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A review of technology evolution and risk of autonomous vehicles

Budi Nugroho*[a], Abdurrakhman Prasetyadi[a], Cahyo Trianggoro[b], Muhammad Yudhi Rezaldi[a,c], Rabiah Abdul Kadir[d]

[a]*Research Center for Data and Information Science; National Research and Innovation Agency, Bandung 40135, Indonesia*
[b]*Research Center for Public Policy; National Research and Innovation Agency, Jakarta 12710, Indonesia*
[c]*Visual Communication Design, Faculty of Creative Industry; Telkom University, Bandung 40257, Indonesia*
[d]*Institute of Visual Informatics; University Kebangsaan Malaysia, Selangor 43600, Malaysia*

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Abstract

The development of autonomous vehicles (AVs) have become a prominent research topic; however, many survey studies focus either on enabling technologies or on isolated risk issues. This approach therefore provides limited insight into how both dimensions of AV development evolve together. The present study employs scientometric analysis of Scopus-indexed journal articles to map the knowledge base of AV technology evolution and risk. The results of the study highlight influential documents and productive countries, identify major research clusters using the log-likelihood ratio (LLR), and reveal thematic shifts across three periods (early, middle, and late). To strengthen the analytical contribution, the revised manuscript synthesizes the interaction between technology phases, dominant methods, associated risks, and corresponding research responses. The findings indicate that early AV studies emphasized autonomy and dynamics. However, there was a subsequent shift towards systems, control, and learning. Moreover, there has been an increasing convergence with risk themes such as cybersecurity, safety assessment, and anomaly detection. These findings of this study offer a more integrated understanding of the co-evolution of AV research and indicate priority challenges for the safe deployment of learning-based methods. Ultimately, the insights provided in this review offer a valuable foundation for policymakers, automotive engineers, and researchers to develop holistic strategies that concurrently address technical innovations and their associated safety or regulatory risks.

Keywords: Autonomous vehicle; AV; Deep learning; Risk assessment; Technology evolution

1. Introduction

The development of autonomous vehicles (AVs) has emerged as a major research and development priority within the automotive sector [1]. Earlier forecasts suggested that, by 2030, the reliability and affordability of AVs would reach a threshold sufficient to enable a substantial share of human driving to be replaced, thereby generating significant social and economic benefits [2]. An AV is generally defined as a vehicle capable of operating without continuous human intervention while navigating towards a predetermined destination [3]. To achieve this capability, an AV must be able to perceive its environment, predict the movement of surrounding objects, and plan a safe trajectory while avoiding static and dynamic obstacles [4]. In recent decades, advancements in sensing, control, and computing technologies have led to a substantial expansion in the field of AV research [5]. Toyota Corporation is frequently identified as a leading actor in AV patents, followed by Bosch, Denso, Hyundai, Ford Global Technologies, and General Motors. The development and patenting of core traffic control systems, such as intelligent control units, vision systems, information processing systems, and navigation-orientation systems, are essential for achieving autonomous control over vehicle movement [6]. A number of preceding studies have examined the technological development of AV. For instance, [7] predicted the development of AV patents based on AV type using social network analysis. In contrast, [8] evaluated global AV technology patents in terms of knowledge development and diffusion. Similarly, [9] conducted a comparative analysis of patents across four key technologies and the top 15 companies, while [10] reported on comparisons among the top 20 companies. As discussed in other reviews, the technology trends in AV technology, system architectures, and enabling technologies are of particular significance [11–13].

*Corresponding Author.
Email: budi045@brin.go.id.
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Despite this growing body of work in this area, the extant literature still tends to examine technological advances and AV-related risks as separate streams. Existing reviews frequently focuses on the role of enabling technologies, patent development, and public perception, while providing limited explanation of how specific technological phases generate new categories of risk and how the research community responds to those risks. The main contribution of this study is twofold. Firstly, it provides a comprehensive overview of the publication trends relevant to AV technology and AV risk. Secondly, it synthesizes the co-evolution between these two areas of research.

