanns, L. Kästner, E. Schmidt, A. Sesing, and K. Baum, "What do we want from explainable artificial intelligence (xai)?—a stakeholder perspective on xai and a conceptual model guiding interdisciplinary xai research," *Artificial Intelligence*, vol. 296, p. 103473, 2021.
- [13] R. Dwivedi, D. Dave, H. Naik, S. Singhal, R. Omer, P. Patel, B. Qian, Z. Wen, T. Shah, G. Morgan, and R. Ranjan, "Explainable ai (xai): Core ideas, techniques, and solutions," *ACM Computing Surveys*, vol. 55, no. 9, pp. 1–33, 2023.
- [14] K. Weitz, D. Schiller, R. Schlagowski, T. Huber, and E. André, ""do you trust me?" increasing user-trust by integrating virtual agents in explainable ai interaction design," in *Proceedings of the 19th ACM International Conference on Intelligent Virtual Agents*, 2019, pp. 7–9.
- [15] A. Deeks, "The judicial demand for explainable artificial intelligence," *Columbia Law Review*, vol. 119, no. 7, pp. 1829–1850, 2019.
- [16] K. Muhammad, A. Ullah, J. Lloret, J. D. Ser, and V. H. C. de Albuquerque, "Deep learning for safe autonomous driving: Current challenges and future directions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 7, pp. 4316–4336, 2021.
- [17] D. Omeiza, H. Webb, M. Jirotka, and L. Kunze, "Explanations in autonomous driving: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 10 142–10 162, 2021.
- [18] S. Atakishiyev, M. Salameh, H. Yao, and R. Goebel, "Explainable artificial intelligence for autonomous driving: A comprehensive overview and field guide for future research directions," *arXiv preprint arXiv:2112.11561*, 2021.
- [19] É. Zablocki, H. Ben-Younes, P. Pérez, and M. Cord, "Explainability of deep vision-based autonomous driving systems: Review and challenges," *International Journal of Computer Vision*, vol. 130, no. 10, pp. 2425–2452, 2022.
- [20] Z. Chaghazardi, S. Fallah, and A. Tamaddoni-Nezhad, "Explainable and trustworthy traffic sign detection for safe autonomous driving: An inductive logic programming approach," *Electronic Proceedings in Theoretical Computer Science*, vol. 385, pp. 201–212, 08 2023.
- [21] P. Feifel, F. Bonarens, and F. Köster, "Reevaluating the safety impact of inherent interpretability on deep neural networks for pedestrian detection," in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2021, pp. 29–37.
- [22] M. Losch, M. Fritz, and B. Schiele, "Semantic bottlenecks: Quantifying and improving inspectability of deep representations," *International Journal of Computer Vision*, vol. 129, pp. 3136–3153, 2021.
- [23] J. Martínez-Cebrián, M.-A. Fernández-Torres, and F. Díaz-De-María, "Interpretable global-local dynamics for the prediction of eye fixations in autonomous driving scenarios," *IEEE Access*, vol. 8, pp. 217 068–217 085, 2020.
- [24] A. Oltramari, J. Francis, C. Henson, K. Ma, and R. Wickramarachchi, "Neuro-symbolic architectures for context understanding," in *Knowledge Graphs for eXplainable Artificial Intelligence: Foundations, Applications and Challenges*. IOS Press, 2020, pp. 143–160.
- [25] A. Plebe and M. D. Lio, "On the road with 16 neurons: Towards interpretable and manipulable latent representations for visual predictions in driving scenarios," *IEEE Access*, vol. 8, pp. 179 716–179 734, 2020.
- [26] K. Yoneda, N. Ichihara, H. Kawanishi, T. Okuno, L. Cao, and N. Suganuma, "Sun-glare region recognition using visual explanations for traffic light detection," in *2021 IEEE Intelligent Vehicles Symposium (IV)*, 2021, pp. 1464–1469.
- [27] S. V. Albrecht, C. Brewitt, J. Wilhelm, B. Gyevnar, F. Eiras, M. Dobre, and S. Ramamoorthy, "Interpretable Goal-based Prediction and Planning for Autonomous Driving," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*, May 2021, pp. 1043–1049.
- [28] M. Antonello, M. Dobre, S. V. Albrecht, J. Redford, and S. Ramamoorthy, "Flash: Fast and light motion prediction for autonomous driving with Bayesian inverse planning and learned motion profiles," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2022, pp. 9829–9836.
