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Systematic Review

Deep Learning and Autonomous Vehicles: Strategic Themes, Applications, and Research Agenda Using SciMAT and Content-Centric Analysis, a Systematic Review

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Abstract: Applications of deep learning (DL) in autonomous vehicle (AV) projects have gained increasing interest from both researchers and companies. This has caused a rapid expansion of scientific production on DL-AV in recent years, encouraging researchers to conduct systematic literature reviews (SLRs) to organize knowledge on the topic. However, a critical analysis of the existing SLRs on DL-AV reveals some methodological gaps, particularly regarding the use of bibliometric software, which are powerful tools for analyzing large amounts of data and for providing a holistic understanding on the structure of knowledge of a particular field. This study aims to identify the strategic themes and trends in DL-AV research using the Science Mapping Analysis Tool (SciMAT) and content analysis. Strategic diagrams and cluster networks were developed using SciMAT, allowing the identification of motor themes and research opportunities. The content analysis allowed categorization of the contribution of the academic literature on DL applications in AV project design; neural networks and AI models used in AVs; and transdisciplinary themes in DL-AV research, including energy, legislation, ethics, and cybersecurity. Potential research avenues are discussed for each of these categories. The findings presented in this study can benefit both experienced scholars who can gain access to condensed information about the literature on DL-AV and new researchers who may be attracted to topics related to technological development and other issues with social and environmental impacts.

Keywords: artificial intelligence; deep learning; autonomous vehicles; autonomous driving; systematic review; research agenda

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1. Introduction

Given the massive increase in vehicle traffic worldwide, issues such as road safety, traffic congestion, CO_2 emissions, and sustainability are becoming critical [1]. Concerning safety, according to the World Health Organization [2], every year road traffic accidents cause 1.35 million deaths worldwide; additionally, 20 to 50 million people experience non-fatal injuries. Furthermore, the negative impact of traffic congestion on pollution, greenhouse gas emissions, and people's health is well documented [3,4].

In this context, autonomous vehicles (AVs) have grown in importance as a potential solution to these challenges, boosted by the rapid expansion of artificial intelligence (AI) applications in this area [1,5]. Both safety and sustainability factors contribute to this increased interest. In terms of safety, critical reasons for car crashes were estimated to be more than 90% related to human errors, whereas vehicle failures were responsible for 2% [6]. Furthermore, AVs can help with fuel economy, reduced pollution, car sharing, and improved traffic flow [5].

Given the rapid increase in scientific production of AVs and AI, this topic has become conducive to conducting systematic literature reviews (SLRs) to organize knowledge on the topic. For instance, Nascimento et al. [1] conducted a SLR to investigate how AI-based systems impact AV safety, and Parekh et al. [7] looked into the current state of research and development in environment detection, pedestrian detection, path planning, motion control, and vehicle cybersecurity for AVs. Some authors have been expanding the discussions on AVs to address topics of paramount importance to society; for instance, Kostrzewski et al. [8] discussed the Internet of Vehicles (IoV) and sustainability, specifically focusing on issues related to Environmental, Social, and Corporate Governance (ESG). From another perspective, some authors have focused on particular aspects; Jebamikyous and Kashef [9] focused on AV perception related to Semantic Segmentation and Object Detection; Pavel et al. [10] on RGB camera vision; and Fayyad et al. [11] on sensor fusion algorithms for perception, localization, and mapping. Other studies have concentrated on specific area of AI, such as deep learning (DL). Mozaffari [12] reviewed research on DL-based approaches for vehicle behavior prediction, whereas Cui et al. [13] studied DL applications for data fusion approaches that leverage both image and point cloud.

A critical analysis of the existing SLRs on AI and AVs reveals some methodological similarities, including the absence of quantitative methods and the use of traditional approaches such as content analysis to examine a limited number of documents. Thus, using quantitative approaches to investigate the academic production regarding AI and AVs can be of great value, especially when bibliometric software are used, which are powerful tools for analyzing large amounts of data and for providing a holistic understanding on strategic themes of a particular field of knowledge [14].

To address this gap, the objective of this paper is to identify the strategic themes and trends in DL-AV research. To accomplish this, it employs the Science Mapping Analysis Tool (SciMAT) and content-centric analysis to identify how DL has been applied in AV projects, as well as the main techniques, models, and datasets. Based on that, two research questions guided this study:

- RQ1: What are the strategic themes of DL and AVs?
- RQ2: What are the trends and opportunities related to DL-AV for researchers and practitioners?

The remainder of this paper is organized as follows. Section 2 describes the methodological procedures to conduct scientific mapping and contributions of the SciMAT application. Section 3 presents the results and discussion based on the strategic diagrams and cluster networks generated by SciMAT, in addition to the outcomes of content analysis. Finally, Section 4 presents the conclusions, limitations, and suggestions for future studies.

2. Materials and Methods

2.1. Research Protocol

The databases chosen for this research were Scopus and Web of Science (WoS) due to a combination of important features, including their wide global and regional coverage of scientific journals [15], which encompasses journals from other relevant databases such as Emerald and IEEE; its high-quality peer-reviewed journals in the areas of interest when compared to EBSCO, Google Scholar, or others [15]; and the availability of compatible metadata for bibliometric analysis software [16].

Prior SLRs, e.g., [1,8,11], were used as a basis for developing the search string, which was defined as follows: ("artificial intelligence" OR "deep learning") AND ("autonomous vehicle*" OR "autonomous driv*" OR "self-driv*"). The following criteria were used as filters: only journal articles and reviews; publications from 2017 to 2022; document available in English; and search terms appear in the title, abstract, or keywords.

The identification of studies followed the PRISMA protocol as depicted in Figure 1. The PRISMA 2020 Checklist proposed by Page et al. [17] can be found in the Supplementary Material.