This present study aims to enhance understanding of the knowledge development and diffusion patterns in AV research by addressing two research questions:

1. In what ways have AV technology advances and research themes evolved over time?

2. Which risk categories emerge in conjunction with these technological developments?

2. Method

This present study employs scientometric analysis, a method that provides a broad perspective from which knowledge structures and dynamic research trends can be identified [14]. Combined with visualization tools, scientometric analysis can provide concrete insight into a research domain and its underlying evolutionary trajectories [14]. The study was conducted in consecutive stages: tool selection, data collection, data processing and analysis, visualization and presentation, and interpretation of findings [15]. Firstly, the study constructed networks through document co-citation analysis, keyword co-occurrence analysis, cluster identification, and collaboration analysis [16, 17]. A comprehensive search was conducted in the Scopus database with the bibliographic records collected in August 2022. The Scopus database was utilized as the primary database because it provides extensive multidisciplinary coverage, standardized bibliographic metadata, and compatibility with CiteSpace and Bibliometrix workflows. This choice also ensured consistency in indexing fields across all retrieved records. Nevertheless, the utilization of a single database constitutes a methodological limitation and should be interpreted as a bounded representation of the field, as opposed to an exhaustive census of all AV literature.

The original search was conducted with a focus on journal articles in English, with the subject area SOCI excluded from the analysis. The exclusion was intended to maintain a technology-oriented corpus; however, as reviewer feedback correctly notes that social acceptance and risk perception are also relevant to AV risk research. Accordingly, the present revision explicitly acknowledges the potential for exclusion of SOCI may under-representation of social and behavioral risk dimensions.

The search process can be summarized as follows: (1) the title and title-abstract-keyword fields were utilized to identify the records from Scopus; (2) restriction was made to English-language journal articles; (3) records assigned to the SOCI subject area were excluded; and (4) the resulting records were screened for consistency with the topic of AV technology evolution and risk. On August 29, 2022, this procedure yielded 269 publications, which constituted the final dataset used in the current analysis. This value is employed consistently throughout the revised manuscript.

Table 1 demonstrates the query terms used to retrieve the data related to AV technology evolution and risk. The analysis and visualization of AV publication trends, technological evolution, and risk were conducted using CiteSpace, which is appropriate for the exploitation of the knowledge base, knowledge domains, emerging trends, and their evolution as it is capable of categorizing data into different time sub-periods for longitudinal analysis [18, 19]. Furthermore, Bibliometrix in R was utilized for thematic evolution analysis to complement the network-based outputs from CiteSpace [20].

Table 1. The search strategy

Database	Query Detail Terms	Result of Database
Scopus	(TITLE (*autonomous AND vehicle*) AND TITLE-ABS-KEY (*technology AND evolution*) OR TITLE-ABS-KEY (risks)) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j")) AND (EXCLUDE (SUBJAREA , "SOCI"))	269 articles

To enhance conceptual clarity, Table 2 synthesizes the relationship between technology evolution and risk evolution observed in the scientometric results. Rather than treating both as parallel themes, the table links dominant technological emphases, associated risk categories, and the research responses that appear in the mapped literature.

3. Results and Discussion

3.1. Research trends of technology evolution and risk of AV

The distribution of 269 published articles on the evolution of AV technology and risk began with Robinson's 1986 article entitled *Applications of National Defense for Autonomous Underwater Vehicles*. Fig. 1 depicts the growth trend for this research area from 1986 to 2022. The number of publications has been observed to generally follow an increasing trajectory, with several temporary declines. The most significant decline occurred in 2014 at approximately -50%. Since 2015, the number of publications has increasingly exceeded the trend line, indicating accelerated growth in recent years. When compared with the average growth rate of modern science, which Bornmann estimates at approximately 8–9% per year [21], the annual growth rate of AV technology evolution and risk publications in this dataset is 23.94%.

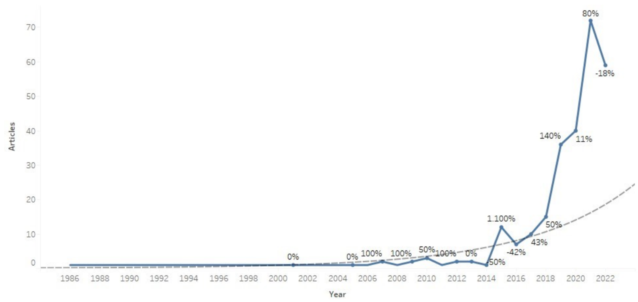

Fig. 1. Growth trend of publications on AV technology evolution and risk (1986–2022). The figure indicates a marked acceleration after 2015.