- [29] C. Brewitt, B. Gyevnar, S. Garcin, and S. V. Albrecht, "GRIT: fast, interpretable, and verifiable goal recognition with learned decision trees for autonomous driving," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2021.
- [30] C. Brewitt, M. Tamborski, C. Wang, and S. V. Albrecht, "Verifiable goal recognition for autonomous driving with occlusions," *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2023.
- [31] A. Ghoul, I. Yahiaoui, A. Verroust-Blondet, and F. Nashashibi, "Interpretable Goal-Based model for Vehicle Trajectory Prediction in Interactive Scenarios," in *2023 IEEE Intelligent Vehicles Symposium (IV)*, Jun. 2023, pp. 1–6.
- [32] J. P. Hanna, A. Rahman, E. Fosong, F. Eiras, M. Dobre, J. Redford, S. Ramamoorthy, and S. V. Albrecht, "Interpretable Goal Recognition in the Presence of Occluded Factors for Autonomous Vehicles," in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sep. 2021, pp. 7044–7051.
- [33] B. Gyevnar, M. Tamborski, C. Wang, C. G. Lucas, S. B. Cohen, and S. V. Albrecht, "A human-centric method for generating causal explanations in natural language for autonomous vehicle motion planning," in *IJCAI Workshop on Artificial Intelligence for Autonomous Driving*, 2022.
- [34] B. Gyevnar, C. Wang, C. G. Lucas, S. B. Cohen, and S. V. Albrecht, "Causal explanations for sequential decision-making in multi-agent systems," in *International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS)*, 2024.
- [35] F. Henze, D. Faßbender, and C. Stiller, "How Can Automated Vehicles Explain Their Driving Decisions? Generating Clarifying Summaries

- Automatically,” in *2022 IEEE Intelligent Vehicles Symposium (IV)*, Jun. 2022, pp. 935–942.
- [36] K. Klein, O. De Candido, and W. Utschick, “Interpretable Classifiers Based on Time-Series Motifs for Lane Change Prediction,” *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 7, pp. 3954–3961, Jul. 2023.
- [37] R. Kridalukmana, H. Lu, and M. Naderpour, “Self-Explaining Abilities of an Intelligent Agent for Transparency in a Collaborative Driving Context,” *IEEE Transactions on Human-Machine Systems*, vol. 52, no. 6, pp. 1155–1165, Dec. 2022.
- [38] N. Muscholl, M. Klusch, P. Gebhard, and T. Schneeberger, “EMIDAS: Explainable social interaction-based pedestrian intention detection across street,” in *Proceedings of the ACM Symposium on Applied Computing*, 2021, pp. 107–115.
- [39] M. Neumeier, M. Botsch, A. Tollkühn, and T. Berberich, “Variational Autoencoder-Based Vehicle Trajectory Prediction with an Interpretable Latent Space,” in *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, Sep. 2021, pp. 820–827.
- [40] M. Wu, F. R. Yu, P. X. Liu, and Y. He, “A Hybrid Driving Decision-Making System Integrating Markov Logic Networks and Connectionist AI,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 3, pp. 3514–3527, Mar. 2023.
- [41] H. Zheng, Z. Zang, S. Yang, and R. Mangharam, “Towards explainability in modular autonomous system software,” in *2023 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2023, pp. 1–8.
- [42] A. Charroud, K. El Moutaouakil, V. Palade, and A. Yahyaoui, “Xdll: Explained deep learning lidar-based localization and mapping method for self-driving vehicles,” *Electronics*, vol. 12, no. 3, p. 567, 2023.
- [43] T. Ponn, T. Kröger, and F. Diermeyer, “Identification and explanation of challenging conditions for camera-based object detection of automated vehicles,” *Sensors*, vol. 20, no. 13, p. 3699, 2020.
- [44] W. Shi, G. Huang, S. Song, Z. Wang, T. Lin, and C. Wu, “Self-supervised discovering of interpretable features for reinforcement learning,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 5, pp. 2712–2724, 2020.
- [45] Z. Cui, M. Li, Y. Huang, Y. Wang, and H. Chen, “An interpretation framework for autonomous vehicles decision-making via shap and rf,” in *2022 6th CAA International Conference on Vehicular Control and Intelligence (CVCI)*. IEEE, 2022, pp. 1–7.
- [46] H. Hu, Q. Wang, M. Cheng, and Z. Gao, “Trajectory Prediction Neural Network and Model Interpretation Based on Temporal Pattern Attention,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 3, pp. 2746–2759, Mar. 2023.