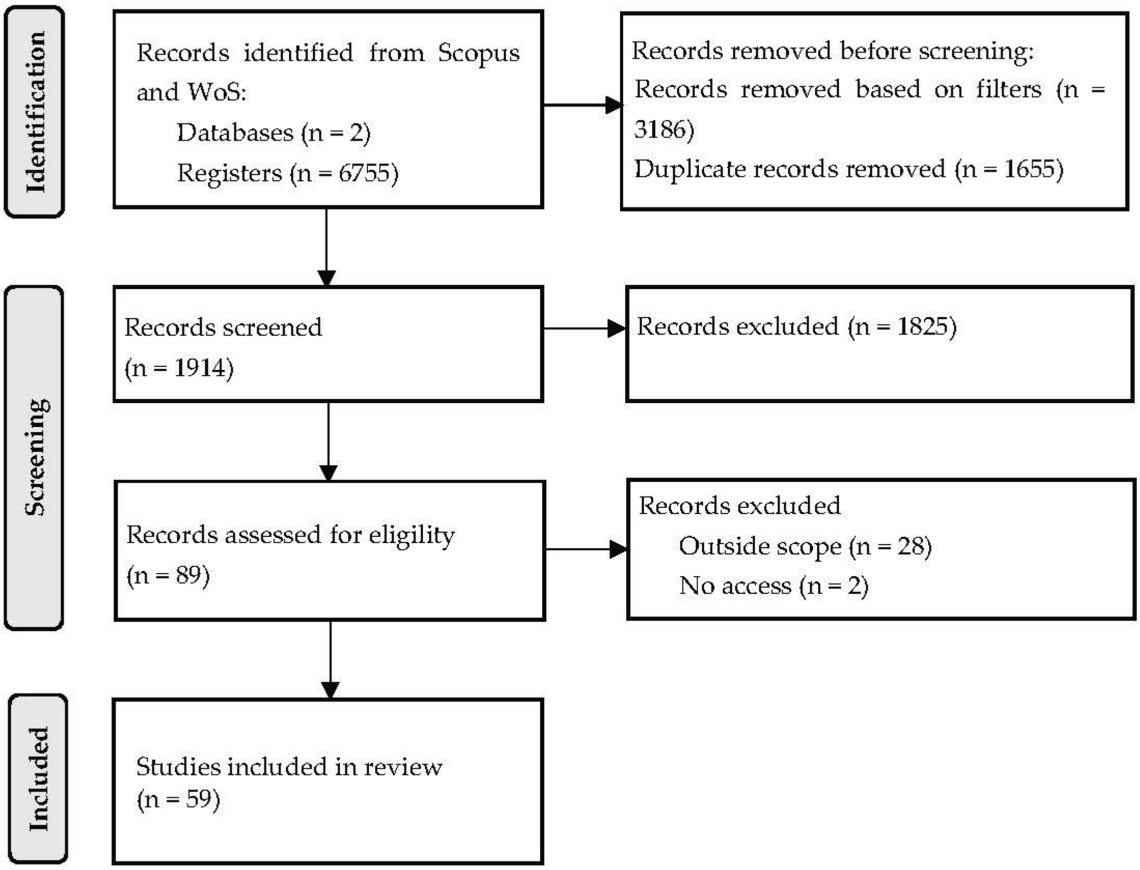

Figure 1. PRISMA flow diagram. Source: Developed by the authors based on Page et al. [17].

After applying these filters and removing the duplicates, the initial search resulted in 1914 articles. The screening process commenced by having two reviewers independently examine the titles, abstracts, and keywords of the articles. Subsequently, the researchers' analyses were compared, and a total of 89 articles were chosen for the subsequent stage of analysis. Then, a content analysis following Elo and Kyngäs's [18] recommendations was performed to evaluate the adequacy of the studies for the scope of the research. This process resulted in 61 articles that were fully read to determine scope appropriateness. Only two documents were excluded as the research did not have access, resulting in a final sample of 59 articles.

This process was conducted in June 2022. As recommended by Tranfield et al. [19], an update search to identify potential studies was conducted in June 2023, with no changes to the final sample. The data from the 59 articles was then extracted from the Scopus and WoS databases by creating a file in the RIS (Research Information Systems) extension, which allowed uploading to the SciMAT software [20]. This review was not registered.

2.2. Science Mapping Analysis Tool (SciMAT) Application

After the data retrieval, the recommendations of Cobo et al. [20] were followed to structure the application of SciMAT as summarized in Figure 2.

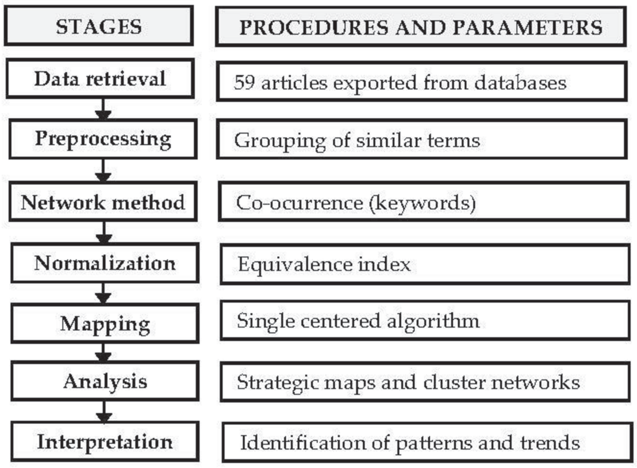

Figure 2. Methodological procedures for the application of SciMAT. Source: Developed by the authors based on Cobo et al. [20].

In the preprocessing stage, similar terms were grouped using singular/plural, 1- and 2-character difference, and manual evaluation by meaning (e.g., "Internet of Things" and "IoT"). This process resulted in 573 groups of words.

As proposed by Cobo et al. [20] and Furstenau et al. [21], the sample was divided into time periods (TP) in order to facilitate chronological analysis and the identification of evolutionary patterns: TP1 (2017–2018), TP2 (2019–2020), and TP3 (2021–2022), with 2, 22, and 36 articles, respectively.

SciMAT's co-word analysis capabilities allow researchers to identify key topics, concepts, and themes that are prevalent within a given research domain [20,22]. By analyzing the frequency and co-occurrence of specific terms in the literature, SciMAT is a powerful tool to uncover the underlying thematic structure of a field and identify emerging research areas or interdisciplinary connections [23]. The main graphic outcomes from SciMAT are the strategic diagrams and network structures.

The strategic diagram (Figure 3) represents the centrality (degree of importance) of the themes on the *X* axis and the density (degree of development) on the *Y* axis, resulting in four quadrants: (Q1) motor themes, which are important topics with high development; (Q2) basic and transversal themes, which may become motor themes in the future due to their high centrality; (Q3) emerging or declining themes, which require a qualitative analysis to determine the extent to which they are emerging or declining; and (Q4) highly developed and isolated themes, which are themes that have lost importance because of the appearance of a new concept or technology [21,22].

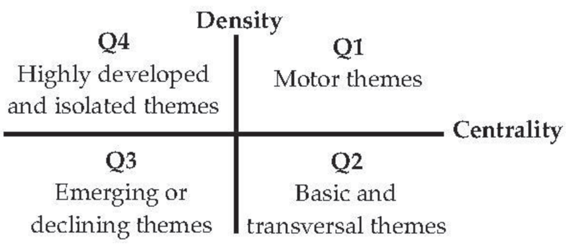

Figure 3. Generic representation of the strategic diagram. Source: Developed by the authors based on Cobo et al. [20].