Table 2. Conceptual synthesis of technology evolution and risk evolution in AV research

Phase / thematic emphasis	Dominant methods or technical focus	Associated risk emphasis	Research response in the mapped literature	Basis in present results
Early period (1986–2005): autonomy and dynamics	Foundational vehicle dynamics, navigation, and control studies	Operational uncertainty and collision/safety concerns	Risk-aware planning and safety-oriented control concepts	Thematic evolution and early clusters
Middle period (2006–2021): systems and control	System integration, motion planning, decision making, and intelligent transportation concepts	Safety engineering, accident prevention, and reliability of autonomous operation	Simulation-based testing, control refinement, and path-planning optimization	Keyword co-occurrence, cluster analysis, and trending topics
Late period (2021–2022): learning, data, risk, and control	Deep learning, deep reinforcement learning, perception, and software-oriented autonomy	Cybersecurity threats, anomaly/intrusion risks, sensor spoofing, and data vulnerabilities	Cybersecurity mitigation, anomaly detection, and safety validation frameworks	Trend topics, discussion on risk, and software/cybersecurity clusters

3.2. Document co-citation analysis

As demonstrated in Fig. 2, the document co-citation network generated by CiteSpace, comprises 359 nodes and 947 links. The time slice was set to a duration of one year, and the top-cited publication during each slice was restricted to the most representative items. In a co-citation network, two publications are linked when they are cited jointly by subsequent publications [16]. Nodes represent cited references, while the size of the node reflects the frequency of citations and, by implication, relative influence within this research area.

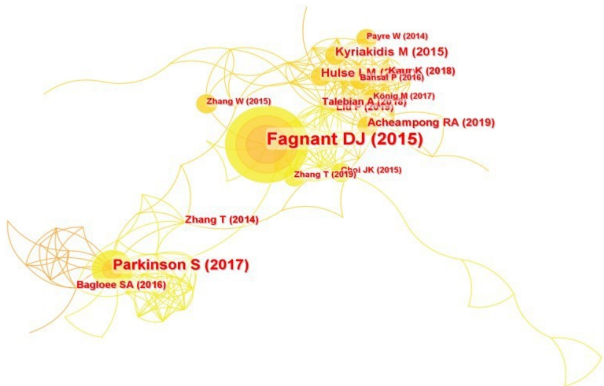

Fig. 2. Document co-citation network. Larger nodes indicate more frequently co-cited references, while link colors indicate the period in which the co-citation relationship first appeared.

As demonstrated in Fig. 2, the evolution of AV technology and AV risk have developed as an active and increasingly interconnected research area. The ten most frequently cited publications from 1986 to 2022 are presented in Table 3. It is important to note that the most influential references are not limited to core engineering problems; they also address public acceptance, national readiness, and cybersecurity. This pattern indicates an evolution in the field, from a focus on technical capability to a broader socio-technical understanding of deployment risk.

3.3. Keyword co-occurrence analysis

As illustrated in Fig. 3, the co-occurrence network of keywords has been labelled with 75% of the most frequently occurring terms. The network contains 342 nodes and 1544 links. A node represents a keyword, while a line between two nodes represents a co-occurrence relationship. The size of node reflects term frequency, and line colors indicate the time of a connection to firstly emerge [16]. Keyword co-occurrence analysis has been demonstrated to be a useful tool to demonstrate the knowledge base of a research domain as keywords provide concise summaries of article content [22]. Table 4 lists the 50 most frequently used keywords, with a total co-occurrence frequency of 3334.