- [47] M. Li, Y. Wang, H. Sun, Z. Cui, Y. Huang, and H. Chen, “Explaining a Machine-Learning Lane Change Model With Maximum Entropy Shapley Values,” *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 6, pp. 3620–3628, 2023.
- [48] Y. Ma, S. Song, L. Zhang, L. Xiong, and J. Chen, “Lane Change Analysis and Prediction Using Mean Impact Value Method and Logistic Regression Model,” in *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, Sep. 2021, pp. 1346–1352.
- [49] D. Omeiza, S. Anjomshoae, H. Webb, M. Jirotko, and L. Kunze, “From spoken thoughts to automated driving commentary: Predicting and explaining intelligent vehicles’ actions,” in *2022 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2022, pp. 1040–1047.
- [50] D. Omeiza, H. Web, M. Jirotko, and L. Kunze, “Towards accountability: Providing intelligible explanations in autonomous driving,” in *2021 IEEE Intelligent Vehicles Symposium (IV)*, 2021, pp. 231–237.
- [51] P. M. Dassanayake, A. Anjum, A. K. Bashir, J. Bacon, R. Saleem, and W. Manning, “A deep learning based explainable control system for reconfigurable networks of edge devices,” *IEEE Transactions on Network Science and Engineering*, vol. 9, no. 1, pp. 7–19, 2022.
- [52] M. Zemni, M. Chen, É. Zablocki, H. Ben-Younes, P. Pérez, and M. Cord, “Octet: Object-aware counterfactual explanations,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 15062–15071.
- [53] Y. Fang, H. Min, X. Wu, X. Lei, S. Chen, R. Teixeira, and X. Zhao, “Toward interpretability in fault diagnosis for autonomous vehicles: Interpretation of sensor data anomalies,” *IEEE Sensors Journal*, vol. 23, no. 5, pp. 5014–5027, 2023.
- [54] L. Hacker and J. Seewig, “Insufficiency-driven dnn error detection in the context of sofif on traffic sign recognition use case,” *IEEE Open Journal of Intelligent Transportation Systems*, vol. 4, pp. 58–70, 2023.
- [55] M. Keser, G. Schwalbe, A. Nowzad, and A. Knoll, “Interpretable model-agnostic plausibility verification for 2d object detectors using domain-invariant concept bottleneck models,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 3890–3899.
- [56] J. Kronenberger and A. Haselhoff, “Dependency decomposition and a reject option for explainable models,” *arXiv preprint arXiv:2012.06523*, 2020.
- [57] W. Bao, Q. Yu, and Y. Kong, “DRIVE: Deep Reinforced Accident Anticipation with Visual Explanation,” in *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, Oct. 2021, pp. 7599–7608.
- [58] G. Chen, Y. Zhang, and X. Li, “Attention-based highway safety planner for autonomous driving via deep reinforcement learning,” *IEEE Transactions on Vehicular Technology*, 2023.
- [59] C. Di Franco and N. Bezzo, “Interpretable run-time monitoring and replanning for safe autonomous systems operations,” *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2427–2434, 2020.
- [60] C. Gall and N. Bezzo, “Gaussian process-based interpretable runtime adaptation for safe autonomous systems operations in unstructured environments,” in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2021, pp. 123–129.
- [61] L. H. Gilpin, V. Penubarthi, and L. Kagal, “Explaining Multimodal Errors in Autonomous Vehicles,” in *2021 IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA)*, Oct. 2021, pp. 1–10.
- [62] J. Gorospe, S. Hasan, M. R. Islam, A. A. Gómez, S. Girs, and E. Uhlemann, “Analyzing Inter-Vehicle Collision Predictions during Emergency Braking with Automated Vehicles,” in *2023 19th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, Jun. 2023, pp. 411–418.
- [63] M. Karim, Y. Li, and R. Qin, “Toward Explainable Artificial Intelligence for Early Anticipation of Traffic Accidents,” *Transportation Research Record*, vol. 2676, no. 6, pp. 743–755, 2022.
- [64] R. Nahata, D. Omeiza, R. Howard, and L. Kunze, “Assessing and explaining collision risk in dynamic environments for autonomous driving safety,” in *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*. IEEE, 2021, pp. 223–230.
- [65] L. M. Schmidt, G. Kontes, A. Plinge, and C. Mutschler, “Can you trust your autonomous car? interpretable and verifiably safe reinforcement learning,” in *2021 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2021, pp. 171–178.