SciMAT generates cluster networks to support the analysis of theme co-occurrence, providing a view of the degree of interaction between themes and subthemes [20]. The network structures are useful for the analyses, since they help in understanding the magnitude of the impact of a theme in the area and the strength of the connection between themes [20,24–26].

It is important to mention that this study concentrated on the thematic network structures of the motor themes with the highest density and centrality indicators. The choice to focus on motor themes is suitable for the objective of this study, which is to analyze the thematic evolution and trends in DL-AV research, as proposed by Gibbin et al. [23].

2.3. Content-Centric Analysis

In addition to the bibliometric analysis, a content-centric analysis [27] of the articles was performed. The methodological procedures followed the recommendations of Bardin [28]. Among the content analysis approaches proposed by this author, the categorical analysis technique was used, which is appropriate for data analysis through coding and thematic organization. Figure 4 shows its integration into the methodological approach of the study.

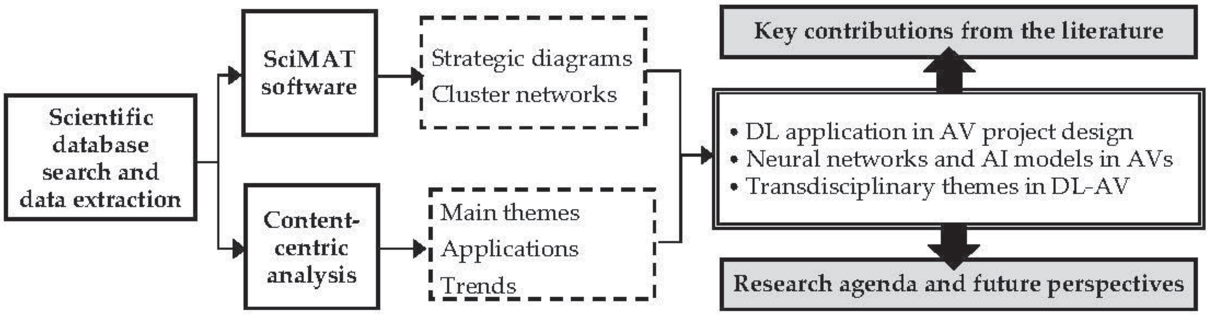

Figure 4. Integration of methods and research outcomes. Source: Authors.

Content-centric analysis is an essential methodological approach for advancing knowledge, particularly in rapidly evolving fields characterized by significant advancements in recent years [27], such as the case of DL-AV.

This stage of the study was performed based on the following steps: pre-analysis, coding, classification, and interpretation. According to Bardin [28], pre-analysis refers to the construction of the corpus, which consists of the material to be analyzed (see Section 2.1 of Materials and Methods, which explains the methodological procedures followed to define the sample). The coding and classification of the articles was performed considering the following elements: themes, DL techniques, components of AV project design, AI models, and datasets. Finally, the interpretation involved combining the results of bibliometric analysis with SciMAT and content analysis, which served as the basis for developing this paper.

3. Results and Discussion

Due to the main characteristic of the software used being its visual power, it was deemed pertinent to present the results and discussion in an integrated manner in this section, allowing for greater clarity of the relationship between the findings and the figures generated by SciMAT. Thus, the results and discussion for this study were organized as follows: strategic diagrams (Section 3.1), cluster networks (Section 3.2), and content analysis (Section 3.3).

3.1. Strategic Diagrams

SciMAT generated two strategic diagrams: 2019–2020 (Figure 5a) and 2021–2022 (Figure 5b). There were no motor themes identified for the period 2017–2018.

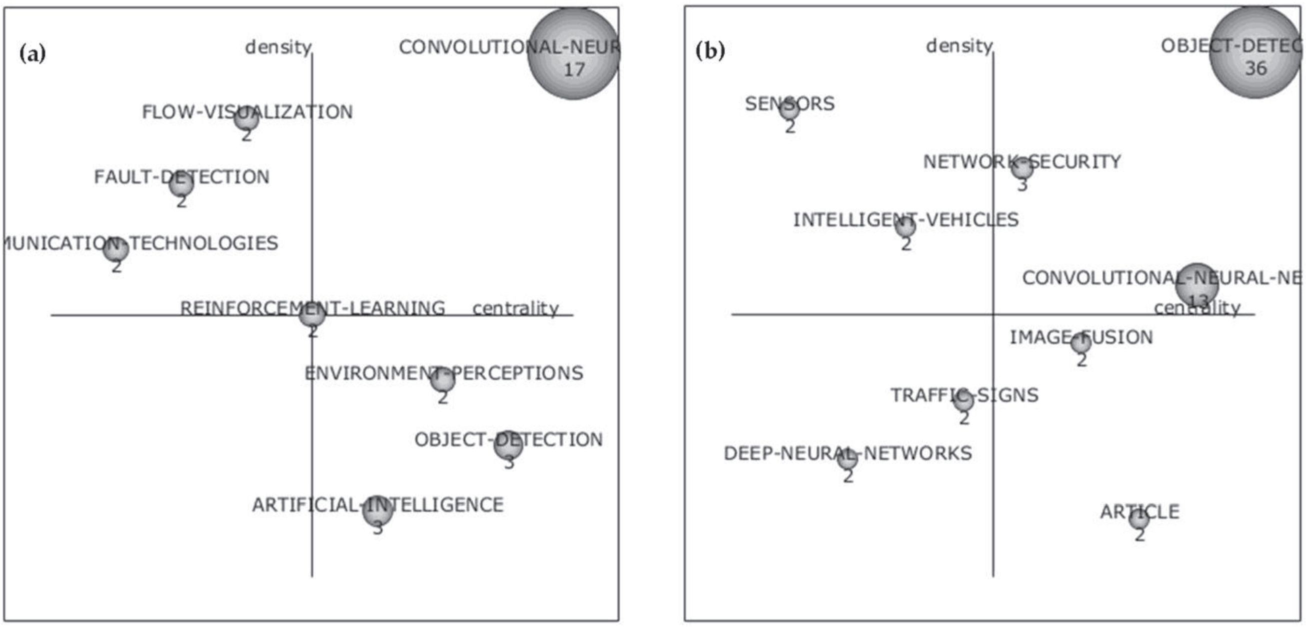

Figure 5. Strategic diagrams for the motor themes of the periods (**a**) 2019–2020 and (**b**) 2021–2022. Source: Generated by SciMAT.

The cluster "OBJECT-DETECTION" appears in Q2 of 2019–2020 and then moves to Q1 as the most relevant motor theme in 2021–2022. According to Cobo et al. [20], Q2 refers to basic and transversal themes. These are important topics, but they have not yet been fully developed; thus, the shift to Q1 in the subsequent period indicates that researchers began to explore further and increased academic production on this theme.