Table 3. Top ten most influential documents

Author	Title	Cited Frequency	Year
Fagnant D.J.	Preparing a Nation for Autonomous Vehicles	16	2015
Parkinson S.	Cyber Threats Facing Autonomous and Connected Vehicles	9	2017
Hulse L.M.	Perceptions of Autonomous Vehicles	6	2018
Kyriakidis M.	Public Opinion on Automated Driving	6	2015
Acheampong R.A.	Capturing The Behavioural Determinants Behind The Adoption of Autonomous Vehicles	5	2019
Kaur K.	Trust in Driverless Cars	4	2018
Talebian A.	Predicting The Adoption of Connected Autonomous Vehicles	4	2018
Bagloee S.A.	Autonomous Vehicles	4	2016
Liu P.	Willingness To Pay For Self-Driving Vehicles	4	2019
Zhang T.	Defending Connected Vehicles Against Malware	4	2014

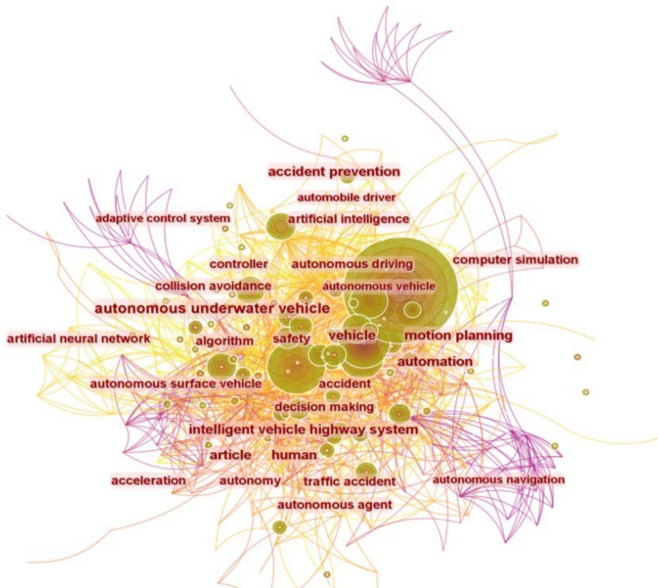

Fig. 3. Keyword co-occurrence network. The map shows how technology-oriented and risk-oriented terms co-appear within the AV literature.

As demonstrated in Fig. 3 and Table 4, the most frequent

Table 4. Most frequently used keywords

Count	Keywords	Count	Keywords
184	autonomous vehicle	11	article
38	risk assessment	10	deep learning
33	vehicle	10	behavioral research
30	accident	10	unmanned surface vehicle
29	autonomous underwater vehicle	9	car driving
26	motion planning	9	connected and autonomous vehicle
26	autonomous driving	9	autonomous agent
25	decision making	9	forecasting
23	risk perception	9	intelligent system
20	intelligent vehicle highway system	9	algorithm
17	human	9	uncertainty analysis
17	roads and street	8	automobile driving
16	automation	8	machine learning
15	navigation	7	simulation
15	safety engineering	7	risk management
13	safety	7	internet of thing
13	traffic accident	7	decisions making
13	trajectory	7	automotive industry
13	autonomous surface vehicle	6	of autonomous underwater vehicle
13	collision avoidance	6	automated vehicle
12	automobile driver	6	intelligent transportation system
12	artificial intelligence	6	optimization
11	controller	6	deep reinforcement learning
11	reinforcement learning	6	road vehicle
11	accident prevention	6	risk analysis

terms include autonomous vehicle , risk assessment , vehicle , and accident . This pattern is analytically significant as it indicates that the literature is structured around two interconnected dimensions: enabling technical capability (e.g., motion planning, decision-making, automation, artificial intelligence) and risk governance (e.g., risk assessment, risk perception, safety engineering, accident prevention). It can be thus posited that the keyword map supports the argument that AV research has gradually evolved from a capability-building agenda to a capability-and-risk agenda.

A second observation is that learning-related terms remain less frequent in comparison to that of established safety and motion-planning terms. However, these learning-related terms emerge as strategic bridge topics in the subsequent period. This suggests that deep learning and reinforcement learning are not merely new technical topics; they are also part of the field's response to increasingly complex perception, prediction, and control problems that bear new safety and cybersecurity implications.

Fig. 4 illustrates the growth of selected keywords. Risk assessment, autonomous underwater vehicles, vehicle, and motion planning show fluctuating trajectories, while autonomous vehicle and accident remain comparatively stable over time.