- [66] M. Abukmeil, A. Genovese, V. Piuri, F. Rundo, and F. Scotti, “Towards explainable semantic segmentation for autonomous driving systems by multi-scale variational attention,” in *2021 IEEE International Conference on Autonomous Systems (ICAS)*, 2021, pp. 1–5.
- [67] L. Gou, L. Zou, N. Li, M. Hofmann, A. K. Shekar, A. Wendt, and L. Ren, “Vatld: A visual analytics system to assess, understand and improve traffic light detection,” *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 2, pp. 261–271, 2021.
- [68] E. Haedecke, M. Mock, and M. Akila, “ScrutinAI: A Visual Analytics Approach for the Semantic Analysis of Deep Neural Network Predictions,” in *EuroVis Workshop on Visual Analytics (EuroVA)*, J. Bernard and M. Angelini, Eds. The Eurographics Association, 2022.
- [69] S. Kolekar, S. Gite, B. Pradhan, and A. Alamri, “Explainable ai in scene understanding for autonomous vehicles in unstructured traffic environments on indian roads using the inception u-net model with grad-cam visualization,” *Sensors*, vol. 22, no. 24, p. 9677, 2022.
- [70] H. Mankodiya, D. Jadav, R. Gupta, S. Tanwar, W.-C. Hong, and R. Sharma, “Od-xai: Explainable ai-based semantic object detection for autonomous vehicles,” *Applied Sciences*, vol. 12, no. 11, p. 5310, 2022.
- [71] T. Nowak, M. R. Nowicki, K. Ćwian, and P. Skrzypczyński, “How to improve object detection in a driver assistance system applying explainable deep learning,” in *2019 IEEE Intelligent Vehicles Symposium (IV)*, 2019, pp. 226–231.
- [72] V. S. Saravarajan, R.-C. Chen, C.-H. Hsieh, and L.-S. Chen, “Improving semantic segmentation under hazy weather for autonomous vehicles using explainable artificial intelligence and adaptive dehazing approach,” *IEEE Access*, vol. 11, pp. 38194–38207, 2023.
- [73] D. Schinagl, G. Krispel, H. Possegger, P. M. Roth, and H. Bischof, “Occam’s laser: Occlusion-based attribution maps for 3d object detectors on lidar data,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2022, pp. 1141–1150.
- [74] C. Schorr, P. Goodarzi, F. Chen, and T. Dahmen, “Neuroscope: An explainable ai toolbox for semantic segmentation and image classification of convolutional neural nets,” *Applied Sciences*, vol. 11, no. 5, p. 2199, 2021.
- [75] J. Wang, Y. Li, Z. Zhou, C. Wang, Y. Hou, L. Zhang, X. Xue, M. Kamp, X. L. Zhang, and S. Chen, “When, where and how does it fail?

- a spatial-temporal visual analytics approach for interpretable object detection in autonomous driving,” *IEEE Transactions on Visualization and Computer Graphics*, vol. 29, no. 12, pp. 5033–5049, 2023.
- [76] T. Jiang, Y. Liu, Q. Dong, and T. Xu, “Intention-Aware Interactive Transformer for Real-Time Vehicle Trajectory Prediction in Dense Traffic,” *TRANSPORTATION RESEARCH RECORD*, vol. 2677, no. 3, pp. 946–960, Mar. 2023.
- [77] P. Kochakarn, D. De Martini, D. Omeiza, and L. Kunze, “Explainable Action Prediction through Self-Supervision on Scene Graphs,” in *2023 IEEE International Conference on Robotics and Automation (ICRA)*, May 2023, pp. 1479–1485.
- [78] H. Liu, J. Zhao, and L. Zhang, “Interpretable and flexible target-conditioned neural planners for autonomous vehicles,” in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 10076–10082.
- [79] A. Mishra, U. Soni, J. Huang, and C. Bryan, “Why? why not? when? visual explanations of agent behaviour in reinforcement learning,” in *2022 IEEE 15th Pacific Visualization Symposium (PacificVis)*. IEEE, 2022, pp. 111–120.
- [80] H. Shao, L. Wang, R. Chen, H. Li, and Y. Liu, “Safety-enhanced autonomous driving using interpretable sensor fusion transformer,” in *Conference on Robot Learning*. PMLR, 2023, pp. 726–737.
- [81] S. Teng, L. Chen, Y. Ai, Y. Zhou, Z. Xuanyuan, and X. Hu, “Hierarchical interpretable imitation learning for end-to-end autonomous driving,” *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 1, pp. 673–683, 2022.