The literature analysis helps to understand this finding. Fujiyoshi et al. [29] presented techniques used before and after DL in the context of convolutional neural networks (CNNs), revealing the impact on image recognition (i.e., object detection and image classification, among other image-related tasks). Furthermore, Wen and Jo [30] presented the evolution of several computer vision tasks in AVs, including object detection, demonstrating how these were fueled by new sensors used in AV perception. Thus, the evolution of the topic of object detection in AVs in recent years can be associated with the revival of CNN research and sensor innovations. As examples, LiDAR [31] and RADAR [32] sensors contributed to enhancing the precision of environment recognition. With the advancement of AV hardware, current models account for not only images captured by cameras, but also the LiDAR point cloud and/or distance measured by the RADAR [13].

The cluster "CONVOLUTION-NEURAL-NETWORK" is the only one that is positioned in Q1 in the period 2019–2020 and, despite its reduced density, remains a motor theme in the period 2021–2022. CNN and object detection are both hot topics in DL and AV research. It is worth noting that, while object detection is a type of problem to be solved, CNN is a potential approach to solving it [33].

The analysis of the remaining quadrants reveals additional important themes in DL-AV research. For the period 2019–2020 (Figure 5a), Q2 shows the presence of the cluster "ENVIRONMENT-PERCEPTIONS", which is directly related to perception tasks including object detection and recognition. It is also interesting to note that the cluster "REINFORCEMENT LEARNING", which is related to the learning process in which an agent learns based on feedback from the environment [34], was placed between the quadrants, despite not becoming a motor theme.

The most recent strategic diagram (2021–2022) (Figure 5b) reveals additional important DL-AV research topics, such as the Q1 cluster "NETWORK-SECURITY". Given that AI models are in control of AV behaviors [12], this is a critical motor theme. In Q2, the cluster "IMAGE-FUSION" is directly related to sensor fusion, which is a process of perception of the environment using various types of sensors such as cameras, LiDAR, and RADAR [12,28]. Furthermore, the cluster "TRAFFIC SIGNS" should be noted as it refers to the importance of advancing knowledge on the detection process and correct classification of traffic signs in order for AVs to take the appropriate actions in accordance with traffic laws [26,31].

3.2. Cluster Networks

Considering the motor themes with highest density and centrality, network structures were generated by SciMAT for the periods 2019–2020 (Figure 6a) and 2021–2022 (Figure 6b):

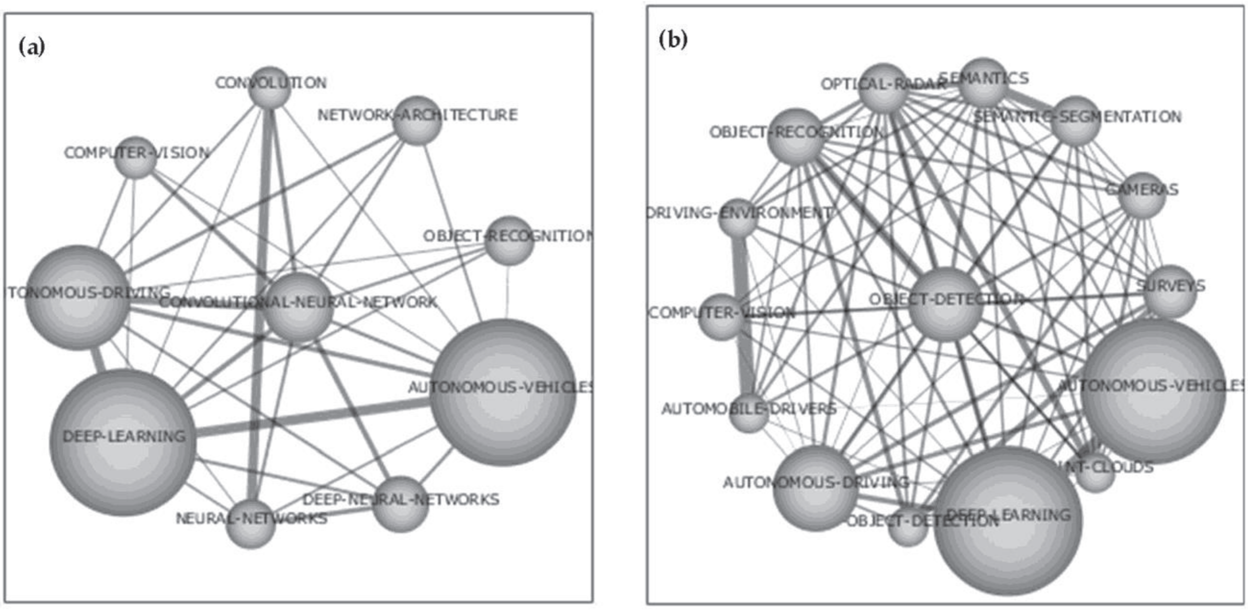

Figure 6. Cluster networks for the motor themes of the periods (**a**) 2019–2020 and (**b**) 2021–2022. Source: Generated by SciMAT.

For the period 2019–2020 (Figure 6a), the cluster "CONVOLUTION-NEURAL-NETWORK" is the main one, which is associated with 17 articles. This central cluster (motor theme) connects to other clusters (sub-themes) related to technical aspects (e.g., deep neural networks and network architecture) and applications (e.g., computer vision and object recognition). As observed in the strategic diagrams, although the cluster related to CNN decreased in density and centrality in the period 2021–2022 (see Figure 5), its position as a motor theme was sustained, and it is worth noting that it is linked to 13 articles in this period.

Considering the network structure for the period 2021–2022 (Figure 6b), the central cluster is "OBJECT-DETECTION" with 36 articles. The connections observed indicate a strong association with cluster "OBJECT-RECOGNITION", as well as with "OPTICAL-RADAR" and "CAMERAS".

The integrated examination of strategic diagrams, cluster networks, and content analysis provides a chronological and conceptual understanding of the relevance of the motor themes and their connections. Object detection techniques reached a critical threshold in 2010, as the simplest techniques for extracting features from images became saturated [35]. The reinvention of CNN studies [33] transformed research on DL tasks with images, including object detection. The main advancement of CNNs was the capability of robust learning regarding high-level image feature representation [33,36]. The Region CNN (RCNN) [37] contributed to the evolution of object detection studies. Following this, a number of other models emerged, including: Spatial Pyramid Pooling Networks (SPPNets) [38], Fast RCNN [37], Faster RCNN [39], Feature Pyramid Networks (FPNs) [40], You Only Look Once (YOLO) [41], Single Shot MultiBox Detector (SSD) [42], and RetinaNet [43]. This demonstrates that the increased interest in DL techniques for object detection is directly related to the increase in CNN research, indicating that the motor theme associated with

CNN loses some space to object detection, despite their evolution being closely linked in most cases [33,34,44].