3.4. Clustering identification and interpretation

Following an exploration of the knowledge base through keyword co-citation analysis, cluster analysis was employed to identify knowledge-domain clusters. Cluster analysis provides a clear map of the intellectual basis of a specialization. Noun terms were extracted from the titles, keywords, or abstracts, with the most frequent phrases then used as cluster labels [16]. This present study identifies 13 main clusters, which are labeled using the Log-Likelihood Ratio (LLR) algorithm, as illustrated in Fig. 5. The network has a moderate modularity of 0.5791, indicating that it is adequately classified into loosely coupled clusters [23]. The silhouette values, as presented in Table 5, are mostly above 0.8, indicating satisfactory cluster homogeneity. The largest cluster is designated #0 and the smallest is designated #12.

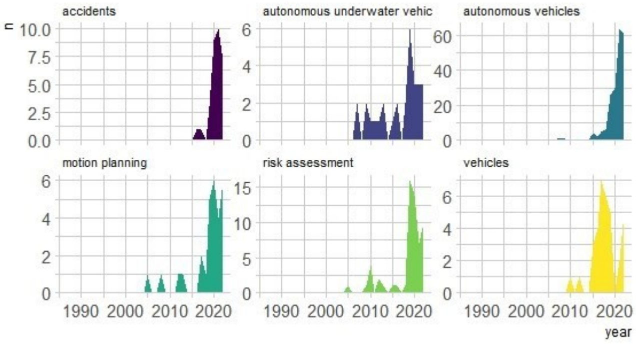

Fig. 4. Growth of selected co-occurring keywords over time. The figure indicates stable attention to *autonomous vehicle* and *accident*, with stronger fluctuation in risk assessment and motion-planning topics.

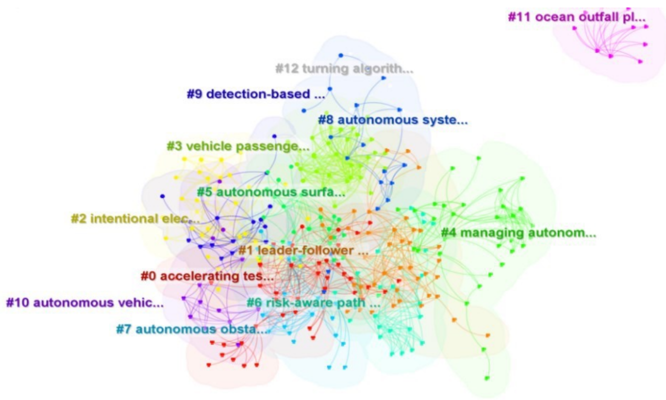

Fig. 5. Knowledge-domain clusters identified by CiteSpace. The cluster map indicates the coexistence of testing, control, path-planning, software, and cybersecurity-oriented themes.

Table 5. Top clusters labeled by LLR

Cluster ID	Size	Silhouette	mean(Year)	Label (LLR)
0	44	0.818	2016	accelerating testing
1	43	0.815	2016	leader-follower formation control
2	36	0.662	2020	intentional electromagnetic interference
3	35	0.815	2019	vehicle passenger
4	32	0.801	2015	managing autonomous underwater vehicle deployment
5	27	0.71	2020	autonomous surface vehicle
6	23	0.893	2015	risk-aware path planning
7	23	0.824	2018	autonomous obstacle avoidance
8	20	0.826	2020	autonomous system
9	19	0.809	2021	detection-based trajectory planning
10	14	0.904	2020	autonomous vehicle software
11	11	1	2013	ocean outfall plume characteristics
12	5	0.955	2018	turning algorithmization

The largest cluster (#0) comprises 44 members and has a silhouette value of 0.818. One representative publication proposes an open-source software method for evaluating AV acceleration through computer simulation, which explains why the LLR algorithm labeled this cluster as accelerating testing [24]. The second-largest cluster, labeled leader-follower formation control (#1), encompasses 43 members and a silhouette value of 0.815.