- [82] K. Wang, J. Hou, and X. Zeng, “Lane-Change Intention Prediction of Surrounding Vehicles Using BiLSTM-CRF Models with Rule Embedding,” in *Proceedings - 2022 Chinese Automation Congress, CAC 2022*, vol. 2022-January, 2022, pp. 2764–2769.
- [83] S.-Y. Yu, A. V. Malawade, D. Muthirayan, P. P. Khargonekar, and M. A. A. Faruque, “Scene-Graph Augmented Data-Driven Risk Assessment of Autonomous Vehicle Decisions,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 7941–7951, Jul. 2022.
- [84] E. Aksoy and A. Yazici, “Attention model for extracting saliency map in driving videos,” in *2020 28th Signal Processing and Communications Applications Conference (SIU)*, 2020, pp. 1–4.
- [85] K. Chitta, A. Prakash, and A. Geiger, “Neat: Neural attention fields for end-to-end autonomous driving,” in *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, 2021, pp. 15773–15783.
- [86] L. Culterra, L. Seidenari, F. Becattini, P. Pala, and A. Del Bimbo, “Explaining autonomous driving by learning end-to-end visual attention,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 2020, pp. 340–341.
- [87] J. Chen, S. E. Li, and M. Tomizuka, “Interpretable end-to-end urban autonomous driving with latent deep reinforcement learning,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 6, pp. 5068–5078, 2022.
- [88] J. Dong, S. Chen, M. Miralighi, T. Chen, and S. Labi, “Development and testing of an image transformer for explainable autonomous driving systems,” *Journal of Intelligent and Connected Vehicles*, vol. 5, no. 3, pp. 235–249, 2022.
- [89] Y. Feng, W. Hua, and Y. Sun, “NLE-DM: Natural-Language Explanations for Decision Making of Autonomous Driving Based on Semantic Scene Understanding,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 9, pp. 9780–9791, Sep. 2023.
- [90] J. Kim, A. Rohrbach, T. Darrell, J. Cannby, and Z. Akata, “Textual explanations for self-driving vehicles,” in *Proceedings of the European conference on computer vision (ECCV)*, 2018, pp. 563–578.
- [91] M. A. Kühn, D. Omeiza, and L. Kunze, “Textual explanations for automated commentary driving,” *arXiv preprint arXiv:2304.08178*, 2023.
- [92] K. Mori, H. Fukui, T. Murase, T. Hirakawa, T. Yamashita, and H. Fujiyoshi, “Visual explanation by attention branch network for end-to-end learning-based self-driving,” in *2019 IEEE intelligent vehicles symposium (IV)*. IEEE, 2019, pp. 1577–1582.
- [93] Y. Tashiro and H. Awano, “Pay attention via quantization: Enhancing explainability of neural networks via quantized activation,” *IEEE Access*, vol. 11, pp. 34 431–34 439, 2023.
- [94] Y. Xu, X. Yang, L. Gong, H.-C. Lin, T.-Y. Wu, Y. Li, and N. Vasconcelos, “Explainable object-induced action decision for autonomous vehicles,” in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 9520–9529.
- [95] S. Yang, W. Wang, C. Liu, and W. Deng, “Scene understanding in deep learning-based end-to-end controllers for autonomous vehicles,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 1, pp. 53–63, 2019.
- [96] H. Wang, P. Cai, Y. Sun, L. Wang, and M. Liu, “Learning interpretable end-to-end vision-based motion planning for autonomous driving with optical flow distillation,” in *2021 IEEE International Conference on Robotics and Automation (ICRA)*, 2021, pp. 13 731–13 737.
- [97] B. Wei, M. Ren, W. Zeng, M. Liang, B. Yang, and R. Urtasun, “Perceive, attend, and drive: Learning spatial attention for safe self-driving,” in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 4875–4881.
- [98] Z. Zhang, R. Tian, R. Sherony, J. Domeyer, and Z. Ding, “Attention-based interrelation modeling for explainable automated driving,” *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 2, pp. 1564–1573, 2023.
- [99] Y. Zhang, W. Wang, X. Zhou, Q. Wang, and X. Sun, “Tactical-level explanation is not enough: Effect of explaining av’s lane-changing decisions on drivers’ decision-making, trust, and emotional experience,” *International Journal of Human–Computer Interaction*, vol. 39, no. 7, pp. 1438–1454, 2023.
- [100] A. Corso and M. J. Kochenderfer, “Interpretable safety validation for autonomous vehicles,” in *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2020, pp. 1–6.