3.3. Content-Based Thematic Analysis

To complement the analysis performed using the strategic diagrams and cluster networks generated by SciMAT, content analysis was used to improve the robustness of the results. The iterative process of analyzing and classifying the articles yielded three useful categories for organizing DL-AV research knowledge: DL applications in AV project design; neural networks and AI models used in AVs; and transdisciplinary themes in DL-AV research. Each of the categories is discussed in the following sections.

3.3.1. DL Applications in AV Project Design

According to Pendleton et al. [45], AV architecture is typically composed of four components: perception, localization, planning, and control. The first component, perception, is concerned with understanding the environment and detecting obstacles. The second component, localization, enables the AV to locate itself, i.e., to estimate its position in the environment accurately. Planning entails predicting the future position of the targets (relative to the vehicle) in order to anticipate and plan the vehicle's trajectory from point A to point B. The system can operate once it has a trajectory plan. The execution is conducted by the control component, which produces the correct generation of the car's movements, including the angular position of the steering wheel and the specified speed control flow, in order to safely achieve the planned path [45].

Based on the framework proposed by Pendleton et al. [45], each article was categorized in terms of the component examined. Of the 59 articles reviewed, 16 did not specify the AV design component under consideration, and 12 addressed more than one. The results are summarized in Figure 7.

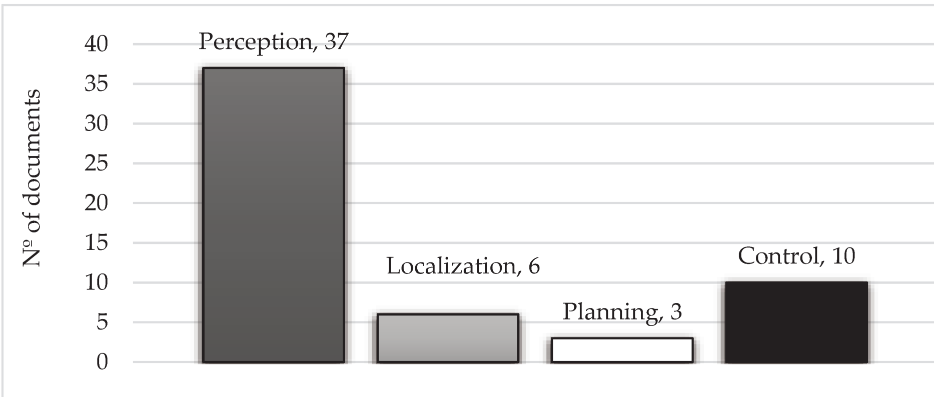

Figure 7. Mapping of DL applications in AV project design. Source: Authors.

The prevalence of articles dealing with perception is evident. Perception is typically the first component designed in AV projects, as it refers to the vehicle's perception of the environment, including tasks such as semantic segmentation, object detection, and object recognition [46,47]. Sensor research using cameras, LiDAR, or RADAR is included in AV perception studies. Another area of research is sensor fusion, which involves combining different sensors [26,48,49].

Research dealing with the control component is related to end-to-end AV projects in both industry and universities, and it can be defined as simplified AV designs consisting of two main parts: perception and control. End-to-end projects are trained models that capture the environmental situation through frames of video images captured by a camera and, based on the analysis of the environment, take driving actions by controlling vehicle parameters such as wheel twisting angle and speed through acceleration and braking processes [50].

End-to-end projects are more efficient than four-component AV designs (perception, localization, planning, and control) because they are faster to prototype; additionally, these systems are designed to learn from a large number of experiments rather than relying on the various parts of the entire project [48–50]. As a result, there is a limited number of articles addressing DL applications on the localization and planning components. Moreover, these components were not always addressed as central topics, but rather as supporting elements. As an example, Fayyad et al. [11] discussed sensor fusion, which is normally used for perception, but in the context of system localization by fusing data collected from various types of sensors.

In terms of DL applications in AV project design, the main trend observed is the improvement of techniques (and models) for object detection and recognition, as this is a critical component of the project. Another opportunity is to develop new (or improve existing) control techniques for use in end-to-end AV projects. Researchers can consider the increased use of AV simulators such as Carla or ApolloScape, which allow development and training of an external AI model before embarking on a simulator to test its behavior in a virtual environment. Furthermore, more detailed exploration of AI models for the localization and planning processes of AVs is required, as this is a topic that has received little attention and offers many opportunities for innovation.

3.3.2. Neural Networks and AI Models Used in AVs

The content analysis enabled the mapping of neural network techniques used in AVs (Figure 8).

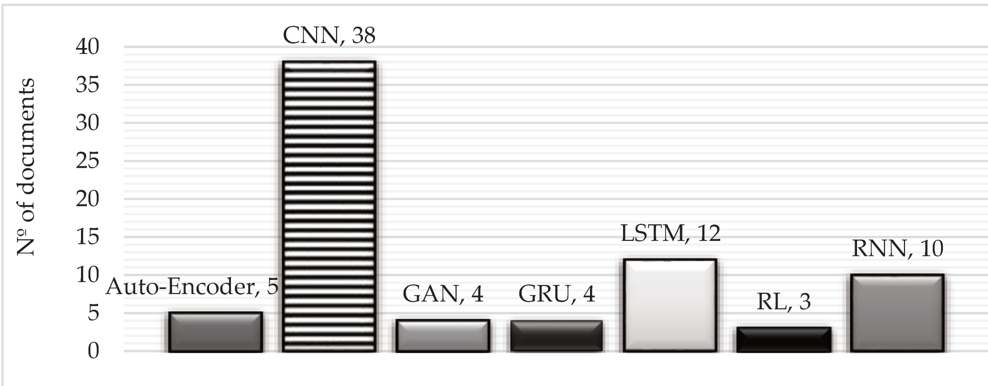

Figure 8. Mapping of neural network techniques used in AVs. Source: Authors.

CNN was clearly the most commented on in the sample analyzed, which is consistent with previous analyses using SciMAT software. Another technique worth mentioning is the Recurrent Neural Network (RNN), which is related to Long Short-Term Memory (LSTM). These techniques are widely applied in pattern recognition in sequential data such as text, genomes, handwriting, spoken words, sensor data, stock exchange data, videos, and so on [51–53]. RNN can also be used in non-sequence information problems, such as computer vision problems, e.g., [51].