This cluster includes work on formation tracking control for underactuated autonomous marine surface vehicles under environmental disturbances [25]. Another notable cluster is risk-aware path planning (#6), which contains 23 members and a silhouette value of 0.71. This cluster includes studies oriented towards enhancing the safety and reliability of autonomous operation in coastal or uncertain environments. For instance, [26] proposed a risk-aware Markov Decision Process to support probabilistic ocean prediction in autonomous underwater vehicle operation.

From an interpretive perspective, the clustering results reinforce the co-evolution argument advanced in this paper. Clusters such as accelerating testing , detection-based trajectory planning , and autonomous vehicle software reflect the increasing software- and validation-intensity of AV development. In contrast, clusters such as intentional electromagnetic interference and risk-aware path planning indicate that risk has become embedded within technical problem solving rather than treated as an external concern.

3.5. *Discovering thematic change*

Utilizing the bibliometric library in R [20], we obtained the thematic evolution of this research area across three distinct periods: early, middle, and late. In the initial period (1986–2005), the dominant themes were autonomous and dynamics . During the middle period (2006–2021), the dynamics theme shifted toward systems , while autonomous persisted. In the final period (2021–2022), the autonomous theme underwent an expansion towards public and control , while the vehicle-related theme underwent diversification into system , risk , control , and learning. Table 6 presents a more detailed presentation of the thematic transitions.

Table 6. Thematic change

From	To	Terms	Weighted Inclusion Index	Occurrences
autonomous–1986-2005	autonomous–2006-2021	autonomous;vehicles	1.00	3
dynamic–1986-2005	systems–2006-2021	dynamic	1.00	2
autonomous–2006-2021	autonomous–2022-2022	autonomous;vehicles	0.83	201
autonomous–2006-2021	control–2022-2022	connected;logistics	0.33	4
autonomous–2006-2021	data–2022-2022	network	0.16	13
autonomous–2006-2021	risk–2022-2022	performance;neural	0.07	6
based–2006-2021	control–2022-2022	safety	0.10	2
based–2006-2021	data–2022-2022	impact	0.42	6
based–2006-2021	learning–2022-2022	sensor	0.45	10
control–2006-2021	control–2022-2022	road;data;integrated	0.24	25
control–2006-2021	vehicle–2022-2022	learning;algorithm	0.24	16

The thematic transition is significant as it demonstrated that risk is not merely an auxiliary topic appended to AV research. Rather, risk emerges more clearly in the late period when the literature becomes increasingly data-driven and learning-oriented. In other words, as AV technology becomes more software intensive and dependent on sensing, data integration, and machine learning, risk research also becomes more specialized. This shift results in a transition from generic safety concerns toward cybersecurity, detection, and validation challenges.

Deep reinforcement learning, deep learning, and the Internet of Things became the most recent topics in 2022. Meanwhile, risk-related themes such as risk assessment and risk perception were particularly visible in 2020.

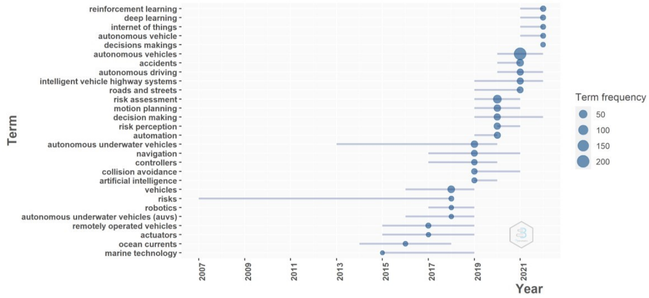

Fig. 6. Trend topics. The figure highlights the recent prominence of deep learning, deep reinforcement learning, and Internet of Things, alongside the earlier rise of risk assessment and risk perception.

3.6. *Collaborating patterns*

A total of 880 authors (98.32%) from 47 countries collaborated across the 269 Scopus-indexed documents. Fig. 7 illustrates the international collaboration network in which China is the most collaborative country (69), followed by the United States (48) and the United Kingdom (26).