- [101] J. DeCastro, K. Leung, N. Aréchiga, and M. Pavone, “Interpretable policies from formally-specified temporal properties,” in *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2020, pp. 1–7.
- [102] M. Kang, W. Lee, K. Hwang, and Y. Yoon, “Vision transformer for detecting critical situations and extracting functional scenario for automated vehicle safety assessment,” *Sustainability*, vol. 14, no. 15, p. 9680, 2022.
- [103] Y. Li, H. Wang, L. M. Dang, T. N. Nguyen, D. Han, A. Lee, I. Jang, and H. Moon, “A deep learning-based hybrid framework for object detection and recognition in autonomous driving,” *IEEE Access*, vol. 8, pp. 194 228–194 239, 2020.
- [104] B. G. Buchanan and R. G. Smith, “Fundamentals of expert systems,” in *Annual Review of Computer Science: Vol. 3*, 1988. USA: Annual Reviews Inc., Sep. 1988, pp. 23–58.
- [105] C. Rudin, “Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead,” *Nature Machine Intelligence*, vol. 1, no. 5, pp. 206–215, May 2019.
- [106] D. Kaur, S. Uslu, K. J. Rittichier, and A. Durresi, “Trustworthy Artificial Intelligence: A Review,” *ACM Computing Surveys*, vol. 55, no. 2, pp. 39:1–39:38, Jan. 2022.
- [107] N. Burkart and M. F. Huber, “A Survey on the Explainability of Supervised Machine Learning,” *Journal of Artificial Intelligence Research*, vol. 70, pp. 245–317, May 2021.
- [108] B. Gyevnar, N. Ferguson, and B. Schafer, “Bridging the Transparency Gap: What Can Explainable AI Learn From the AI Act?” in *Proceedings of the 26th European Conference on Artificial Intelligence ECAI 2023*, Krakow, Poland, Oct. 2023.
- [109] D. Feng, A. Harakeh, S. L. Waslander, and K. Dietmayer, “A review and comparative study on probabilistic object detection in autonomous driving,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 9961–9980, 2021.
- [110] European Commission. (2019) Ethics guidelines for trustworthy ai. [Online]. Available: <https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai>
- [111] NIST AI. (2023) Artificial intelligence risk management framework (ai rmf 1.0). [Online]. Available: https://airc.nist.gov/AI_RMF_Knowledge_Base/Playbook
- [112] L. Alzubaidi, A. Al-Sabaawi, J. Bai, A. Dukhan, A. H. Alkenani, A. Al-Asadi, H. A. Alwzazy, M. Manoufali, M. A. Fadhel, A. Albahri et al., “Towards risk-free trustworthy artificial intelligence: Significance and requirements,” *International Journal of Intelligent Systems*, vol. 2023, 2023.
- [113] J. Andráško, O. Hamul'ák, M. Mesářík, T. Kerikmäe, and A. Kajander, “Sustainable data governance for cooperative, connected and automated mobility in the european union,” *Sustainability*, vol. 13, no. 19, p. 10610, 2021.
- [114] E. Parliament. (2016) Regulation (eu) 2016/679 of the european parliament and of the council of 27 april 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data and repealing directive 95/46/ec (general data protection regulation). [Online]. Available: <https://data.europa.eu/eli/reg/2016/679/oj>
- [115] X. Li, Z. Chen, J. M. Zhang, F. Sarro, Y. Zhang, and X. Liu, “Dark-skin individuals are at more risk on the street: Unmasking fairness issues of autonomous driving systems,” *arXiv preprint arXiv:2308.02935*, 2023.

- [116] K. Eykholt, I. Evtimov, E. Fernandes, B. Li, A. Rahmati, C. Xiao, A. Prakash, T. Kohno, and D. Song, "Robust physical-world attacks on deep learning visual classification," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 1625–1634.
- [117] X. Yuan, P. He, Q. Zhu, and X. Li, "Adversarial examples: Attacks and defenses for deep learning," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 9, pp. 2805–2824, 2019.
- [118] SAE J3016, "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles," Apr. 2021. [Online]. Available: https://doi.org/10.4271/J3016_202104
- [119] A. M. Nascimento, L. F. Vismari, C. B. S. T. Molina, P. S. Cugnasca, J. B. Camargo, J. R. d. Almeida, R. Inam, E. Fersman, M. V. Marquezini, and A. Y. Hata, "A systematic literature review about the impact of artificial intelligence on autonomous vehicle safety," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 12, pp. 4928–4946, 2020.