Regarding neural network techniques used in AVs, a research opportunity is to further explore new techniques such as liquid neural networks and transformers. The liquid neural network (LNN) was created by researchers at the Massachusetts Institute of Technology's (MIT's) Computer Science and Artificial Intelligence Laboratory, and its main feature is that it learns on the fly, rather than just during training. To accomplish this, such networks modify their equations in order to continuously adapt to new data inputs, hence the name "liquid". This enables decision making based on changing data streams, such as in medical diagnostics and autonomous vehicle driving [54,55].

Transformer is an architecture designed to solve sequence-to-sequence tasks while handling complex dependencies. This architecture computes its input and output representations without using sequence-aligned RNNs or convolutional layers, instead relying on the mechanism of attention [56]. Vaswani et al. [57] introduced this model, which employs the attention mechanism while accounting for the influence of various parts of the input data. It has primarily been used in natural language processing (NLP) tasks, but recent research shows promising results in other tasks, such as video comprehension.

AI models used in AV design are built using one (or more) DL techniques. The content analysis enabled the identification of more than 100 different models, of which the most frequently mentioned are shown in Figure 9.

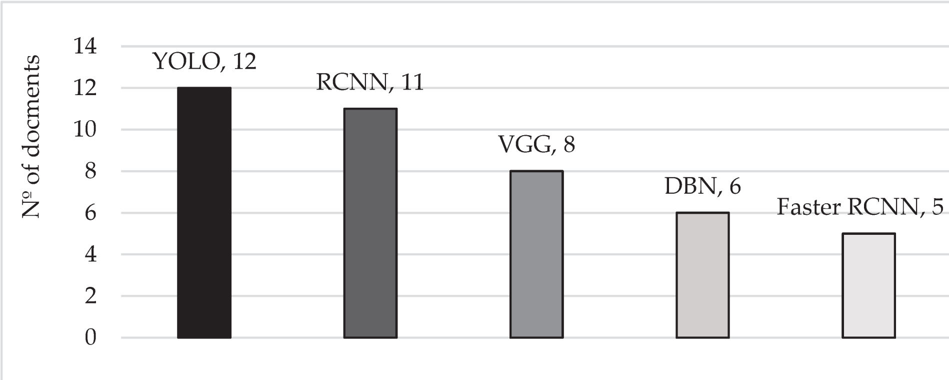

Figure 9. Mapping of AI models used in AV projects. Source: Authors.

When developing a machine-learning project, one of the first things to be studied and defined is the dataset that will be used for training, testing, and validation of the model or algorithm. A robust and reliable database is required in the development of AV projects in order to perform AI model training and validation. Thus, the datasets were also mapped (Figure 10).

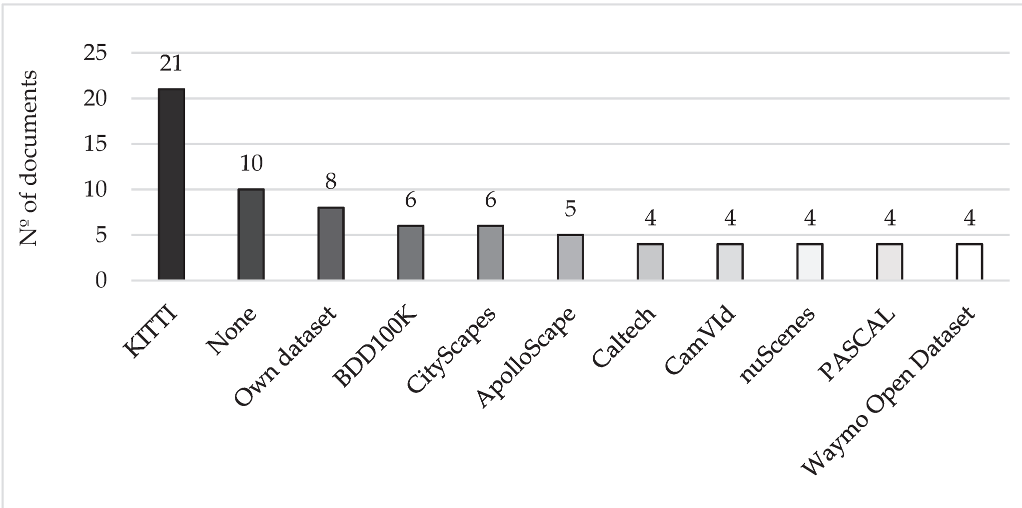

Figure 10. Mapping of datasets used in AV projects. Source: Authors.

The KITTI benchmark [56] is a popular and widely used benchmark in the design of AVs. This dataset was developed by researchers at the Karlsruhe Institute of Technology and the Toyota Technological Institute (KITTI). Its goal is to contribute to the research and development of AV projects, specifically stereo tasks, optical flow, visual odometry or SLAM, and 3D object detection.

Geiger et al. [56] asserted that KITTI is composed of 389 stereo and optical flow image pairs, 39.2 km of stereo visual odometry sequences, and over 200,000 annotations of 3D objects captured in cluttered scenarios. Hours of recordings of various traffic scenarios, in daytime and various weather conditions, were used to collect the data. As illustrated in Figure 11, the dataset for vision tasks was created using the standalone driving platform.

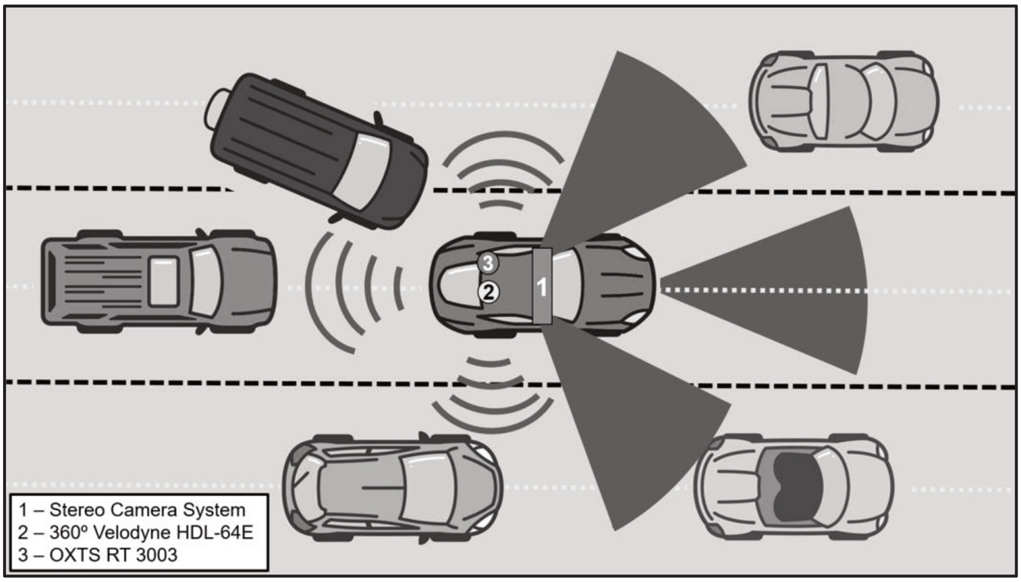

Figure 11. Scheme of the KITTI platform with use of sensors for collecting data. Source: Authors.