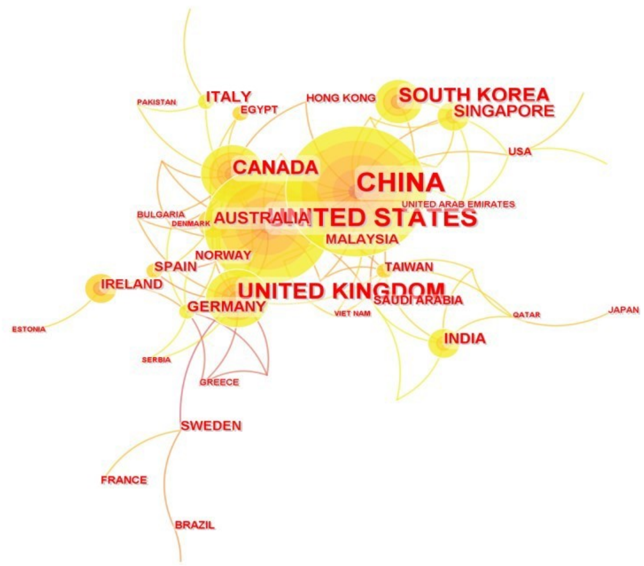

Fig. 7. International collaboration network. Larger nodes represent countries with higher collaboration intensity in the AV technology evolution and risk literature.

Table 7 shows countries collaborating on the risk-related topic. Rather than regarding these counts as mere descriptive statistics only, they can be interpreted as indicators of where risk-oriented AV research has become institutionally concentrated. China leads in collaboration frequency, which may reflect the scale of national investment in intelligent mobility, rapid urban deployment contexts, and the need to address safety and cybersecurity at scale. South Korea and Singapore also appear prominently despite smaller absolute counts, suggesting targeted and comparatively focused collaboration networks around advanced mobility testing and digital infrastructure.

Table 7. Collaborating countries on the risk topic

Countries	Years	Freq	Degree	Sigma
China	2015	69	16	1.00
South Korea	2012	19	3	1.00
Singapore	2018	11	6	1.00
Malaysia	2017	6	3	1.00
United States	2020	4	5	1.00

This pattern indicates that research into risk-oriented AV may be determined by national regulatory readiness, industrial deployment agendas, and the availability of testing ecosystems. However, the present dataset does not directly measure those institutional factors.

Table 8 delineates the countries engaged in collaborative endeavor on the technology-evolution topic. Evidence suggests that the United Kingdom, Australia, and Germany are significant contributors, which may indicate stronger concentration in systems engineering, simulation, and planning-oriented AV research. In comparison to the risk topic, the technology-evolution topic appears to be distributed across countries with established research ecosystems in the domain of automotive engineering, intelligent transportation, and robotics.

Table 8. Collaborating countries on the technology-evolution topic

Countries	Years	Freq	Degree	Sigma
United Kingdom	2012	26	12	1.00
Australia	2017	11	8	1.00
Germany	2016	8	9	1.00
Ireland	2019	6	3	1.00
Egypt	2021	4	2	1.00
Greece	2016	3	3	1.00
Bulgaria	2019	3	3	1.00
Serbia	2019	2	2	1.00
Estonia	2021	2	1	1.00
Switzerland	2016	1	3	1.00

Tables 7 and 8 indicate that the geography of AV research is not uniform across topics. It appears that risk-oriented collaboration is more concentrated in settings where deployment pressure and digital-infrastructure integration are strong. In contrast whereas technology-evolution research is more broadly associated with established engineering and mobility research hubs.

3.7. Discussion

The second research question poses an inquiry into the nature of risk associated with the development of AV technology. As demonstrated in the mapped literature, the risk discussion can be grouped into at least five categories. Firstly, technical and safety risks relate to collision avoidance, motion-planning failure, uncertain perception, and reliability of autonomous control. Secondly, cybersecurity risks concern attacks on autonomous control systems, vehicle communications, and connected software components. Thirdly, data and sensor integrity risks include spoofing, interference, and corrupted perception inputs. Fourthly, the operational and infrastructure risks concern the reliability of AV function under real-world environmental and traffic conditions. Fifth, governance and regulatory risks concern the institutional capacity required to certify, monitor, and control AV deployment. Furthermore, establishing trust between human users and automated navigation interfaces is critical, as demonstrated in the context of advanced navigation systems [27].