- [120] Q. A. Ribeiro, M. Ribeiro, and J. Castro, "Requirements engineering for autonomous vehicles: a systematic literature review," in *Proceedings of the 37th ACM/SIGAPP Symposium on Applied Computing*, 2022, pp. 1299–1308.
- [121] R. Sheh, "Explainable artificial intelligence requirements for safe, intelligent robots," in *2021 IEEE International Conference on Intelligence and Safety for Robotics (ISR)*, 2021, pp. 382–387.
- [122] T. Miller, "Explanation in artificial intelligence: Insights from the social sciences," *Artificial intelligence*, vol. 267, pp. 1–38, 2019.
- [123] C. Molnar. (2023) Interpretable Machine Learning. [Online]. Available: <https://christophm.github.io/interpretable-ml-book/>
- [124] G. Schwalbe and B. Finzel, "A comprehensive taxonomy for explainable artificial intelligence: a systematic survey of surveys on methods and concepts," *Data Mining and Knowledge Discovery*, pp. 1–59, 2023.
- [125] T. Speith, "A review of taxonomies of explainable artificial intelligence (xai) methods," in *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, 2022, pp. 2239–2250.
- [126] S. Jain and B. C. Wallace, "Attention is not explanation," *arXiv preprint arXiv:1902.10186*, 2019.
- [127] I. E. Kumar, S. Venkatasubramanian, C. Scheidegger, and S. Friedler, "Problems with Shapley-value-based explanations as feature importance measures," in *Proceedings of the 37th International Conference on Machine Learning*. PMLR, Nov. 2020, pp. 5491–5500.
- [128] S. Mohseni, N. Zarei, and E. D. Ragan, "A multidisciplinary survey and framework for design and evaluation of explainable ai systems," *ACM Transactions on Interactive Intelligent Systems (TiiS)*, vol. 11, no. 3-4, pp. 1–45, 2021.
- [129] J. Van Brummelen, M. O'Brien, D. Gruyer, and H. Najjaran, "Autonomous vehicle perception: The technology of today and tomorrow," *Transportation research part C: emerging technologies*, vol. 89, pp. 384–406, 2018.
- [130] S. D. Pendleton, H. Andersen, X. Du, X. Shen, M. Meghjani, Y. H. Eng, D. Rus, and M. H. Ang Jr, "Perception, planning, control, and coordination for autonomous vehicles," *Machines*, vol. 5, no. 1, p. 6, 2017.
- [131] C. E. Tuncali, G. Fainekos, D. Prokhorov, H. Ito, and J. Kapinski, "Requirements-driven test generation for autonomous vehicles with machine learning components," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 2, pp. 265–280, 2019.
- [132] B. Paden, M. Čáp, S. Z. Yong, D. Yershov, and E. Frazzoli, "A survey of motion planning and control techniques for self-driving urban vehicles," *IEEE Transactions on intelligent vehicles*, vol. 1, no. 1, pp. 33–55, 2016.
- [133] C. Altafini, "Following a path of varying curvature as an output regulation problem," *IEEE Transactions on Automatic Control*, vol. 47, no. 9, pp. 1551–1556, 2002.
- [134] E. Frazzoli, M. A. Dahleh, and E. Feron, "Trajectory tracking control design for autonomous helicopters using a backstepping algorithm," in *Proceedings of the 2000 American Control Conference. ACC (IEEE Cat. No. 00CH36334)*, vol. 6. IEEE, 2000, pp. 4102–4107.
- [135] L. Chen, P. Wu, K. Chitta, B. Jaeger, A. Geiger, and H. Li, "End-to-end autonomous driving: Challenges and frontiers," *arXiv preprint arXiv:2306.16927*, 2023.
- [136] A. Tampuu, T. Matiisen, M. Semikin, D. Fishman, and N. Muhammad, "A survey of end-to-end driving: Architectures and training methods," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 4, pp. 1364–1384, 2022.
- [137] B. Kitchenham and S. Charters, "Guidelines for performing Systematic Literature Reviews in Software Engineering," School of Computer Science and Mathematics, Keele University, Keele, UK, EBSE Technical Report EBSE-2007-01, Jul. 2007.
- [138] I. Stepin, J. M. Alonso, A. Catala, and M. Pereira-Fariña, "A Survey of Contrastive and Counterfactual Explanation Generation Methods for Explainable Artificial Intelligence," *IEEE Access*, vol. 9, pp. 11974–12 001, 2021.