Other datasets identified, such as CityScapes, BDD100K, ApolloScape, Caltech, CamVId, nuScenes, PASCAL, and Waymo Open Dataset, are very similar to KITTI but were created by other research groups from universities or companies, using different platforms and sensors for data collection.

Finally, it is worth mentioning that more than 73 different datasets were found. A total of ten articles did not present specific datasets, and eight articles presented their own datasets, which means that the researchers developed an AI project in which a dataset was created for training, validation, and testing of the proposed model (or technique) [58].

3.3.3. Transdisciplinary Themes in DL-AV Research

In addition to the topics with a more technical focus related to DL and AV, it is important to recognize emerging issues that transcend the limits of disciplines.

Four themes stand out as having a high potential for development in future research:

- Energy: Vega et al. [59] and Balasekaran et al. [60] highlighted the issue of energy efficiency, owing to the fact that AI models, in general, have a high computational cost and, as a result, require large amounts of energy resources;
- Legislation: Thiele-Evans et al. [61] and Ning et al. [62] discussed the legislation of commercial implementation of AVs, comparing the progress in this area in various countries;
- Ethics: Cunneen et al. [63] addressed ethics in AV projects, a topic that is directly related to legislation, because in many countries, the main debate for approving commercial use of AVs is about ethical barriers. The trolley problem is the most well-known ethical issue concerning AVs [60];
- Cybersecurity: Khan et al. [64] and Deng et al. [48] concentrated on AI models that can aid in the detection of AV computational system attacks. Furthermore, Jiang et al. [65] investigated how attacks on AVs are carried out by experimentally replicating some scenarios. One possible attack is on the interaction of corrupted data in vehicle model training, so that the AV model is trained with "poisoned" data, causing it to make errors in actual decisions.

3.4. Research Agenda Proposal and Future Perspectives

Based on the insights from the strategic diagrams and cluster networks generated by SciMAT and the content analysis of the selected articles, a research agenda was developed. Table 1 presents the research questions and suggested references.

Table 1. Research agenda for DL-AV.

Topics	Research Questions	References
DL application in AV project design	• How can DL techniques be applied to optimize the design and performance of AV projects?	[66,67]
	• What are the key challenges and considerations in integrating DL algorithms into AV design processes?	[6,68,69]
Neural networks and AI models used in AVs	• How can DL contribute to enhancing safety, efficiency, and user experience in AVs?	[9,12,70]
	• How can specific neural network architectures, including CNNs and RNNs, be used in innovative ways in AVs for tasks such as object recognition, path planning, and decision making?	[71,72]
	• What specific training and fine-tuning approaches can be employed to optimize the performance of neural networks in enhancing object recognition, path planning, and decision-making capabilities in AVs?	[73]
	• What are the limitations and potential risks associated with neural network-based techniques in AV applications?	[74,75]
	• What cutting-edge AI models are tailored for AVs, and how do they enhance functionalities like adaptive decision making and real-time environment perception?	[74,76,77]
	• How do dataset availability and quality impact the performance and reliability of AI models in AVs, and how can dataset limitations be addressed to improve model robustness and generalization?	[78,79]
Transdisciplinary themes in DL-AV	• What are the ethical challenges in using AI models and datasets in AV research, specifically regarding biases in decision making, privacy concerns, and societal impact? How can these challenges be mitigated to ensure responsible deployment of AI in AVs?	[80–82]
	• What DL approaches can be used to address energy efficiency challenges in AVs, such as optimizing power consumption, maximizing battery life, and minimizing energy waste during operations?	[83]
	• What are the legal and regulatory challenges of integrating DL algorithms into AVs, including liability, safety regulations, and compliance with transportation laws? How can these challenges be addressed to facilitate the widespread adoption of DL technologies in AVs?	[84–86]
	• What ethical and cybersecurity challenges arise from using DL in AVs, specifically in terms of privacy, data integrity, adversarial attacks, and system vulnerabilities? How can these challenges be effectively addressed to ensure safe and secure operations while maintaining ethical standards and protecting user privacy?	[79,87]

Several potential research avenues emerge when considering DL applications in AV project design. The exploration of DL techniques has the potential to revolutionize the design and performance of AV projects. By leveraging DL algorithms, researchers can delve into unexplored territories and uncover new possibilities for optimizing the overall functionality, efficiency, and safety of AVs. This includes developing advanced perception systems, adaptive decision-making algorithms, and intelligent control strategies that can significantly enhance the capabilities of AVs, leading to a paradigm shift in the field [66,67]. Furthermore, integrating DL algorithms into AV design presents a complex landscape with various challenges and considerations. Researchers must navigate issues such as computational resource requirements, algorithmic complexity, model interpretability, and real-time constraints. Moreover, ensuring seamless integration with existing components and systems, addressing hardware limitations, and designing robust validation and testing frameworks are crucial aspects to overcome in order to successfully harness the power of DL in AV design [6,68,69]. In addition, the potential of DL in enhancing safety, efficiency, and user experience in the realm of AVs is substantial. DL techniques enable more accurate and reliable perception of the environment, allowing AVs to make better-informed decisions and react swiftly to changing situations. Additionally, DL can optimize energy consumption, improve route planning, and enhance the overall comfort and convenience for passengers, revolutionizing the way we perceive and interact with AVs [9,12,70].

The future perspectives of DL applications in AV project design are promising. By leveraging the power of DL algorithms, researchers can unlock new frontiers in enhancing the capabilities and performance of AVs [35,77]. This includes advancements in perception systems, decision-making algorithms, and control strategies, enabling autonomous vehicles to navigate complex environments with improved efficiency and safety [1,88]. Additionally, DL can drive innovation in areas such as advanced sensor fusion, real-time object detection and recognition, and adaptive path planning, leading to the development of more robust and reliable AVs [7].