The development of AVs involves various cybersecurity risks, including attacks on autonomous control systems, vehicle communication channels, and software components. Defensive responses are commonly classified into security architecture, intrusion detection, and anomaly detection [28]. Various cyber threats have been reported, including falsification or modification of traffic signs, GPS spoofing, and distributed denial-of-service attacks on vehicular ad hoc networks. Physical attacks have also been discussed, such as noise-based attack augmentation, pattern-based attack augmentation, box attack augmentation, and generative adversarial attacks [29]. Another risk is direct interference with perception systems. For instance, bright light projected toward a vehicle camera may degrade model performance, while interference with Li-DAR equipment by transmitting signals at the same frequency as the scanner may force the vehicle to slow down or even stop [30]. These examples illustrate the manner in which the shift toward learning-based perception broadens the risk landscape from conventional mechanical safety towards adversarial manipulation of data and sensors.

Given these risks, it is imperative to establish a framework for regulatory governance. Regulation should encompass formal decision-making procedures and a regulatory body that ensures AV-related rules are implemented effectively [31]. Consequently, the scientometric evidence suggests that research on AV risk should be interpreted as a multifaceted problem wherein technological sophistication and risk exposure simultaneously escalate.

3.7.1. Issues and Challenges

In the original manuscript, this section tended to read as a concise narrative review detached from the scientometric results. The present revision therefore condenses the section and explicitly links each challenge to the trends identified in the mapping analysis, especially the recent rise of learning, control, software, and detection-related topics.

1. **Learning-based traffic prediction.** The increasing popularity of deep learning and deep reinforcement learning as illustrated in Fig. 6 indicates a growing interest in data-driven traffic representation. However, traffic flow remains stochastic and nonlinear, which makes prediction accuracy, generalizability, and robustness critical challenges for AV deployment [32–35].

2. **Path planning under uncertainty.** Clusters such as risk-aware path planning and detection-based trajectory planning illustrate that route generation is no longer solely an optimization problem; it is also a risk-management problem. Consequently, deep learning, imitation learning, and deep reinforcement learning have been explored to address dynamic interaction, negotiation with other road users, and urban complexity [36–43].

3. **Collision and failure-risk assessment.** The public and scholarly concern regarding AV safety remains significant [5, 44]. In response to this challenge, recent studies have

explored deep predictive models for collision risk assessment and adaptive stress testing for identifying the most likely failure paths in simulation [45–47]. It is evident that these approaches align with the field's broader movement towards software-intensive validation and testing.

4. Conclusion and Future Work

This present study provides a scientometric review of the evolution and risk of AV technology, using a dataset of 269 Scopus-indexed journal articles. The results indicate an annual publication growth rate of 23.94%, identify the most influential references and collaboration patterns, and reveal 13 major clusters labeled by the LLR algorithm. Of particular significance is the clarification that AV research has evolved not only in terms of technical capability but also in terms of risk complexity. Early work emphasized autonomy and dynamics, the middle period focused more strongly on systems and control, and the late period increasingly incorporated learning, software, and explicit risk-related themes. The study also provides a structured response to the second research question by grouping AV risks into technical and safety risks, cybersecurity risks, data and sensor integrity risks, operational and infrastructure risks, and governance and regulatory risks. This synthesis strengthens the argument that risk does not develop independently of technology; rather, it intensifies and differentiates as AV systems become more connected, data-driven, and learning-based. This present study remains subject to several limitations. Firstly, the dataset exclusively drawn from Scopus and encompassed publications up to August 2022. Secondly, the exclusion of the SOCI subject area may results in an underrepresentation of social acceptance and behavioral risk dimensions. Thirdly, the search string may omit related terminology such as self-driving vehicle or autonomous driving . It is recommended that future research extend the longitudinal coverage beyond 2022, broaden the database strategy and keyword set, and investigate how regulatory, industrial, and social factors determine the co-evolution of AV technologies and risks. The implementation of such extensions would facilitate a more comprehensive and contemporary account of the field.

Author Contribution

All authors contributed equally as the main authors. All authors read and approved the final paper.

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