- [139] N. J. van Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, vol. 84, no. 2, pp. 523–538, Aug. 2010.
- [140] M. E. Tipping and C. M. Bishop, "Probabilistic principal component analysis," *Journal of the Royal Statistical Society Series B: Statistical Methodology*, vol. 61, no. 3, pp. 611–622, 1999.
- [141] L. Van der Maaten and G. Hinton, "Visualizing data using t-sne," *Journal of machine learning research*, vol. 9, no. 11, 2008.
- [142] G. E. Hinton, A. Krizhevsky, and S. D. Wang, "Transforming auto-encoders," in *Artificial Neural Networks and Machine Learning – ICANN 2011*, T. Honkela, W. Duch, M. Girolami, and S. Kaski, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 44–51.
- [143] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," in *2017 IEEE International Conference on Computer Vision (ICCV)*, Oct. 2017, pp. 618–626.
- [144] M. R. Endsley, "Toward a Theory of Situation Awareness in Dynamic Systems," *Human Factors*, vol. 37, no. 1, pp. 32–64, Mar. 1995.
- [145] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," *Advances in neural information processing systems*, vol. 30, pp. 4765–4774, 2017.
- [146] R. Krajewski, J. Bock, L. Kloecker, and L. Eckstein, "The highd dataset: A drone dataset of naturalistic vehicle trajectories on german highways for validation of highly automated driving systems," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 2118–2125.
- [147] M. D. Zeiler and R. Fergus, "Visualizing and understanding convolutional networks," in *Computer Vision – ECCV 2014*, D. Fleet, T. Pajdla, B. Schiele, and T. Tuytelaars, Eds. Cham: Springer International Publishing, 2014, pp. 818–833.
- [148] W. Bao, Q. Yu, and Y. Kong, "Uncertainty-based traffic accident anticipation with spatio-temporal relational learning," in *Proceedings of the 28th ACM International Conference on Multimedia*, 2020, pp. 2682–2690.
- [149] T. Kadir and M. Brady, "Saliency, scale and image description," *International Journal of Computer Vision*, vol. 45, no. 2, pp. 83–105, 2001.
- [150] J. T. Springenberg, A. Dosovitskiy, T. Brox, and M. A. Riedmiller, "Striving for simplicity: The all convolutional net," in *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Workshop Track Proceedings*, 2015.
- [151] M. Gadd, D. de Martini, L. Marchegiani, P. Newman, and L. Kunze, "Sense-Assess-eXplain (SAX): Building Trust in Autonomous Vehicles in Challenging Real-World Driving Scenarios," in *2020 IEEE Intelligent Vehicles Symposium (IV)*, Oct. 2020, pp. 150–155.
- [152] T. Menzel, G. Bagschik, L. Isensee, A. Schomburg, and M. Maurer, "From functional to logical scenarios: Detailing a keyword-based scenario description for execution in a simulation environment," in *2019 IEEE Intelligent Vehicles Symposium (IV)*, 2019, pp. 2383–2390.
- [153] V. Petsiuk, A. Das, and K. Saenko, "Rise: Randomized input sampling for explanation of black-box models," *arXiv preprint arXiv:1806.07421*, 2018.
- [154] D. Brajovic, N. Renner, V. P. Goebels, P. Wagner, B. Fresz, M. Biller, M. Klaeb, J. Kutz, J. Neuhuetler, and M. F. Huber, "Model reporting for certifiable ai: A proposal from merging eu regulation into ai development," *arXiv preprint arXiv:2307.11525*, 2023.
- [155] M. Wäschle, F. Thaler, A. Berres, F. Pölzlauer, and A. Albers, "A review on AI Safety in highly automated driving," *Frontiers in Artificial Intelligence*, vol. 5, 2022.
- [156] J. Wang and R. Jia, "Data Banzhaf: A Robust Data Valuation Framework for Machine Learning," in *Proceedings of Machine Learning Research*, vol. 206, 2023, pp. 6388–6421.
- [157] C. Wang, F. Guo, R. Yu, L. Wang, and Y. Zhang, "The application of driver models in the safety assessment of autonomous vehicles: Perspectives, insights, prospects," *IEEE Transactions on Intelligent Vehicles*, 2023.
- [158] N. Elhage, N. Nanda, C. Olsson, T. Henighan, N. Joseph, B. Mann, A. Askell, Y. Bai, A. Chen, T. Conerly et al., "A mathematical framework for transformer circuits," *Transformer Circuits Thread*, vol. 1, 2021.



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