Regarding neural network techniques used in AVs, the revolutionary utilization of specific neural network architectures, such as CNNs and RNNs, has the potential to transform AVs. By leveraging CNNs, researchers can achieve state-of-the-art performance in object recognition, enabling AVs to accurately identify and track objects in their surroundings. RNNs, on the other hand, offer the capability of modeling sequential data and making informed predictions, facilitating tasks like path planning and decision making in complex and dynamic environments [71,72]. The full potential of neural networks can be unlocked by employing advanced training and fine-tuning approaches. Through techniques like transfer learning, data augmentation, and ensemble methods, researchers can enhance the object recognition, path planning, and decision-making capabilities of AVs. By leveraging large-scale datasets and adopting sophisticated training strategies, neural networks can achieve higher accuracy, robustness, and adaptability, leading to more reliable and efficient AV systems [73]. Moreover, neural network-based techniques in AV applications come with limitations and potential risks that need to be carefully investigated. These include issues such as interpretability, potential biases in decision making, robustness to adversarial attacks, and safety concerns. Researchers must delve into these challenges, striving to develop methods that provide transparency, fairness, and resilience to ensure the safe and reliable operation of AVs in real-world scenarios [74,75].

Embracing cutting-edge AI models tailored for AVs opens up new possibilities for enhancing functionalities such as adaptive decision making and real-time environment perception. State-of-the-art AI models, including reinforcement learning algorithms, generative adversarial networks, and transformer models, can revolutionize how AVs perceive, analyze, and interact with their environment. These models enable advanced cognitive abilities, adaptability, and intelligent responses, significantly elevating the capabilities of AVs [74,76,77]. Dataset availability and quality play a crucial role in the performance and reliability of AI models in AVs. Researchers need to illuminate the impact of datasets on model performance, ensuring that the data used for training and testing is representative, diverse, and accurately annotated. Moreover, addressing limitations such as data scarcity, domain shifts, and biases is essential to improve the robustness and generalization of AI models, enabling more reliable and trustworthy AV systems [78,79]. From another perspective, navigating the ethical challenges in using AI models and datasets in AV research requires careful consideration to ensure responsible AI deployment. Mitigating biases in decision-making algorithms is essential to avoid unfair or discriminatory outcomes. Privacy concerns related to data collection and usage must be addressed to protect the personal information of users and maintain their trust. Moreover, considering the societal impact of AVs is crucial to ensure that they align with ethical principles and contribute positively to communities, fostering equitable access and social well-being [80–82].

The integration of neural networks and AI models in AVs holds immense potential for shaping the future of transportation. Neural networks enable AVs to process vast amounts of data, learn from them, and make intelligent decisions in real time [89]. With the advancement of AI models, autonomous vehicles can exhibit enhanced capabilities in various aspects, including perception, decision making, and behavior prediction. This opens up avenues for improving the overall performance, reliability, and safety of AVs, paving the way for widespread adoption and acceptance of this transformative technology [86].

Finally, transdisciplinary themes in DL-AV have high potential to advance knowledge and practice in the field. Pioneering DL approaches is essential to overcome energy efficiency challenges in AVs. Optimizing power consumption and maximizing battery life are critical factors in extending the range and endurance of AVs. DL techniques can be utilized to develop innovative algorithms that minimize energy waste during operation, leading to more sustainable and environmentally friendly AV systems. By harnessing the power of DL, researchers can drive advancements in energy-efficient technologies and pave the way for a greener future of transportation [83]. Tackling the legal and regulatory hurdles associated with integrating DL algorithms into AVs is paramount for their widespread adoption. Ensuring liability and safety compliance are crucial aspects to build public trust and confidence in autonomous systems. Navigating transportation laws and regulations is necessary to address challenges related to accountability, responsibility, and potential legal implications. Collaboration between researchers, policymakers, and industry stakeholders is essential to establish a comprehensive legal framework that promotes the safe and lawful integration of DL technologies into AVs [84–86]. Lastly, addressing the ethical and cybersecurity challenges posed by DL in AVs is imperative to ensure safe and secure operations. Safeguarding privacy and data integrity is crucial to protect the personal information collected by AVs from unauthorized access or misuse. Mitigating the risk of adversarial attacks, where malicious actors manipulate sensor inputs to deceive the system, is vital for maintaining the integrity and reliability of AVs. Implementing robust cybersecurity measures, such as encryption and intrusion detection systems, is essential to safeguard against potential vulnerabilities and maintain the trust of users in the security of autonomous systems [79,87].

The transdisciplinary themes that emerge from the intersection of DL and AVs offer exciting possibilities for the future. DL techniques can be applied not only to enhance the technical aspects of AVs but also to address broader societal and ethical considerations [8]. For example, research can explore how DL can improve the interpretability and transparency of autonomous systems, enabling better human–machine collaboration and trust [88]. Furthermore, investigations into the socio-economic impacts, legal frameworks, and ethical implications of deep learning in autonomous vehicles can shape the development and deployment of this technology in a responsible and inclusive manner [82]. By embracing a transdisciplinary approach, researchers can unlock new insights and drive paradigmatic advancements in the field of DL-AV, as well as in science and engineering more broadly [90].

4. Conclusions

In a scenario of rapid increase in scientific production on topics related to AVs and AI, the systematization of knowledge is of great value so that discoveries are enhanced and new projects are created.

The integrated bibliometric and content analysis approach enabled the identification of strategic themes (RQ1) and trends (RQ2) in DL-AV research. The findings presented in this study can benefit both experienced scholars who can gain access to condensed information about the literature on DL-AV and new researchers who may be attracted to topics related to technological development and other issues with social and environmental impacts (e.g., safety and sustainability).

Identification of motor themes and research opportunities can fuel collaboration among researchers from all areas of knowledge, integrating concepts, theories, and methods primarily from computing, environmental, and social sciences for enhancing debates on themes such as energy, legislation, ethics, and cybersecurity in the context of AVs. Another significant contribution of this study was the proposal of a research agenda and future perspectives regarding three topics: DL application in AV project design; neural networks and AI models used in Avs; and transdisciplinary themes in DL-AV. It is expected that research will advance in these areas and provide valuable contributions to individuals, organizations, and society as a whole.

It is important to state the limitations of this study. The methodology's shortcomings involve the focus on the Scopus and WoS databases considering publications from 2017 to June 2023. Despite the fact that these are high-quality, representative bases of global scientific production, it is important that future research include other recognized databases and increase the sample analyzed. Another methodological limitation is the use of only one type of software, SciMAT. This tool has proven suitable for the intended objective, but it would be of great value to have studies that complement and compare the results with other extensively used software, such as VOSviewer, while also leveraging its additional benefits, such as bibliometric data on authorship and research collaboration. Regarding the scope of the analyzed documents, this study primarily focuses on journal articles. It is crucial for future studies to incorporate recent contributions published in other scientific dissemination channels. More comprehensive approaches can be adopted, including grey literature. Finally, the methodology used in this study was centered on examining the structures of networks of motor themes with the highest degrees of density and centrality, which opens up several avenues for future research to expand the analysis of transversal, highly developed, and/or new emerging themes.

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